2016

ACTIVELY MANAGED EQUITY MUTUAL FUNDS

- *A COMPREHENSIVE STUDY OF ACTIVELY MANAGED EQUITY MUTUAL FUNDS*
- *EVIDENCE FROM NORWAY, 2005 – 2015*

Copenhagen Business School, Summer 2016
Master's Thesis
Cand.merc. Applied Economics & Finance

Authors:
Fredrik Bøe Sædberg
Sondre Eng Henriksen

Supervisor: Tim Mondorf

Date of submission: 11.05.2016
Number of standard pages: 120
Number of characters: 252,145

Abstract

This thesis presents a comprehensive study on actively managed equity mutual funds domiciled in Norway and mainly investing in the Norwegian market, during the period from December 2005 to December 2015. By the use of a survivorship bias free dataset consisting of 47 funds, we aim to elucidate our main problem statement; do actively managed equity mutual funds outperform a passive benchmark in Norway? In addition, we aim to clarify several sub-questions in regards to our main problem statement, conducted by applying a range of well-established and recognized financial models.

The entire study is viewed from an investor's perspective to provide relevant results which are in the interest of any potential investors looking to invest in actively managed Norwegian equity mutual funds. We examine Norwegian fund managers' stock picking skills, along with market timing abilities by applying single index models. Moreover, we relax the traditional assumption of a constant risk level by introducing additional information variables to our dataset. That is, we investigate mutual fund performance in both an unconditional and conditional setting. Following the analysis of performance and abilities, we examine if the relationship between fund expenses and net performance is in accordance with theory. Furthermore, we investigate if previous well-performing funds tend to continue to perform well and if poor performing funds tend to continue to perform poorly. That is, we implement tests for performance persistence on our dataset. Ultimately, we apply the innovative measure *Active Share* to our dataset to investigate the relationship between the level of activity and performance. Furthermore, the Active Share measure helps us investigate whether funds are correctly priced and if active investment strategies are more successful than passive investment strategies.

Our results suggest that Norwegian actively managed equity mutual funds do in fact outperform a passive benchmark on average. However, there is a clear tendency that the funds' fees erase the outperformance. That is, the investors do not benefit from active management. Moreover, we do find evidence of some fund managers displaying superior stock picking abilities and of some managers displaying superior market timing abilities. However, we do *not* find evidence of both abilities being present at the same time, which would be the type of fund being most appealing to investors. On the other hand, we do find evidence of some fund managers displaying negative stock picking skills and some managers displaying negative market timing abilities. Nevertheless, these capabilities are not present at the same time. In terms of performance and fund expenses, we find evidence of the cheapest funds being the best performers on average, which is in direct contrast with theory. Furthermore, we

are *not* able to detect any pieces of evidence of performance persistence among Norwegian actively managed equity mutual funds. Hence, a strategy where an investor buys previous winners will not automatically lead to abnormal returns in subsequent periods. Similarly, an investor buying past losers would not automatically receive below average returns in subsequent periods.

When applying the Active Share measure, we find that the majority of funds claiming to be active are truly passive. Moreover, there is no relationship between the level of activity and performance. In fact, the least active funds in our sample perform better than the most active. Moreover, the most active funds seem to be the most expensive on average, which is in accordance with theory. However, looking at individual funds, this is not always true, as this implies that an investor could be in danger of paying for active management but receiving passive management. Ultimately, we find no evidence for active investment strategies performing better than passive investment strategies. In total, our results indicate that investors in Norwegian actively managed equity mutual funds do not receive the product and return they are paying for.

Table of Contents

1.0 Introduction

1.1 Background

Equity mutual funds in Norway have gained a lot of traction from the beginning of the millennium until today. The Norwegian households have become increasingly wealthier during the same period, explaining much of the increase in mutual fund popularity. As the wealth increases, people are looking for alternative investment opportunities other than the traditional savings account in the local bank. The lingering desire to add to one's pension, or only making more out of one's salary, are some of the reasons why an increasing number of Norwegians become fund investors. Especially in today's market, with record low interest rates, mutual fund investments stands out as a tempting alternative. Here, an average person, with no financial insight whatsoever, can obtain professional portfolio management, diversification benefits and easy access to global securities markets by just paying a fee. By doing this, the investors take on greater risk, but also have the potential for higher returns. However, an important question arises; do the investors get what the return they deserve? Is pricey active fund management better than its cheaper alternative; passive fund management?

Empirically, there have been conducted several studies on mutual fund performance following the introduction of the CAPM framework in the 1960's. However, as the decades have passed by, there is still no conclusive answer to whether active fund management outperforms passive fund management. Past research has found ambiguous results, leaving investors puzzled. Recently, the debate between active and passive investments has reached the media's attention, moving the debate from academic papers onto the public scene of tabloid newspapers and prime time news broadcastings. Government entities have taken the interest, and especially the Scandinavian countries are starting to put active fund management under scrutiny. Active funds have been heavily criticized, from both governments and media, for not being active enough, and thus not providing the service they are charging their investors.

In this study, we seek to investigate the matter further. We are performing a comprehensive study of actively managed equity funds in Norway, searching for evidence of significance outperformance from active funds during the last decade. Throughout the study, we aim to answer the most important questions from an investor's point of view. Specifically, we test the fund managers' micro-forecasting skills and macro-forecasting skills. In other words, we test their stock picking abilities and their market timing skills by the use of well-established and highly praised financial models. Moreover, we investigate if there is evidence of performance persistence among the active Norwegian funds; do the winners continue to win and do the losers continue to lose? Of equal interest, we test whether fund performance and obtained returns can be attributed to fund manager's skill, or if the performance is simply due to luck. At the end of the study, we look deeper into how active Norwegian mutual funds truly are, to shed some light on the mentioned debate that is attracting publicity in the media. Following these analyses, we also investigate whether the level of activity matches the fund expenses and performance, to see whether investors receive what they are entitled.

Previous research on Norwegian mutual funds has been scarce, and the industry is relatively unexplored. The most notable contribution came from Gjerde & Sættem's study in 1991, along with Che, Norli & Priestly (2009) and Sørensen (2009). The absolute majority of the research on the field has been performed on the US market, which is not surprising taken the size of the US market into consideration. Moreover, the fact that the Norwegian market is smaller than the U.S market could mean it is under less scrutiny, and market imperfections could prove to be more prominent. Thus, it is in direct contrast to the Efficient Market Hypothesis – the theoretical foundation for our study.

1.2 Problem Statement

The focus of this study is to elucidate whether active management accomplishes its primary goal:

Do actively managed equity mutual funds outperform a passive benchmark in Norway?

To fully answer the problem statement, and perform a comprehensive study of the actively managed Norwegian mutual fund market, the following sub-questions will also be elucidated:

- ***Are actively managed funds able to display superior stock picking abilities?***
- ***Are actively managed funds able to demonstrate superior market timing skills?***
- ***Is there any evidence of performance persistence among active Norwegian equity mutual funds?***
- ***Do investors investing in Norwegian equity mutual funds get the product and return they are paying for?***
- ***Are Norwegian equity mutual funds fairly priced?***

1.3 Contribution

Our study will be a great contribution to the limited research and literature conducted on Norwegian mutual fund performance. In addition to being a classic performance study, the study will complement previous research, such as that of Sørensen (2009). Previous research usually applies one model, while we apply several models, both in an unconditional and a conditional setting, to investigate the Norwegian equity fund market. We firmly believe that this provides a complete picture of the market, as it makes it possible to analyze the results from different models in light of each other.

Unlike previous studies, we investigate actively managed mutual fund performance across different time horizons to determine if active management is preferable in shorter time horizons. Specifically, we look at a 5-year horizon, in addition to the original 10-year horizon, in order to answer this question. Moreover, we put Norwegian mutual fund performance during the financial crisis under scrutiny to analyze if active management is preferable during recessions. Ultimately, we compare the results from the financial crisis with results from general market downturns, to determine if the performance during the financial crisis is coinciding with negative market evolvements. By performing these analyses, we believe that we fill a gap in previous studies; previously the focus has been unilaterally on overall performance, not periodic performance.

The most significant contribution comes from our introduction of Active Share on the market. As far as our knowledge goes, previous Active Share research on the Norwegian market has been concentrated on the relation between Active Share and net alpha. We take the research one step further, by looking at the relationship between Active Share and Total Expense Ratio, to investigate whether Norwegian investors get the product they are entitled. Moreover, we expand previous research by using the Active Share to identify investment strategies. Applying this model enables us to investigate the effect of investment strategies on performance; are some strategies better than others?

1.4 Delimitations

There are more than 460 000 funds available to investors in the global market today, covering all types of different investable funds. To properly elucidate our main problem statement, the scope of this study, and our sub-questions mentioned above, we introduced a range of selection criteria. Ultimately, we ended up with a sample consisting of 47 Norwegian actively managed equity mutual funds with a minimum lifespan of 2 years. We acknowledge the existence of the endless number of investment opportunities, both within mutual funds and alternative instruments such as ETFs. However, this study is entirely focused on equity mutual funds investing in the Norwegian market. A fund investing more than 20% of its assets in foreign businesses is not regarded as a Norwegian equity fund. This delimitation facilitates the use of one single benchmark for all funds. A natural consequence of our selection criteria is that this study only analyzes and evaluates a small portion of the existing funds in the Norwegian market. Moreover, this study only covers the period from December 2005 through December 2015.

Regarding the models used, several traditional models, all widely applied in current literature on the field, have been carefully chosen. Moreover, the models are selected based on the characteristics of the sample used. An underlying assumption behind this study is that a single-index model can explain a particular fund's return. That is, the excess market return constitutes the only factor in our regression models. To improve the traditional models, we have included a set of information variables, which makes it possible for us to analyze fund performance in an unconditional and conditional setting. Hence, this study ignores other academics' proposed improved models with additional explanatory variables such as the Fama-French three-factor model (1993) and Carhart (1997).

To determine the level of activity within a fund, Cremer & Petajisto's quantitative measure Active Share has been applied. Hence, other measures of activity, such as trading frequency, are ignored in this study. As a consequence, dependent on the investor's opinion of activity, we cannot rule out that a fund might be active even though we have defined it as a passive fund based on our definition.

1.5 Structure of thesis

The remainder of the study is organized as follows; Section 2 provides a description of active and passive management. Furthermore, it provides an introduction to the Norwegian mutual fund industry, along with the main figures and current regulations. Section 3 is a review of previous research and literature that we find relevant to our study. They are included to create some expectations to our results and to form a basis for comparing our results with previous findings. Furthermore, Section 4 provides an in-depth presentation and discussion of the theory used in this study, including the theoretical foundation on which the study is built, performance measures and the issue of survivorship bias. Section 5 deals with the methodology and describes the construction of our data sample. Moreover, in section 6 we test our econometric hypotheses and present our empirical findings. Our results are further analyzed and summarized in section 7 before we reach a conclusion which is provided in section 8. Ultimately, in section 9 we provide suggestions for future research.

2.0 Mutual funds in Norway

This section provides an introduction to the topic of active management and the Norwegian fund market. It also includes a presentation of the composition of the Norwegian market in terms of size, regulation and legal framework.

2.1 Active vs. passive management

As our overall objective is to analyze whether active management adds value or not in the Norwegian fund market, it is essential to define the characteristics of active and passive management. Thus, before we dig deeper into the market in which this study is centered, it is a prerequisite to establishing delineation between actively and passively managed funds. As a common trait, irrespective of whether they are actively or passively managed, mutual funds provide three primary advantages to the investor compared to investing in single securities. These are diversification, professional portfolio management and easy access to global securities markets (Bodie et al., 2009). Nevertheless, the similarities between the two categories of managed products end here.

Active mutual funds seek to profit from identifying undervalued securities and by altering portfolio weights following amended market conditions. In contrast, passive funds aim to track a given benchmark portfolio, which implies that the return characteristics will be similar to the reference index less the costs incurred. Since the investment strategy of a passive mutual fund does not utilize resources to identify undervalued securities or to alter portfolio weights, the Total Expense Ratio (TER), described in section 5.8, will usually be much lower compared to those incurred by actively managed funds. In other words, active management has some costs to cover to be perceived appealing by investors. Hence, it follows that the predictive content of the forecasting manager must be sufficiently large to outperform the market and overcome the costs related to conducting such forecasts.

The brief presentation above does not account for the endless number of complicated strategies employed by mutual funds, as there is a continuum of potential strategies available for the two types of mutual funds. There are also several products involving strategies placing themselves in-between active management and tracking benchmarks. An example is Exchange Traded Funds (ETF) which, as opposed to mutual funds, trade like a common stock on a stock exchange. Thus, they experience price changes throughout the day as they are bought and sold. For the average investor, this could be an attractive alternative to the above mentioned mutual funds. However, as the scope of this study focuses on mutual funds, we will not discuss these alternative products further.

Moreover, whereas the overarching premise of active funds is to outperform the market, passive funds seek to track the market. Where the line is drawn between active and passive funds is somewhat arbitrary and open for discussion, especially when considering that some active funds have been accused of being closeted index funds[1] (Elton et al., 2011). Nevertheless, the view employed in general is that once forecasts are introduced into the strategy, we are dealing with an actively managed fund. However, in this study, the active share method (described in section 4.6) is used to determine if a fund is actively managed or not.

2.2 The Norwegian mutual funds defined

A mutual fund is deposits pooled and managed by a company on the behalf of investors, according to a defined investment strategy (Bodie et al., 2009). Hence, a mutual fund is an investment opportunity to access professional money management and diversification. These are two of the advantages of the categories examined of which were described above.

If a new deposit is placed in the fund, the fund's assets under management (AUM) increase by the amount of the investment. In remuneration, the investor receives an ownership share in the portfolio of the fund. The ownership share applies to all stocks in the portfolio. This means that even a small investment can be spread over any number of stocks. Hence, the investment will be well diversified.

All Norwegian mutual funds traded on the Oslo Stock Exchange (OSE) are open-end funds; i.e. investors can buy and sell shares of any fund at any time. In addition, there are no restrictions on the amount of shares the fund will issue. Hence, if demand is high enough, the fund will continue to issue shares no matter how many investors there are. Retail banks also offer customers to invest in mutual fund as an over-the-counter transaction. The ownership system allows for a high degree of flexibility when it comes to entering and exiting the mutual funds, which can be done through simple trades online.

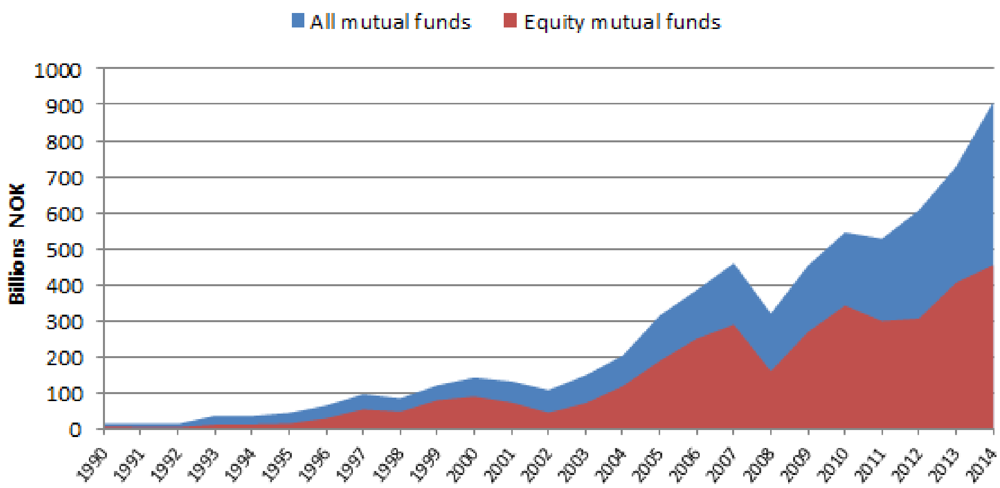
By the time of 1982, there was only one single mutual fund on the OSE, and as presented in Gjerde & Sættem (1991) the market value of Norwegian equity mutual funds was a meagre 290 million NOK. However, the number of funds and assets under management grew rapidly during the 1980s and the 1990s. The trend continued into the new millennium, without loss of momentum. The continuous growth is mainly due to several enhancements in the Norwegian economy. During this period of time

[1] Funds charging fees as if they were actively managed, but invest as a passive index fund.

the Norwegian economy as a whole has grown severely with an average GDP growth just below 3 %. The petroleum industry has played a great role for the enhancements in the economy. However, in this study, we conduct performance analysis on actively managed Norwegian funds. Thus, all investigated funds are exposed to the same economic environment.

The latest reported figures from the end of 2014 states assets under management for the total industry at 907 581 million NOK, where 455 564 million NOK of this is from equity mutual funds (SSB, 2015). Thus, mutual equity funds grow significantly with an increase of 12% in 2014 and 32% in 2013. The evolvement in assets under management from the 1990s to 2014 can be seen in Figure 2.1 below.

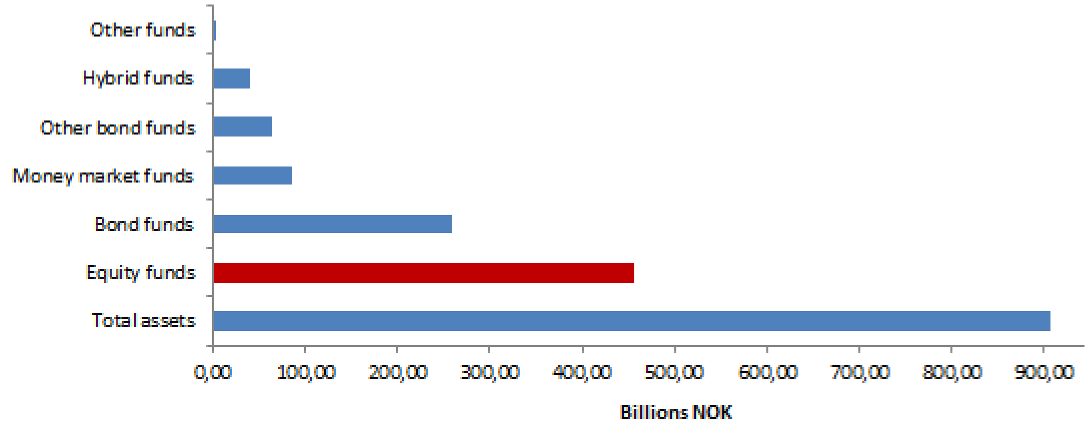
Figure 2.1: Aggregated assets under management (Billion NOK), Source: SSB.no



The Norwegian fund industry is divided into five categories of funds:

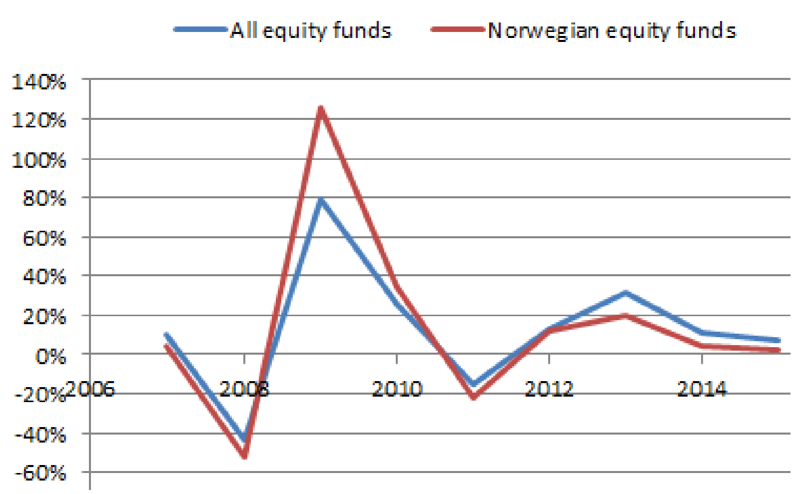
- Equity funds: at least 80% of the capital has to be invested in equities.
- Bond funds: which invest in long-term debt securities and bonds, typically maturing in more than one year.
- Money market funds: investments in short-term debt securities, usually maturing in less than a year.
- Hybrid funds (combination funds): which can invest in both equities and bonds.
- Other funds: funds which do not fall in under any of the other categories.

Figure 2.2: Sum of assets by fund type (Billion NOK), Source: SSB.no



In addition, these categories can be divided further into several subcategories. The main category of interest in this study is Norwegian equity mutual funds. As can be seen from the figure, equity funds account for approximately half of the total fund industry, and is steadily growing along with the total assets in the market. However, since 2000, there has been a negative flow for Norwegian equity funds (Sørensen, 2009). Investors have decreased the share invested in Norwegian equity funds significantly, and have rather sought the diversification benefits associated with equity funds with an international mandate[2]. In 1994, 92% of the capital invested in equity funds, were funds with a Norwegian mandate. However, this figure decreased drastically to 20% by 2015 (VFF, 2016). Nonetheless, equity funds with a Norwegian mandate are still substantial with assets under management estimated to nearly 87 billion NOK in 2014.

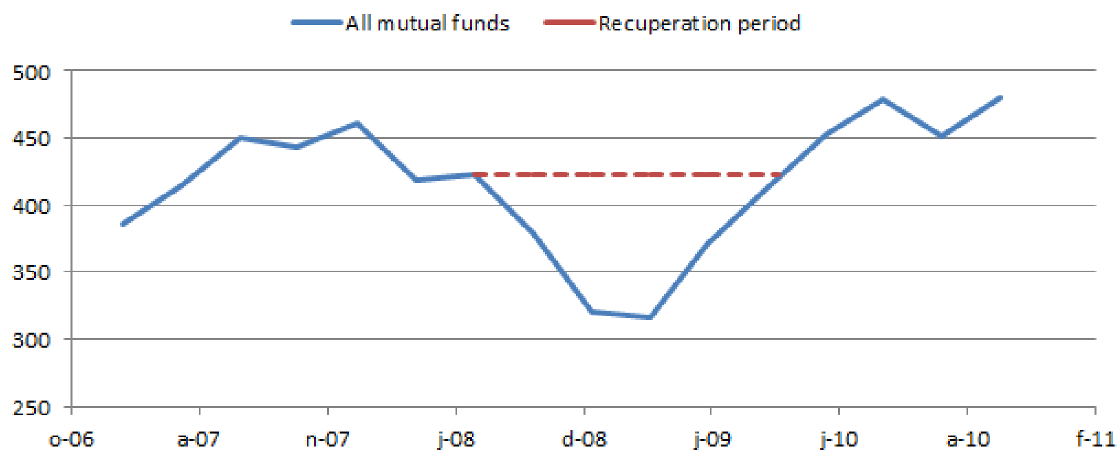
Figure 2.3: Yearly change in equity funds. Source: VFF.no



[2] Funds considered here are Norwegian registered funds with minimum 20% of assets invested internationally.

Furthermore, which can be seen from Figure 2.4, a severe reduction in assets under management occurred from the time the financial crisis struck in September 2007 to June 2009. This is not necessarily due to investors withdrawing their assets, but because of negative returns in relation to the crisis. The impact of the crisis was substantial, reducing the value of the funds by almost 30% at its lowest point relative to its all-time high value in late 2007. However, it should be mentioned that investors not withdrawing their assets during a downturn period also show that they believe in enhanced future performance. The assets under management were recuperated again in late October 2009 after several measures were conducted. Such measures involve bank rescue packages and other regulations made by the authorities. We will test the financial crisis' impact on the Norwegian mutual fund performance in section 6.8.2.

Figure 2.4: AUM during the financial crisis, 2007-2010 (Billions NOK). Source: SSB.no



2.3 Drivers behind the increase in fund popularity

As we pointed out in section 2.2 above, there has been a major increase in fund investments in the Norwegian market. Why do people invest their money in active management? In the following two sub-sections, we try to elucidate this question by looking at two of the major reasons for why active management is an attractive investment product, namely financial innovation and human behavior.

2.3.1 Financial Innovation

One of the primary drivers behind the increase in popularity for active fund management is the recent financial innovation. One does not need to look further back than the beginning of the millennium to discover massive changes in the financial world. The rapid technological innovation is perhaps the single-most important reason behind the financial innovation; private investors are now able to trade whichever securities they desire, from wherever they desire, as long as they have an internet connection. The increase in availability has led to a supply of a wide range of funds, as well as other instruments, all with different risk-levels, investment strategies, target markets, etc. to fulfill the increasing demand from private, corporate, and institutional investors.

Another reason for the increased availability is governmental deregulations, making alternative investments in financial markets more attractive for the average investor. An example is making the tax regulations more lenient for capital gains. In Norway, the current government decided to reduce the tax level on capital gains from 28% to 27% in 2014[3]. Recently, they decided to continue the trend, and reduced the tax level to 25% in 2016[4]. In other words, for each unit of money a Norwegian domiciled investor earns on his financial investments, the investor keeps a larger percentage of the surplus, which increases the incentive to invest in capital markets. On the other hand, following the financial crisis in 2007, there has also been an increase in governmental regulations on other areas within the financial world to avoid another global recession. However, the majority of these rules comprises of transparency laws and increased reporting requirements, which has a larger impact on the financial institutions rather than the private and corporate investors.

Although the financial innovation has been beneficial for most investors, it has also been prone to critique from financial heavy-hitters. Paul Volcker, a respected American economist, claimed that “there is little correlation between the sophistication of a banking system and productivity growth[5].” Besides, he said that “there is no neutral evidence that financial innovation has led to economic growth[6]”. Moreover, some experts also blamed the financial innovation for the financial crisis in 2007.

2.3.2 Human Behavior behind fund investments

Another primary driver behind the increased popularity of funds is the behavior and rationale behind the investments. People in Western Europe, and especially in Norway, have enjoyed increased wealth during the recent decades. In line with the growing wealth and the financial innovation, people are looking for alternative long-term savings with the possibility of a better return than the traditional savings accounts. With record low interest rates, regular savings are less attractive. Thus, fund

[3] https://www.regjeringen.no/no/aktuelt/regjeringen-varsler-veksttiltak-for-nari/id725998/ - downloaded 28.04.2016
[4] http://www.skatt.no/2015/10/07/de-viktigste-nyhetene-i-statsbudsjettet-2016/ - downloaded 28.04.2016
[5] http://uk.reuters.com/article/usa-economy-volcker-idUKN2029103720090220 - downloaded 28.04.2016
[6] The Times of London, ”Wake up gentlemen, world’s top bankers warned by former Fed chairman Volker”, 2009.

management is an attractive alternative for people looking for alternative saving methods. By utilizing active fund management, an average person, with no knowledge of financial markets, can obtain professional diversification benefits and access to global markets by paying a fee. The promise of abnormal returns is intriguing for Norwegians, and as discussed in section 2.2 above, has led to an increase in fund investments.

The pension is another major reason for people to invest in funds. It is well-known that humans live longer than ever, which implies higher living costs for the average person. A study on Norwegian pension behavior by Dybvik & Simonsen (2015), proposes the "Hypothesis of Human Lifecycle", which indicates that humans tend to prefer a smooth consumption through their lives. Moreover, the study claims that Norwegians prefer to save for their retirement during their working years. The traditional government pension plans often fail to sustain the same way of living as the payments are too low, creating an increased demand for private pension savings through funds. Moreover, "The Norwegian Pension Reform" claims that every individual is responsible for the increased longevity, leaving more of the responsibility of fending for their retirement in the hands of each individual[7]. All the factors mentioned above are main reasons behind the increase in popularity for actively managed funds.

2.4 Regulations

As Norway is a member of the European Economic Area (EEA), most Norwegian funds are subject to the same regulations as rest of Europe. This entails following the Undertakings for Collective Investment in Transferable Securities Directives (UCITS). First adopted in 1985, the current directive as of 2016 is the UCITS V (2014), launched with amendments from the UCITS IV (2009). The primary aim of this legal framework is to improve the effectiveness of the internal European investment fund market. In order to enhance the effectiveness of a combined European fund market, the focal points of the harmonized legislation is, among other things, to assure a decent consumer protection as well as to enable a better supply of fund products across member state borders (EU Directive, 2014).

The UCITS V introduced new rules on UCITS depositaries, such as the entities eligible to assume this role, their tasks, delegation arrangements and the depositaries' liability as well as general remuneration principles that apply to fund managers (Ibid). If funds do not act in agreement with the UCITS directive, they are prohibited from being traded freely across Europe. Additionally, Norway has a legislation called "Verdipapirfondloven" (mutual fund act) protecting fund investors by regulating mutual funds. UCITS

[7] http://www.kapitalvekst.no/pensjon/kt-sparevilje-til-pensjon - downloaded 28.04.2016

and “Verdipapirfondloven” are similar and complementary in several ways, especially when it comes to diversification. Further, we find it a prerequisite to highlight three key features of the UCITS-directive:

The UCITS states that a fund must invest in at least 16 different securities[8], by which one security cannot exceed more than 5% of the fund’s total value. However, as stipulated by Article 52 § 2, member states may raise the 5% limit to a maximum of 10%. Norway is among the countries that have utilized this clause. Moreover, for single securities accounting for more than 5% of the total fund value, these securities aggregated cannot exceed 40% of the total fund value. This rule is commonly referred to as the “5/10/40-rule”.

Second, Article 52 § 5 states that the cumulative investment in transferable securities and money market instruments issued by market participants belonging to the same sector may not exceed 20% of the fund value. The purposes of the legislation are to incentivize and secure risk diversification among the holdings of UCITS funds. This rule is particularly important concerning specific market downturns such as those experienced by the financial sector in the recent financial crisis.

Third, regarding the securities available for investment, a UCITS fund is obliged to invest in securities that either is or within the following 12 months will be listed on an exchange or authorized market place. Nevertheless, in agreement with Article 50 §1 and §2, a maximum of 10% of the fund value can be invested in non-listed securities. Approved securities include stocks, money market instruments, bonds, shares of other funds, as well as derivatives.

Also, it should be mentioned that investing in funds carries some tax benefits. Parts of the gain from equity funds are tax-free, as the tax is paid only on capital gains above the so-called shielding rate. Practically, the shielding rate will be equal to the risk-free rate you can get in your bank. Gains above this rate are taxed at 27% (25% from 2016). However, this taxation is only present when you realize the gains. Similarly, losses are tax deductible at the same rate when realized. Furthermore, investors have to pay wealth tax corresponding to the market value of their investment in the fund at the end of the year. The tax is paid for the year which the tax applies. Lastly, dividends are not taxed to avoid any double taxation, also being the reason why funds are exempt from taxes.

[8] In practice, a UCITS fund often holds a larger number of assets than the minimum of 16.

3.0 Literature review

This section presents the key contributions to the rich and protracted stream of academic research on active mutual funds. The reason behind including the academic research is to create some expectations to our results and to form a basis for comparing results. The measures applied in previous research are not necessarily the same we use in this study. However, we find the actual results from previous research interesting for comparison reasons. Additionally, the empirical findings in the U.S., Scandinavian, and Norwegian markets are introduced. The debate on active investments has received great attention in both financial and mainstream media.

With a vast collection of research on actively managed mutual funds present, the research is introduced in different themes. The themes are relevant directly for this study and characterize a shift in the focal point of the research, going from a focus on the performance of active mutual funds as a group, to the performance persistence of individual funds to finally attempting to separate results based on skill from pure luck. The research has been selected from quotations and the publication it appeared in, as well as the linkages to the methods used in this study.

3.1 Framework / historical performance

After the introduction of the CAPM, several important contributions to portfolio performance measures have been added. Treynor (1965), Sharpe (1966), and Jensen's alpha (1968) are the ones that have gained the most traction, with Jensen's alpha being the most praised because of its favorable characteristics. Being an absolute measure of portfolio performance derived directly from the CAPM, Jensen's alpha is easily understandable and easily communicated to investors, which solves the major issue with ratio measures such as Treynor and Sharpe. The performance ratios suffer from the need of comparison across different portfolios to provide useful information. By regressing a portfolio's excess returns[9] on the excess return on the market, Jensen's alpha facilitates comparison between funds versus returns predicted by the CAPM. Despite its favorable characteristics, Jensen's alpha is prone to criticism. The most prominent critique of Jensen's alpha is Roll (1978), who heavily criticized the measure of being flawed due to the rigid assumptions behind the CAPM. Roll especially criticized the premise of a market portfolio, which in practice is impossible to identify. Thus, the alpha is too sensitive to the choice of market proxies.

[9] Fund/portfolio return in excess of the risk free rate of return.

Along with Jensen's alpha, other academics have tried to improve the Treynor ratio and Sharpe ratio to mitigate their disadvantages. Sortino (1983) introduced the Sortino ratio, which is an improvement of the Sharpe ratio, where harmful volatility is differentiated from general volatility. However, the Sortino ratio still suffers from being a ratio and hence difficult to interpret by itself. To address this problem, Modigliani & Modigliani (1997) introduced the M^2, which is a transformation of the traditional Sharpe ratio. The M^2 quantifies the excess return an investor gets from holding a fund opposed to a benchmark index and is thus easily understandable by itself.

Fama (1972) published a paper where he identified two ways an investment manager can outperform the market through forecasting skills. The first way is through forecasting price movements of individual assets, which Fama defined as "micro forecasting". The second way is through forecasting price movements of the stock market as a whole, described as "macro forecasting". In other words, by displaying superior stock picking skills, market timing abilities, or both, an investment manager can successfully outperform the market. Hence, this serves as a direct critique of Jensen alpha, as only the stock picking ability will be picked up in the regression. Treynor & Mazuy (1966) addressed the issue and proposed an extension of the Jensen regression in order estimate the market timing ability properly.

Jensen's alpha has also been criticized for assuming a stable beta, or in other words, a constant risk level. Ferson & Schadt (1996) proposed the application of a conditional model, where the beta estimate is allowed to vary over time. In their conditional model, a vector of some lagged predetermined publicly available information is included in the original, unconditional, Jensen regression. Hence, by considering variations in interest rates, dividend yields and quality spreads in the corporate bond market, Ferson & Schadt claimed to obtain a time-varying risk level which provided a more realistic measure of performance.

A reoccurring issue when measuring fund performance is the omission of non-surviving funds, which is commonly referred to as "survivorship bias". Malkiel (1995) has performed a study on survivorship bias and found evidence of an upward bias of the overall performance measure of funds because the only survivors are high performing funds. Rohleder et al. (2010) supported Malkiel's findings and argued that by omitting defunct funds, one would lose out on critical performance data.
All of the abovementioned literature will serve as a framework for our study, and thus be discussed and explained in greater detail later in the theory section (section 4).

3.2 Identifying the best mutual fund performers

Throughout the research on mutual funds, academics have tried to identify if some of the mutual funds stood out from the underperforming group, and continuously succeeded in delivering an excess return to their investors. To investigate this matter, the persistence of the returns to investors has been examined in increasingly elaborate ways.

Henriksson (1984) examines a data set consisting of 116 open-ended American mutual funds in the period 1968-1980 using the CAPM undertaking market timing strategies as used in Henriksson & Merton (1981). The model assumes the investment manager to choose among discretely different systematic risk for the fund, and that he chooses two targets of risk. The author identifies no evidence supporting the hypothesis that investment managers can forecast substantial changes in the market or that it is necessary to model for more than two levels of systematic risk. The study also implied that funds that earn a superior return from stock selection also seem to have negative market timing ability and performance.

Elton et al. (1993) examine a sample consisting of 143 American mutual funds in the period 1965-1984, using both the Fama-French three-factor model and the CAPM. The authors demonstrate that the results are affected by the particular performance measure being used. Additionally, a significant correlation between the returns in two successive periods is identified. However, this level of performance persistence is concentrated among the poor-performing funds.

In a study of performance persistence for American mutual funds from 1974 to 1988, Hendricks et al. (1993) conclude that the relative returns of mutual funds are persistent. The results are based on mainly growth-oriented funds in a short-term perspective, and particularly in a one-year horizon. Moreover, they test an investment strategy of selecting the relatively best performing funds each quarter, based on returns in the previous four quarters. However, this approach leads to only marginally better performance than the market benchmark indices, with costs related to the management not yet accounted for. In agreement with Elton et al. (1993), the authors identify funds with a poor performance in the most recent year continue to generate relatively poor returns in the short term. Once again, the persistence of the poor-performing funds is higher than that of the good performing funds. Furthermore, the study utilizes the “hot hands‟ and “cold hands” terms to describe the persistent inferior and superior performers, respectively, stating the “cold hands” being more inferior than the “hot hands” are being superior.

To sum up, the academic consensus on performance persistence is far from unambiguous. It has been shown that the empirical findings depend highly on the performance measure of return selected, as well as potential biases in the data set. Nevertheless, it seems evident that identifying funds with consistently inferior performance is easier than identifying consistent top performing funds.

3.3 Skillful management or just pure luck?

The question whether an outperformance of the market is due to a skilled management or just pure luck has been the focus of several recent studies. Thus, the research has shifted from focusing on consistency in the performance by attempting to distinguish luck from skill.

In a study of 935 UK equity funds, Cuthbertson et al. (2008) examine returns in the period 1976-2002, to estimate the influence of luck on the funds' over- and underperformance. The test is conducted by applying the "bootstrapping-method (described further in section 4.3.6). Their study reveals the existence of outperforming abilities among a small number of top performing UK equity mutual funds. However, for the poor-performing funds, the study rejects the hypothesis that the managers are merely unlucky, and hence, the authors infer these funds demonstrate "bad skill". For the majority of funds with superior performance, the abilities can be attributed to "good luck". Additionally, the study underlines the difficulty of isolating these funds, even when they have a long data history. Hence, the authors conclude that it is extremely challenging for the average investor to pinpoint individual active funds demonstrating genuine skill, by looking at their complete track records. Finally, it appears that previous outperforming portfolios cannot be identified ex-ante, whereas previous underperforming funds persist.

Kosowski (2006) examined U.S. domestic equity mutual funds in periods of recession and expansion from 1962 to 2005. The results show mutual fund underperformance documented in the literature stems from expansion periods, and not recessions. During expansion periods, funds tend to have statistically significant negative risk-adjusted performance. The results imply that several unconditional performance measures undervalue the additional value added by active fund managers in times of recession when investors' marginal utility of wealth is high.

In a study of mutual fund data from 1984 to 2006, Fama & French (2009) identify fewer managers were generating a substantial positive return than would be expected from luck. Furthermore, the historical performance of the top funds is concluded to be approximately what should be expected from the extremely lucky funds in a world where the true alpha is zero for all funds. Alpha equal to zero implies that the management adds no value to the return obtained by investors. The authors' estimate of the true alpha is close to zero even for the top three percentiles of historical performers, and negative for the vast majority of actively managed funds.

Cremers & Petajisto (2009) introduce the Active Share Measure and find empirical evidence for being able to predict mutual fund performance. After changing focus from return data to mutual fund holdings, 2,026 U.S. mutual funds are tested in the period 1980-2003. Being pioneers in this field of study, the authors include the weighted holdings of the funds in the analysis. Instead of merely focusing on the performance generated by the funds, Cremers & Petajisto also analyze what measures the fund has taken to outperform the benchmark. They find a consistent and significant average outperformance of 1.26% between the most active funds and conclude that their findings mean that there is some inefficiency in the market that can be exploited by active stock picking. This study will be further described in the theory section (4.6), where Active Share is introduced.

To sum up, the previous studies conducted show that:

1) In general, mutual funds fail to outperform their benchmarks consistently after costs are deducted.
2) Previous outperformance does not seem to correlate with future outperformance.
3) There is some correlation between past underperformance and future underperformance.
4) To distinguish good performance based on skill from good performance based on luck is an important challenge.

For the independent investor, the general implication of the rich empirical research is that it is extremely challenging to identify funds that will deliver good, persistent performance in the future. Even finding a fund that can consistently cover its cost is a difficult task, with no proven solution. However, as proposed by Cremers & Petajisto, active Share has proven to have significant positive correlation with outperformance in initial studies. Nevertheless, it cannot be used as a standalone method for choosing funds. Still, it allows the investor to understand the actual investment activities of the funds.

3.4 Empirical findings in selected markets

3.4.1 Empirical findings in the U.S. fund market

The pioneers of portfolio performance measurement conducted their studies in the U.S. mutual fund market. Since the 1960s, there have been numerous studies on the topic. However, there is still no conclusive and sustainable evidence in which fund managers do possess forecasting abilities. Jensen (1968), Treynor & Mazuy (1966) and Henriksson (1984) all failed to reveal reliable results supporting the fund managers' abilities to outperform the market. Jensen (1967) was only able to find one single statistically significant positive fund, out of 115 in his study. Similarly, Treynor & Mazuy (1966) discovered 1 out of 57 funds demonstrating statistically significant market timing ability. Henriksson (1984) was able to find 3 out of 116 funds presenting significant macro forecasting skills when he utilized his model.

In more recent studies, Ippolito (1989) was able to identify 12 out of 143 funds with significantly positive alphas in the sample period 1965-1984. This evidence suggested a handful of fund managers demonstrating superior stock picking skills. However, the finding was later discarded in the paper by Elton et al. (1993). In this study, the authors correct for the fact that Ippolito (1989) used a faulty S&P 500 benchmark when examining funds investing in none S&P 500 stocks. Hence, they concluded the findings to be reverse. Furthermore, Lee & Rahman (1990) also identify some evidence of micro forecasting skills, as well as presenting significant findings of market timing abilities in 17 out of 93 funds in their sample. However, quite the opposite, Goetzmann, Ingersoll, and Ivkovic (2000) utilizing an adjusted Merton & Henriksson model, found no proof of market timing abilities among American mutual fund managers. That is, no consensus has yet been reached on the subject.

Early studies directed their attention to investigating whether fund managers possessed some micro or macro forecasting abilities. However, in later years, academics have extended this investigation to examine if there exists any persistence in the performance. The phenomena of "hot hands" and "cold hands", as described in section 3.2, have received much attention. There has been carried out many studies on the topic in the American market mainly. Moreover, Grinblatt & Titman (1992) presented evidence of persistence among good performers, whereas Carhart (1997) documents persistence among bad performers, suggesting the "cold hands" phenomenon is present. Malkiel (1995) corroborate both aspects and presents evidence of persistence both among good and bad performers.

3.4.2 Empirical findings in the Scandinavian fund market

As shown in the previous section, the literature on fund performance in the U.S is vast and extensive. However, this has not been the case for the Scandinavian market where the number of studies has been relatively few. Still, there exists no evidence of management's forecasting abilities. Compared to the American market, past studies on the Scandinavian market exhibit varying results of managers' skills.

For the Danish market, Christensen (2003) has conducted a study on Danish mutual funds between 1996 and 2003. According to Christensen, 42% of the Danish fund managers exhibited significantly negative performance while half exhibited neutral performance. However, it was proven market timing ability amongst 14% of the funds, but as only 8% showed outperformance, positive market timing does not necessarily entail positive alpha (stock picking). Additionally, there was no evidence of performance persistence.

In an analysis of the performance of 150 Danish funds in the period 2002-2008, the Danish Central Bank concluded that the investors do not benefit from the economies of scale of mutual fund investing. Instead, the mutual funds exploit the cost advantages of managing a large asset base. Additionally, the Bank criticized the Danish mutual funds for being passive, based on the Tracking Error measure. Additionally, Engsted et al. (2011) provided a report stating that private investors should avoid active mutual funds and instead invest in stocks directly, creating a diversified portfolio.

The Swedish authors Dahlquist et al. (2000) investigated Swedish mutual fund performance for 210 equity, bond and money market funds, restricted to funds investing domestically. The study shows that particular equity funds, bond and money market funds have neutral to significantly negative performance, whereas regular domestic equity funds obtained over-performance. Additionally, the positive Swedish results are reinforced by Wallander (2012) who also finds significant positive performance, albeit no persistence. It is important to emphasize that the focus of this study is exclusively in equity funds. Thus, these findings have to be interpreted with caution.

3.4.3 Empirical findings in the Norwegian fund market

Studies focusing on the Norwegian mutual fund market are quite scarce, to say the least. The first substantial literature we were able to obtain was the paper by Gjerde & Sættem (1991). In this study, the performance of Norwegian mutual funds in the period of 1982 to 1990 is evaluated, utilizing the models of Jensen, Fama, Treynor & Mazuy, as well as Merton & Henriksson. They identify little evidence of fund managers in the Norwegian market possessing stock picking skills. Nevertheless, all funds appeared to outperform the market in the years from 1982 to 1984. However, after these years, the observations were typically below the market index benchmark value. Additionally, the authors find several funds displaying significant market timing coefficients, implying evidence of Norwegian fund managers possessing positive market timing abilities. Still, the authors express some concerns about the instability of the results, with a declining trend of being able to outperform the market.

The study conducted by Che, Norli & Priestley (2009) examines performance persistence among individual investors on the Norwegian stock market. The authors can reveal that some investors, in fact, do exhibit persistent superior performance. Correspondingly, Sørensen (2009) investigates if the same goes for Norwegian mutual funds, but unlike Che et al., he is not able to find decisive evidence of persistence. After examining Norwegian fund managers' stock picking skills, Sørensen concludes: "a blindfolded monkey throwing darts at Dagens Næringsliv's[10] financial pages could select a portfolio that would do just as well as one carefully selected by experts". In any case, after controlling for the factors in the Fama-French three-factor model, Sørensen identifies no significant evidence of risk-adjusted abnormal performance for an equally weighted portfolio of mutual funds in the Norwegian market.

The empirical findings described above show that there is still no definite evidence on management's forecasting abilities. Some studies show signs of stock picking skills for a particular period of time. Other studies suggest market timing skills in certain markets. However, disregarding the Swedish regular equity funds, there is no consistent evidence present that actively managed funds outperforms the market.

[10] Norway's equivalent to the Wall Street Journal

4.0 Theory

4.1 Efficient Market Hypothesis

The theoretical foundation which forms the aim and purpose of this study is the assumptions behind the Efficient Market Hypothesis (EMH). In the years following the release of Fama's (1970) revolutionary paper "Efficient Capital Markets", there was a broad consensus that capital markets were very efficient in reflecting information about individual stocks and the stock market as a whole (Malkiel, 2003). Hence, in regards to active management, the general belief was that new information spread quickly and was immediately incorporated into stock prices, making fundamental[11] and technical[12] analysis to identify "undervalued" stocks useless in the search for abnormal returns[13], as the stocks would be correctly priced at all time.

Furthermore, in addition to the idea of instant market adjustments, the EMH is associated with the idea of a "random walk". The term "random walk" is loosely used to characterize price movements as random deviations from previous prices. If new information is immediately adjusted for in stock prices, then tomorrow's price change will be entirely independent of today's price movements and reflect only tomorrow's news. Tomorrow's news are by definition unpredictable, hence resulting price changes must be random and unpredictable (Malkiel, 2003). Following this argumentation, in the scope of active management, any potential outperformance of the market will be due to luck rather than skill.

By varying the degree to which security prices reflect market information (Bodie et al., 2009), practitioners distinguish between three different forms of the EMH. The first form is known as *weak efficiency* and claims that security prices reflect all past information. From an active management stand, if historical data does not provide any guidance about future developments, i.e. random walk, analyzing previous price patterns will not result in market outperformance. The second form is commonly referred to as *semi-strong efficiency*, where both historical and publicly available information are incorporated in the prevailing security prices. Consequently, neither fundamental nor technical analysis of securities will lead to superior investment decisions. The third, and final, form is known as *strong efficiency*, where insider information, in addition to historical and publicly available information, has been embedded in the market price of securities. Thus, no matter how much information an investment manager has

[11] An analysis of financial information such as asset values, company earnings, liabilities etc., to help investors pick undervalued stocks.
[12] An analysis of past stock prices in an attempt to predict future stock prices.
[13] A stock's return in excess of a benchmark index.

obtained, it will not be possible to outperform the market because all information is reflected in the prevailing prices (Bodie et al., 2009).

The Efficient Market Hypothesis is one of the most debated themes among financial academics, and there is substantial empirical evidence supporting it. Jensen (1969) performed a study on active mutual funds, where he argued that investment managers in active mutual funds would not be able to outperform the market. In fact, the study proved a tendency for active investment managers to underperform the market by the equivalent amount of the fund expenses charged to the investors. Furthermore, Henriksson (1984) found in his study that managers do not exhibit either market timing skills or stock picking skills. All of the mentioned empirical findings are in line with the Efficient Market Hypothesis.

Despite the solid empirical support, some practitioners still question the validity of the EMH. Among them is the *Behavioral Finance School, BSF,* who emphasize the importance of human behavior as market inefficiency. They criticize the fundamental assumption in the EMH of all investors being rational. As a counterargument, they suggest a market where participants are primarily driven by emotions, which leads to market inefficiencies (Bodie et al., 2011). An example of such irrational behavior is investors selling winning stocks and keeping loosing stocks based on the flawed argument that "what goes up, must come down", and that a falling trend will be followed by an increasing trend.

Grossman & Stiglitz (1980) criticized the assumption that information is accessible to all market participants free of charge. In reality, information gathering is both time consuming and costly. Hence, taking into consideration that technical and fundamental analyses are not free of charge, active investment managers are required to generate a return which compensate for these costs. That is, this implies significant outperformance relative to the market over time. This is another direct violation of the standard version of the EMH, where spending resources to obtain additional information is superfluous. Fama (1991) introduced a modified version of the EMH as a response to the critique, where he allowed for temporary mispricing of securities in the market. Consequently, this means that investment managers can utilize their comparative advantage and profit from these temporary mispricing in the short run. However, the model claims that these inefficiencies will be eliminated in the long term.

Valuing equities is far from an exact science, and is often at best an approximation of the true value.

Despite the fact that the EMH, in different versions, has been thoroughly tested in several studies (DeBondt & Thaler 1985, Bernard & Thomas 1989, Jegadeesh & Titman 1993), it is not possible to definitively confirm or reject the EMH before an empirically secure method of valuing equities has been established. Fama (1991) claims that with several valuation models being used by practitioners today, it is not possible to confirm or reject the EMH based on an empirical study, because the results will be impacted by the valuation model in use and the assumptions behind it.

If the financial market truly were efficient, investors would be better off by investing passively, which in practice means buying index funds. On the other hand, if all investors invested passively, the market would not be efficient as no one would seek market information.

4.2 Capital Asset Pricing Model – CAPM

The Capital Asset Pricing Model, commonly referred to as CAPM, was developed from articles by Sharpe (1964), Lintner (1965) and Treynor (1966) (Bodie et al., 2009). The model builds on earlier work of Markowitz (1952) on modern portfolio theory and the mean-variance relation. The CAPM has since become one of the absolute cornerstones of modern portfolio theory and has served as a foundation for a large number of empirical studies on the mutual fund industry.

Built upon some rigid assumptions, the CAPM divides risk into two specific components; specific risk and market risk. The latter is also known as systematic risk, or merely the beta, and quantifies the sensitivity of a portfolio, or an individual security, relative to a change in the overall market. On the other hand, the specific risk is the firm-specific risk component related to the particular security in the portfolio. By creating a well-diversified portfolio, investment managers can diversify away the firm-specific risk, and is thus only compensated for the market risk (Bodie et al., 2009). Moreover, the CAPM describes the linear relationship between expected return and risk. The model is defined by the following relation:

$$E[r_p] = r_f + \beta_p(E[r_M] - r_f)$$

Where,

$E[r_p]$ is the expected return on portfolio *p*

r_f is the return on the risk-free rate

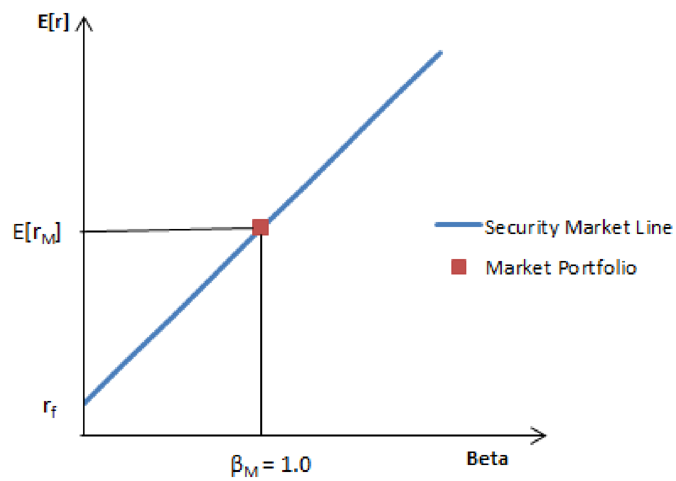
$\beta_p = \frac{Cov[r_i, r_M]}{\sigma_M^2}$ is the beta of portfolio *p* with respect to the market portfolio

$E[r_M]$ is the expected return on the market portfolio

All correctly priced portfolios should plot along the Security Market Line, SML, following from the assumptions behind the CAPM (see Figure 4.1 below). From the SML, one can easily identify whether a portfolio is undervalued (overvalued). If the portfolio is located below (above) the SML, the portfolio is undervalued (overvalued) as the expected return is too low (high) relative to its beta. Thus, the SML provides a benchmark for the evaluation of investment performance.

In equilibrium, different securities will plot along the SML meaning that their expected returns will only differ because of their exposure to market risk, measured by the beta. Given that the Efficient Market Hypothesis holds, all mispriced securities will adjust and return to a point along the SML.

Figure 4.1: Security Market Line, Source: Bodie et al., 2009



Despite being one of the cornerstones in economic literature, the CAPM has been challenged by critics. The rigid assumptions behind the model can limit the CAPM's practical applicability (Mullins, 1982), and it is, at best, a rough simplification of reality. Several empirical tests have been performed on the CAPM, but it has not been possible to validate the model fully. On the other hand, research by Black, Jensen & Scholes (1972) and Fama & McBeth (1973) has supported the linear relationship between average returns and beta.

4.3 Performance Measures

4.3.1 Treynor Ratio and Sharpe Ratio

After the introduction of the CAPM, Treynor (1965) and Sharpe (1966) presented their portfolio performance measures. Both the *Treynor ratio* and the *Sharpe ratio* are commonly applied when comparing past performance of different funds. The Treynor ratio is derived directly from the CAPM, and measures a portfolio's performance per unit of systematic risk, given by beta:

$$Treynor\ Ratio = \frac{r_p - r_f}{\beta_p}$$

An obvious critique of the Treynor ratio is that it only covers diversifiable/systematic risk but does not cover the undiversifiable risk.

Shortly after the presentation of the Treynor ratio, the Sharpe ratio was introduced as an alternative performance measure. Whereas the risk measure in the Treynor ratio is the systematic risk, the Sharpe ratio makes use of portfolio volatility:

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

By comparing the two, we see that the only difference between them is that the Treynor ratio measures the excess return per unit of market risk, whereas the Sharpe Ratio measures the excess return per unit of risk. It is important to note that none of the ratios provide any guidance on the absolute performance of a portfolio, and can thus only be used for comparing purposes. Furthermore, when applying the two ratios, they may well yield different portfolio rankings, especially when comparing poorly diversified portfolios (Bodie et al., 2009).

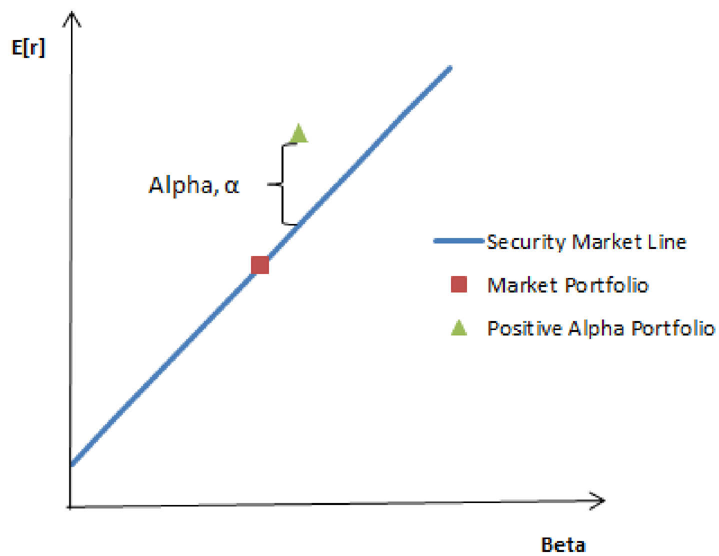
4.3.2 Jensen's Alpha

Along with the introductions of the Treynor and Sharpe ratio, Michael C. Jensen (1967) developed the absolute performance measure *Jensen's alpha*, α. Since its introduction, Jensen's alpha has become one of the most recognized and widely used portfolio performance measures in modern portfolio theory. The alpha is directly derived from the CAPM and measures a fund manager's ability to outperform the market. Therefore, it is of particular interest in a study of active fund management. The Jensen's alpha is found using the following regression:

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f)\varepsilon_i$$

The alpha is the intercept in the regression, and is used to determine the abnormal return of a security/portfolio. In the view of active investment management, a positive alpha, $\alpha_i > 0$, indicates that the portfolio manager has delivered superior performance by creating a return in excess of the market risk exposure of the fund, i.e. abnormal return. Similarly, if the alpha is negative, $\alpha_i < 0$, the manager has underperformed relative to the market (Elton et al., 2011). Furthermore, a positive alpha means that the portfolio lies above the SML, and the opposite is true for a negative alpha. This is illustrated in Figure 4.2 below, which is an extension of Figure 4.1. However, as argued in section 4.1, portfolios will only lie above/below the SML for a short period of time, and any mispriced securities/portfolios will return to equilibrium in the long run. Despite this, if a fund manager continuously identifies the undervalued securities, we end up in a situation where a fund manager outperforms the market in the long run. In the figure below, the distance between the portfolio and the SML is the measure of the alpha:

Figure 4.2: Jensen's Alpha, Source: Own creation



Jensen's alpha is generally preferred over the Treynor and Sharpe ratio by practitioners because the alpha is an absolute measure and not a ratio. It measures performance in percentage points, and can thus easily be communicated to investors. In addition, the alpha is found using a regression which makes it possible to measure its statistical validity.

Despite the fact that Jensen's alpha is one of the most praised and adapted performance measures, it is prone to criticism. Most relevant for this study is the fact that is derived directly from the CAPM, hence it is prone to the same restrictive assumptions. Roll (1978) heavily criticized the CAPM and the alpha, emphasizing the there is no such thing as a true market portfolio. He claimed that a true market portfolio should include all investible assets such as real estate, human capital, art etc., not just tradable securities. Furthermore, Roll concluded that identifying the market portfolio is a tremendously complex task, as no one would know the exact composition of this portfolio. For this reason, any estimate of alpha will be biased by the choice of the benchmark index which serves as a proxy for the market portfolio. This was tested further by Grinblatt & Titman (1989, 1994), who found that alpha estimates varied widely when different benchmark indices was used as proxies for the market.

4.3.3 Alternative Performance Measures

Even though the performance measures mentioned above play an essential part in portfolio theory and are highly praised, they have been improved further. The Sharpe ratio suffers from a major disadvantage, namely that it treats upside and downside volatility the same. For example, high outlier returns could potentially increase the standard deviation, i.e. the denominator, more than the excess return, i.e. the numerator, and thereby lowering the overall Sharpe ratio. Hence, in case of some positively skewed return distributions, one could actually increase the Sharpe ratio by removing some of the largest return securities. This is counterintuitive, as rational investors seek to maximize positive returns. Based on this disadvantage, Frank A. Sortino (1983) introduced the *Sortino ratio*, which is similar to the Sharpe ratio, except it differentiates harmful volatility from general volatility by taking into account downside deviation, which is the standard deviation of negative return securities. This makes the Sortino ratio more applicable when working with highly volatile portfolios. The Sortino ratio is given as:

$$Sortino\ Ratio = \frac{r_p - T}{DR}$$

Where,

r_p is the realized return on a portfolio.

T is the target (required) return on the investment strategy, previously known as the minimum acceptable return (MAR).

DR is the downside deviation, i.e. the standard deviation of negative return securities.

A low Sortino ratio implies that there is a high probability of a significant loss. Despite solving one of the major disadvantages with the Sharpe ratio, the Sortino ratio suffers from the same problem of being impossible to interpret by itself. It needs to be compared across different portfolios to make sense.

Modigliani & Modigliani (1997) addressed this problem, and developed a new performance measure based on the Sharpe ratio, the M^2. In short, they transform the traditional Sharpe ratio into a differential return, which is easily compared to a benchmark index. The M^2 is given as:

$$M^2 = \frac{S_p - S_m}{\sigma_m}$$

Where,

S_p is the Sharpe ratio of the portfolio.

S_m is the Sharpe ratio of the benchmark index, i.e. market portfolio.

σ_m is the standard deviation of the benchmark index, i.e. market portfolio.

The major advantage of the M^2 is that it expresses its result in units of percent, which is easily interpreted and communicated to investors. In practice, M^2 quantifies the excess return an investor gets from holding the investment fund as opposed to the market index.

4.3.4 Market timing ability

Fama (1972) presented a paper on how investment managers can outperform the market not only through superior stock picking ability, but also through market timing ability. He claimed that there are two ways in which an investment manager can outperform the market: First and foremost, the investment manager can predict price movements of individual assets, i.e. stock picking. Secondly, the investment manager can forecast price movements of the general stock market, i.e. market timing (Elton et al., 2012).

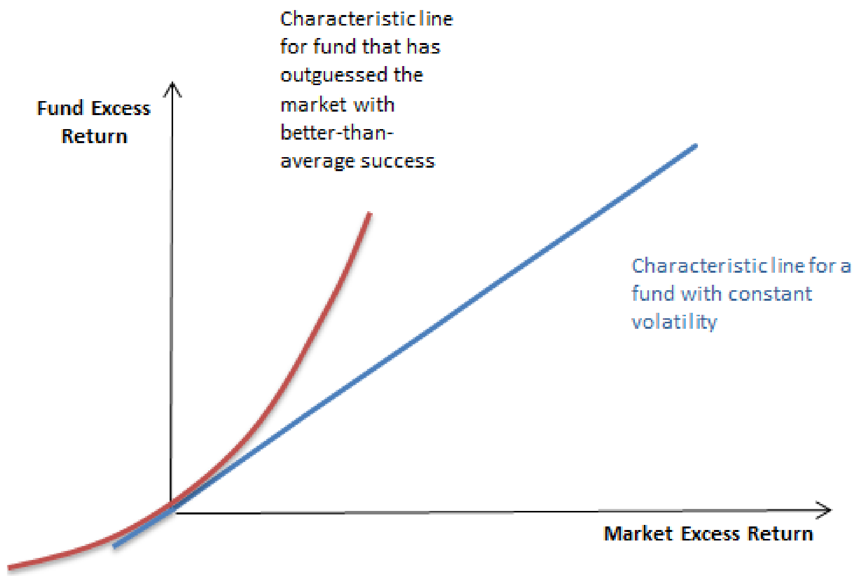
Critics of the market timing argue that due to efficient financial markets, little can be gained from market timing. Moreover, they emphasize the costs involved with buying and selling stocks, such as tax and financial costs.

One can investigate if an investment manager has any market timing intentions by running a regression of the returns of a fund on the market at different time periods. If the investment manager has engaged in market timing, the beta of the regression will be non-stationary. Conversely, if he has not engaged in market timing, the beta will be stationary (Elton et al., 2012). Kon & Jen (1978) discussed in their research that although the regressions sounds relatively simple and straightforward, the betas for each different sub-period will be stationary for that particular period. Moreover, the regression only reveals if the betas differ from each other, not if the actual market timing is successful. Treynor & Mazuy (1966) addressed these issues, and developed a model derived from the CAPM to measure market timing ability:

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + \gamma_i(r_m - r_f)^2 + \varepsilon_i$$

They added the squared excess market return to Jensen's standard regression introduced in section 4.3.2, where the new gamma (γ) coefficient serves as a direct estimate of market timing ability. As we can see from the regression, the alpha is still included to measure the investment manager's stock picking ability. If the gamma coefficient is positive, the investment manager shows market timing skills. This will make his fund characteristic line steeper as his excess return increases. Similarly, if the gamma coefficient is negative, the characteristic line will be flatter. Figure 4.3 below illustrates the relationship between the particular line and market timing:

Figure 4.3: Characteristic line for non-market timer and for a market timer, Source: Treynor & Mazuy (1966)



4.3.5 Performance Persistence

Along with a fund manager's stock picking ability and market timing ability, an intriguing question in regards to performance is whether fund managers who have outperformed the market can do so in the following periods. Of equal interest is whether underperforming fund managers continue to underperform in subsequent periods. One could argue that a fund manager could get lucky and outperform the market in a given period, but performance persistence would be evidence of skill rather than luck. In recent studies, academics have presented several methods of measuring performance persistence.

Goetzmann & Ibbotson (1994) defined funds as winners in a sorting period if the fund's return over a calendar year exceeded the median return. If the fund's return did not exceed the median return, it was defined as a losing fund. Malkiel (1995) continued this approach and used median return as a sorting value. He claimed that when utilizing the median return as the benchmark, the probability of a winner continuing being a winner should equal 50 percent if there is no performance persistence present. Hendricks et al. (1993) developed a different approach, where they examined autocorrelation among mutual fund returns. In the presence of significant autocorrelation, Hendricks et al. argued that it might serve as an indicator of performance persistence.

Furthermore, Blake & Timmermann (1998) developed another method which stands out from the crowd. They examined the European fund market and identified the abnormal returns for the previous two years. Then they created two equally weighted portfolios, one consisting of the best performing quartile among the identified abnormal returns, and one comprised of the worst-performing quartile. These portfolios were held for one month before they were rebalanced based on the same procedure. When the portfolios had been detained for a sufficient amount of time, and a time-series was generated, they ran the portfolios through a Jensen regression. To confirm performance persistence, Blake & Timmermann expected the portfolio consisting of the best performing funds to yield a positive alpha and the portfolio comprised of the worst performing funds to yield a negative alpha.

4.3.6 Distinguishing skill from luck

Some mutual fund managers can outperform their benchmark, but are this due to possession of skills or because of luck? In recent studies, the authors have focused more on distinguishing skill from luck, by shifting focus from performance consistency alone to the underlying cause of the performance. Kosowski et al. (2006) described a statistical bootstrap technique to examine the performance of U.S open-end, domestic equity funds industry. Their bootstrap approach reveals that a considerable minority of fund managers can pick stock well enough to generate excess return after deduction of costs. Subsequently, Cuthbertson, Nitzsche & O'Sullivan (2008) applied a similar bootstrap approach, with the conclusion that UK mutual funds demonstrate "bad skills". For the majority of funds with superior performance, they conclude that this can be attributed "luck". Thus, based on previous empirical studies, it is hard for the individual investor to identify mutual funds that demonstrate genuine skills.

Moreover, to explain the bootstrapping technique applied, the following model of equilibrium return is used.

$$r_{i,t} = \alpha + \beta_i' X_t + \varepsilon_{i,t}$$

Where,

$r_{i,t}$ is the excess return

T_i is the number of observations for each fund

X_t is the matrix of risk factors

$\varepsilon_{i,t}$ is the residuals

The first step of the bootstrap technique is to estimate the model for each fund and save the estimated beta vectors and residuals. Then a random sample is drawn from the residuals (with replacement) with the same length as the original sample (Ibid). By retaining the original chronological ordering of the matrix of risk factors, the authors use the resampled bootstrap residuals to generate simulated excess returns for each fund, under the null hypothesis that the excess return, in this case, the alpha, is equal to zero (Ibid).

Moreover, they estimate the performance model using the simulated returns to obtain a new alpha value (Ibid). The process mentioned above is then repeated 1000 times, and the new alpha values computed for each fund represent a sampling variation around the true value of zero (by construction). Hence, the authors construct a separate "luck distribution" for each of the ordered funds in the performance distribution, all of which are exclusively due to luck (Ibid). The original alphas are then compared with its appropriate "luck distribution". If the original value is greater than the 5% upper tail cut off point from the simulated luck distribution, they reject the null that performance is due to luck. Hence, they infer that the fund manager has good skills. If the original value is less than the 5% lower tail cut off point from the simulated luck distribution, the null is also rejected. However, in this case, fund managers are inferred to possess negative skills. Thus, a 90% confidence interval is being used, as opposed to the 95% being used in the rest of the study.

Fama & French (2009) applied the same bootstrapping technique with a few modifications on U.S. equity mutual funds. They reveal no evidence that any managers possess skills on a level high enough to cover the fees they impose on investors. As a matter of fact, the authors show that fewer managers are generating excessively returns than would be expected based on luck. Additionally, the top historical performance observed is determined to be approximately what should be expected from the luckiest funds in a world where the true alpha is equal to zero for all funds (Ibid). Fama & French conclude that their estimate of the true alpha is close to zero, even for the top three percentiles of historical performance.

For the Norwegian market, Sørensen (2009) examines the performance and persistence of all Norwegian equity mutual funds listed on OSE between 1982 and 2008. The author concludes there is no evidence of risk-adjusted abnormal performance for an equally weighted portfolio of mutual funds (Ibid). Furthermore, Sørensen finds several inferior fund products in the left tail of the cross-sectional distributions of alphas. In the end, he only finds weak signs of skill in the right tail.

4.4 Conditional and Unconditional Models

When using the unconditional Jensen regression, see section 4.3.2, a fundamental assumption is that the mean-variance criterion holds, although in reality means and variances vary over time (Bodie et al., 2009). Moreover, the unconditional Jensen regression assumes that the risk level remains constant over time, due to the stationary beta estimate in CAPM. To check whether the risk levels remained constant or not, Jensen (1969) split his sample period into two and examined the correlation between the beta-estimates of the two sub-periods. Identifying a correlation of 0.74, Jensen considered the correlation high enough to serve as an evidence of stationary risk levels. His findings have later been supported by Ippolito (1989) and Malkiel (1995), who both found a strong correlation between betas of subsequent periods. However, this procedure could be flawed. Kon & Jen (1978) argue that dividing a sample period into several sub-periods will still have the same assumption of a constant beta in the sub-periods. In fact, earlier, Campanella (1972) found evidence of non-stationary risk levels in mutual funds.

Based on this critique, Ferson & Schadt (1996) and Chen & Knez (1996) proposed the application of a conditional model, where the beta estimate is allowed to vary over time. The researchers blamed the unconditional market timing models for the fund managers' apparent lack of forecasting abilities because they overlook the time variation in risk levels. An acknowledged solution is to add some predetermined information variables to the unconditional Jensen regression. The conditional model includes Z_{t-1}, which is a vector of some lagged predetermined information variables. A linear relation between these conditional variables and the variation in beta is assumed. Hence, the new beta can be expressed as:

$$\beta_{i,t} = \beta_{i,0} + \beta_i' Z_{t-1}$$

Applying the new beta to the unconditional Jensen regression, the modified conditional regression becomes:

$$r_i - r_f = \alpha_i + \beta_{i,0}(r_m - r_f) + \beta_i' Z_{t-1}(r_m - r_f) + \varepsilon_i$$

The new conditional Jensen regression use a set of instruments which has the ability to indicate security risks and returns over time, along with the market excess returns as explanatory variables. This model can be regarded as an unconditional multi-factor model, using the excess return on the market as the first factor and the cross products of the excess market return with each lagged information variable as additional factors capturing the covariance between the conditional beta and the expected market returns (Jagannathan & Wang, 1996). In their initial study, Ferson & Schadt (1996) decided on five different information variables:

1. The lagged level of the one-month Treasury bill yield
2. The lagged dividend yield of the CSRP value weighted AMEX and NYSE stock indices.
3. A lagged measure of the slope of the term structure.
4. A lagged quality spread in the corporate bond market
5. A dummy variable for the month of January.

When Ferson & Schadt tested for the significance of their information variables, they found that only the first three variables were significant regarding predicting power for the beta variations. The last two variables were deemed insignificant. All of the abovementioned information variables are publicly available, which implies that according to the Efficient Market Hypothesis, see section 4.1, a fund manager using the conditional model should achieve an alpha equal to zero.

4.5 Survivorship bias

Survivorship bias is a central and recurring issue when measuring mutual fund performance, and refers to the issue of low-performance funds ceasing to exist during an observation period. It is a well-documented and acknowledged fact that mutual funds that are willing to take on higher risk have a higher probability of default. In the case that the fund takes advantage of the increased risk and outperforms the market, it will most likely survive, which implies that the fund gambled and won. However, the funds that gamble and lose will lose popularity and eventually cease to exist.

Funds that become defunct in an observation period will be omitted from the sample due to the lack of complete data. Academics (e.g. Malkiel, 1995) claims that this creates an upward bias of the overall performance estimate because the only survivors are the high performing funds. Rohleder et al. (2010) argue that a fund which terminates its operations has most likely been underperforming for an extended period of time, implying that we lose out on critical performance data. Other studies provide results which indicate that the effect of survivorship bias is negligible. For instance, Grinblatt & Titman (1994) estimated survivorship bias as low as 0.5 percent in their dataset.

However, addressing the survivorship bias is important because international evidence suggests that funds do not exit the sample randomly; it is the worst performing funds that become defunct. How we address the survivorship bias in this study is discussed further in section 5.10.

There has been little research on the survivorship bias in the Norwegian market. However, Sørensen (2009) identified a significant survivorship bias when assessing Norwegian funds market from 1982 – 2008. He found that defunct funds had underperformed relative to surviving funds by -0.27% per month, or -3.24% in annual terms, which was a highly statistically significant result. Moreover, there was a difference in returns of 0.84% between the entire sample of funds and existing funds, which is comparable to another empirical finding on the U.S market (0.8% by Brown & Goetzmann in 1995) and the Swedish market (0.7% by Dahlquist et al. in 2000). These finding further emphasizes the importance of addressing the survivorship bias in our study.

4.6 Measures of active management

4.6.1 Active Share

A central part of this study is to determine whether a fund is active or not. *Active Share* is a model proposed by Cremers & Petajisto (2009) which has gained a lot of traction with practitioners recently. Active Share measures how active mutual funds are in order to identify future outperforming managers.

In practice, Active Share defines how much the fund portfolio differs from the benchmark portfolio in percent. Implicitly, this means that an index fund will have an Active Share of 0% because it mimics the benchmark accurately. Cremers & Petajisto uses an Active Share of 60% as a threshold for a fund to be classified as an active fund. The Active Share is given as: is given as:

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N}|w_{fund_i} - w_{benchmark_i}|$$

Where,

w_{fund_i} is the weight of stock *i* in the fund.

$w_{benchmark_i}$ is the weight of the same stock in the benchmark index.

Thus, the Active Share illustrates the percentage of the fund that does not overlap with the index. Given that a fund cannot take short or levered positions, the Active Share will lie within the interval [0%, 100%]. Table 4.1 below illustrates the calculations, using a portfolio consisting of four stocks:

Table 4.1: Active Share, Source: Own Production

	Weight in Portfolio	Weight in Benchmark	Absolute Difference
Stock 1	50%	30%	20%
Stock 2	5%	0%	5%
Stock 3	20%	20%	0%
Stock 4	25%	30%	25%
Sum	100%	100%	50%
Active Share			**25%**

Looking at the formula, one can see that the difference is calculated in absolute values, which means that positive and negative differentiation is counted. Thus, this "double counts" the active positions as being both overweight in one stock and underweight in another. Hence, the absolute difference is divided by two for the Active Share to equal 100% for a portfolio with no overlap with the benchmark index.

In their initial study, Cremers & Petajisto found that the funds with the highest Active Share significantly outperformed their benchmark indices after fees, whereas low Active Share funds significantly underperformed after fees. They included data from 2,026 funds in the period from 1980 to 2003 from the U.S. market in their research.

4.6.2 Tracking Error

The Tracking error measures the standard deviation from the benchmark. In other words, it calculates the variation of the fund returns that is not explained by movements in the benchmark index. Hence, an actively managed fund should have a high tracking error whereas the benchmark index should have a tracking error approximately equal to zero.

Tracking Error is defined as:

$$Tracking\ Error = Std.Dev[r_{fund} - r_{index}]$$

4.6.3 Active Share and Tracking Error combined – Identifying investment strategies

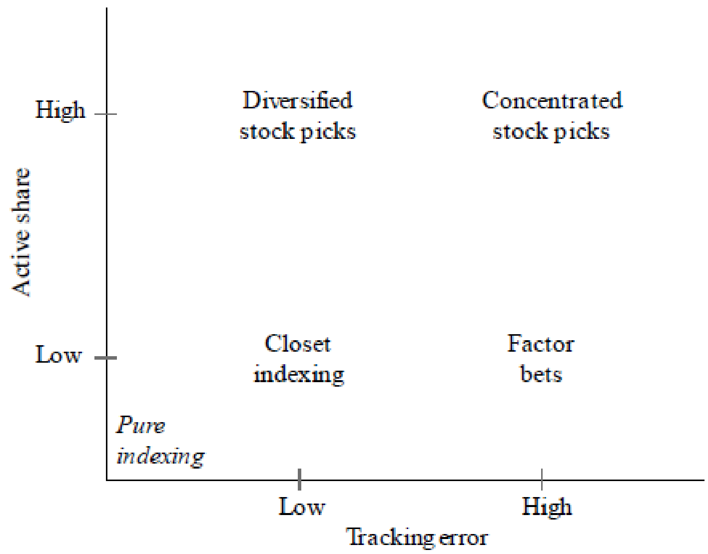
Cremers & Petajisto claims that fund managers can deliver outperformance relative to the benchmark in two specific ways; either by stock picking or by market timing (a combination of the two is also a possibility). The fundamental idea behind active fund management is to create value by selecting outperforming stocks relative to the benchmark with similar exposure to non-diversifiable risk. Moreover, they can create value by adjusting their portfolio holdings concerning market predictions and movements.

In regards to Tracking Error, stock picking, and market timing contributes differently; according to their study, Cremers & Petajisto claims that "stock pickers may only bear the diversifiable risk while market timers will take the systematic risk relative to the index[14]." Hence, market timers will obtain a relatively high Tracking Error while stock pickers can reduce their Tracking Error by diversifying their risk. In other words, Tracking Error understates the level of active management of stock pickers with well-diversified portfolios. Similarly, Tracking Error overstates the degree of active management when managers only invest in a few large portfolios without any desire to individually pick stocks.

By combining the Tracking Error and Active Share, Cremers & Petajisto propose a solution to this problem. Combined the two measures covers the main categories of active management and presents four strategies for active management, each of them illustrated in figure 4.4 below, and explained in greater detail below the figure.

[14] Cremers & Petajisto, "*How active is your fund manager?",* 2009

Figure 4.4: Two dimensions of active management, Source: Cremers & Petajisto (2009)



As we can see from the model, there are four active management approaches; “Closet indexing”, “Factor Bets,” “Diversified stock picks” and “Concentrated stock picks”. A low Active Share combined with a low Tracking Error means in practice that an investor would have to pay the cost of active management, but receive passive investment performance – which is commonly known as closet indexing. A high Active Share combined with a low Tracking Error is defined as “diversified stock picks” by Cremers & Petajisto. Here, a fund will have an overall sector weighting approximately equal to the benchmark index, but a massive investment in stock positions across sectors where the sizes of the stock positions differ from those in the reference point. If a manager focuses more on market timing than stock picking, the fund tends to have a high Tracking Error but a low Active Share, which is called “factor bets.” Finally, “concentrated stock picks” implies that a fund manager tends to invest in few sectors and heavily in some stock-specific position. Hence, the fund is differentiated from the benchmark index when it comes to both stock position sizes and sector weightings. Thus, this strategy the exact opposite of a “closet index fund”, and is regarded as a highly active approach.

Even though it is possible to measure the two dimensions of active management from portfolio holdings and return, there is a significant advantage of using Active Share and Tracking Error. Together, they do not require any assumptions about how the fund manager defines factor portfolios in contrast to a holding based approach, which makes the measure simple and convenient.

5.0 Methodology and Data

5.1 Scientific method and approach

There are some philosophic and scientific directions and approaches one could apply when conducting research. The most popular are positivism, realism, interpretivism and pragmatism. All differ from each other in terms of how reality and knowledge are perceived. For instance, realists tend to believe that whatever we believe now is only an approximation of reality, and we are getting closer to understanding the true reality for every new observation. Interpretivism, on the other hand, claims that academics need to work beyond empiricism and scientific method to successfully interpret reality. However, our study is based on the exact opposite of interpretivism, namely positivism. Positivists claim that all knowledge is based on experience and that pure logic and mathematics forms the basis of knowledge and reality. In other words, positivism is based on empiricism. In our study, we are applying financial models, which have previously been thoroughly tested by academic heavy-hitters and are deeply rooted in empiricism. To successfully answer our problem statement, we need a positivistic view on both the models we apply and our study as a whole.

Regarding reasoning, we apply a “top-down” approach, which is also known as the *deductive* approach. That is, we start with a general theory about our topic, namely the Efficient Market Hypothesis, and narrow it down to more specific hypotheses, which we in turn test to seek confirmation. Ultimately, the deductive approach enables us to test our hypotheses with specific data, which is exactly the approach needed in our study. The opposite of deduction is known as *induction*. Here, one would start with specific observations and move to broader generalizations and develop theories.

5.2 Data Description

The fund data used in this study was collected from *Thomson Reuters Datastream*. The data comprises the period from 31.12.2005 to 31.12.2015, and our intention was to create a sample free of survivorship bias. As described in section 4.5, a sample free of survivorship bias is important as many international studies suggest there is evidence that funds do not exit the sample arbitrary. Thus, the worst performing funds become obsolete (Malkiel, 1995, and Brown et al., 1992).

Cesari & Panetta (2002) accentuate that to make a significant study the funds need to be classified into a homogeneous category. Moreover, the Oslo Stock Exchange (OSE) categorizes equity funds in the following four groups:

1. Norwegian equity funds: assets invested invariably in domestic businesses.
2. Norwegian/international equity funds: a combination of assets being invested in domestic and foreign businesses.
3. International equity funds: assets invested invariably in foreign businesses.
4. Sector equity funds: assets invested in a particular area of the economy.

Our study only considers group 1, Norwegian equity funds, and disregard any funds investing in international equities. Any fund with more than 20% of its assets invested in foreign businesses will not be regarded as a Norwegian equity fund. Hence, using OSEFX as a benchmark (discussed in section 5.4) for funds investing large portions of their assets internationally will not be optimal. Furthermore, it is complicated to adjust consistently for risk exposure, and in turn difficult to gauge whether performance is due to allocation decisions not related to stock picking skills. Hence, we have restricted our sample to funds domiciled in Norway and trading in Norwegian Kroner (NOK). The inclusion of foreign funds or funds trading in foreign currency could also bias the results as a consequence of exchange rate development and different tax systems in the respective countries.

Additionally, the funds have to comply with the EU directives outlined in UCITS. Thus, any funds applying strategies not following UCITS-regulations should be removed. However, as described in section 2.4, Norwegian funds are subject to the same regulations as rest of Europe. Due to the nature and problem statement of this study, we will only include funds that regard themselves as an actively managed fund. Furthermore, to successfully apply the statistical tools discussed in section 4, we will only analyze funds with a minimum lifespan of 2 years as a shorter lifespan provides too few observations.

The selection criteria described above are indeed extensive, but necessary to conduct an accurate analysis of fund performance. It is considered a great advantage to evaluate a standardized sample. Table 5.1, below, reports the number of funds meeting the requirements of our final sample.

Table 5.1: Selection criterias leading to final data sample. Source: Datastream

Selection Criteria	Number of funds
Total Global Market	466 983
Geographic focus: Norway	573
Domicile: Norway	470
Currency: NOK	417
Asset Class focus (Holding based): Equity	86
Geographic focus (Holdings based): Norway	82
Funds Alive	71
Actively managed funds	62
Minimum lifespan of 2 years	47
Data available	**47**

5.3 Computation of return series

To calculate monthly return series, monthly Net Asset Values (NAV) of each fund are used. Both arithmetic and geometric returns have been computed in this study. Conventionally, geometric returns are to be preferred over arithmetic returns regarding evaluating historical figures, as they give a more accurate estimate. When it comes to investment returns, the numbers are not independent of each other. If you lose an amount of money one month, you have that much less capital to generate returns the following months and vice versa. Due to this reality, we need to calculate the geometric average of the investment returns in order to get an accurate measurement of what the actual return over the period has been. Thus, geometric returns are applied in this study.

$$Geometric\ return = \ln(\frac{NAV_t}{NAV_{t-1}})$$

Where:

NAV = net asset value

Ln = the natural logarithm

5.4 Choice of Benchmark

In this study we use performance measures derived from the CAPM-framework, which require us to identify the market portfolio which will be utilized as a benchmark. Following Roll's critique (see section

4.3.2), we need to determine a sufficient proxy for the market portfolio. Moreover, this study requires a consistent use of the same benchmark in all of the regressions, as using different benchmarks would make it practically impossible to comment on relative differences in performance. This further emphasizes the importance of identifying the single-most applicable benchmark. Due to the delimitations of this study, fund managers are restricted to investing a minimum of 80% of their assets in Norwegian securities listed on OSE, which significantly reduces the complexity of finding a suitable proxy/benchmark. The choice of benchmark affects the overall results (see section 4.3.2), which makes it imperative to identify the most applicable benchmark among the feasible alternatives.

All fund providers list a relevant benchmark for their fund to which they compare their performance. In our case, the absolute majority of the funds under scrutiny list Oslo Stock Exchange Mutual Fund Index (OSEFX) as their benchmark. Naturally, this makes OSEFX the first candidate for the benchmark in our regressions. As presented in section 2.4, Norwegian mutual funds are subject to the UCITS-regulation. In short, the regulation states that the mutual funds need to invest in at least 16 different companies, where the weight in every business cannot exceed 10% of the fund's total NAV. For the benchmark index to be entirely applicable, it needs to comply with these UCITS requirements. The OSEFX has the favorable trait of complying with the mentioned requirements. In fact, the OSEFX is a weight-adjusted version of its more familiar cousin OSEBX, which is the benchmark index of the OSE. By complying with the requirements, none of the securities in the index exceeds 10 % of the total index, which makes it an ideal benchmark for mutual fund performance.

The second candidate is the already-mentioned OSEBX. The OSEBX consists of the largest and most tradeable securities on OSE, which is favorable when choosing the benchmark. However, the index suffers from being severely "top-heavy". The four largest companies account for almost 60% of the total index value, which means that it will be close to impossible for a UCITS-compliant fund to outperform the index if the top 4 companies deliver abnormal returns.

The third candidate is Oslo Stock Exchange All-Share Index (OSEAX), which consists of all securities listed on OSE. Intuitively, this might sound like the most natural choice of benchmark. However, the index consists of a vast number of highly illiquid securities, which means that it cannot be replicated without incurring substantial transaction costs.

OSEBX and OSEFX are arguably the more practical candidates, as they are in fact investible indices.

However, as OSEBX is severely “top-heavy” it is not an ideal benchmark for mutual funds. Due to the fact that the OSEFX is designed to comply with the UCITS, and thus is weight-adjusted, it is more applicable when analyzing mutual fund performance. Because of this, we have decided to proceed with OSEFX as the benchmark index for our study.

Table 5.2 below presents the adjusted R^2 for the unconditional Jensen regression for each of the abovementioned possible references. As illustrated in the table, OSEFX has the highest adjusted R^2 and thus on average fits our regression model the best. This further strengthens our confidence in using OSEFX as a benchmark in this study.

Table 5.2: Adjusted R^2 for the Jensen regression for possible benchmark indices. Source: Own creation

Possible Benchmark Index	Adjusted R^2
OSEAX	0.8697
OSEBX	0.8925
OSEFX	0.9110

5.5 Identifying active funds with Active Share

A part of our study concerns the true level of activity within the Norwegian equity mutual fund industry. In order to measure the funds’ true level of activity, we apply the innovative Active Share measure. As discussed in section 4.6.1, Active Share proposed by Cremers & Petajisto (2009) defines how much the fund portfolio differs from the benchmark portfolio in percent. A fund portfolio which does not differ much from the reference portfolio has a low Active Share and should, in theory, have low expenses because of the low trading activity. The idea is that funds mimicking indices should not require high fees because they do not take additional risk, and should therefore not be compensated for doing so. However, there has been evidence of funds charging high fees for active management when they, in reality, mimic an index. The Norwegian regulators were the first in Europe to take action against closet indexing funds charging high fees when they took legal actions against the country’s largest bank in March 2015, claiming the pricing was fraudulent[15]. Soon after, Sweden and Denmark followed and started to investigate closet index funds. Recently, the Scandinavian countries have significantly increased the monitoring of equity fund pricing.

[15] http://www.ft.com/cms/s/0/caad1152-c97e-11e4-a2d9-00144feab7de.html#axzz3zql7Bnqd, downloaded: 11.02.2016

Thus, in addition to identifying active funds, when being compared to the funds' expenses, the Active Share illustrates if the fund pricing is fair. A more in-depth definition of fund expenses is presented in section 5.8.

The derivation of Active Share has been conducted by gathering data on the individual funds' portfolios on December 31st, 2015 through Bloomberg's database and the funds' prospects. Moreover, we have gathered data on the weights in the benchmark index through Oslo Stock Exchange's own database. Unfortunately, not all funds report their portfolio weights, but out of a total of 47 funds we successfully calculated Active Share for 41 funds, which we feel is sufficient to be representative of the Norwegian mutual fund market as a whole. Ideally, Active Share should be calculated over an extended period of time to monitor any changes in portfolio weights, and thus changes in the Active Share. However, we only had access to the weights on December 31st 2015, which gives us only one observation of Active Share for each fund. Cremers & Petajisto argued in their paper that fund portfolios changes marginally through time, which implies that one observation of Active Share should be sufficient to identify whether a fund is active or not.

Cremers & Petajisto's study was performed in the U.S. market. Obviously, the Norwegian market is significantly smaller than the U.S. market. Moreover, there is a limited number of Norwegian large cap stocks, making it difficult for funds to diversify vastly between large Norwegian companies. The threshold of being classified as an active fund, set to 60%, was chosen arbitrary by Cremers & Petajisto. Because of the lack of Norwegian large cap stocks, we selected a threshold of 50% in order to be classified as an active fund in this study. Maintaining an Active Share above 50%, the fund will still have more active investments than passive, and we feel this is sufficient to classify a fund as active.

Furthermore, we have gathered data on the funds' expenses from Morningstar, which we compared to the Active Share to illustrate whether Norwegian mutual funds are reasonably priced, or if they, in essence, are defrauding their investors. The results are presented in section 6.8 of the study.

5.6 Timeframe

The sample will be evaluated over a ten-year period using monthly closing NAV from 31.12.2005 to 31.12.2015. This period contains both a bear market[16] and a bull market[17]. That being said, a study that

[16] Characterized by pessimism
[17] Characterized by optimism

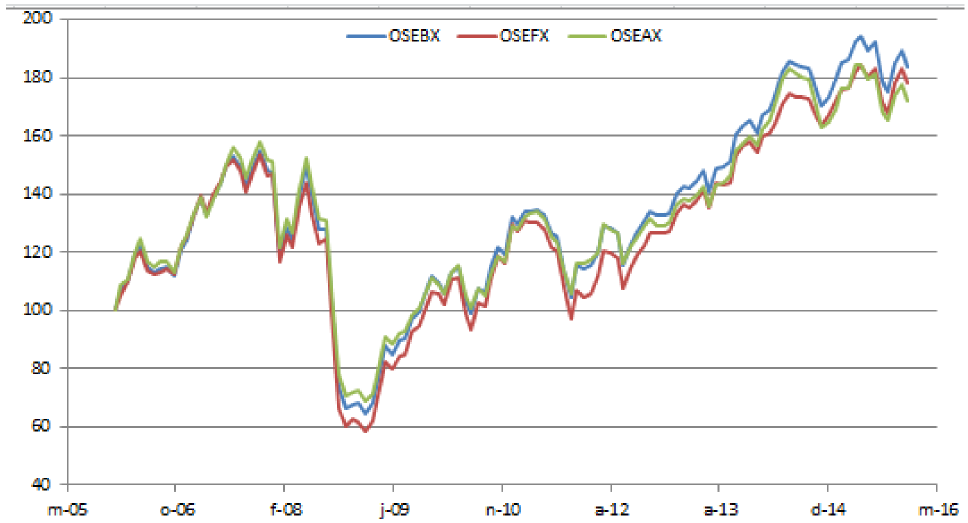
isolate performance in both bull and bear markets could be interesting, especially seen relative to the benchmark. Nevertheless, there is a drawback of having a relatively short timeframe, a disadvantage that is also the reason why most performance evaluations are performed on longer samples. The reason is a fear of statistical skewness and noise, which can severely corrupt the results in short-term evaluations. Additionally, one might argue that to distinguish luck vs. skill sufficiently, a longer period would be required. Although there is some truth to such a critique, few Norwegian funds are operating over such lengths and additionally, a longer period would increase the survivorship bias exponentially. Fama & French (2009) leave out any funds not yet established five years before their sample ends. In this study, this would induce survivorship bias in the dataset.

While identifying significant results may be more probable in a longer sample, it would also entail significant challenges to the robustness (described in section 5.11) of the evaluation. The Norwegian asset management market is relatively young in comparison to the UK and US. Therefore, the available sample of a longer timeframe could prove insignificant as only a marginal portion of the market was considered. Another aspect that would affect the robustness is the issue of survivorship bias. The longer we prolong the sample without accounting for survivor bias, the more influential the bias grows.

To avoid survivorship bias, we conduct individual studies on mutual funds that have ceased during the timeframe of our sample. Since our data consists of monthly returns over a ten year period, the maximum number of observations for any fund in our sample is 120. The main advantage of utilizing monthly returns data rather than daily return data is that with monthly data, returns are more normally distributed. In other words, the simplifying assumption of normality is more reasonable for monthly returns than it is for daily returns. We include any fund with at least a two-year recovery period, thus a minimum of 24 observations, resulting in a sample of 47 domestic equity mutual funds. On average, our funds' return series contain 96 observations. Thus, it is similar to Otten & Bams' (2002) procedure of limiting the sample. However, the advantage of requiring a higher minimum number of observations is to avoid some funds with short return histories. The fund with the fewest observations in our sample consists of 25 observations. Thus, the issue that the regression might be imprecisely estimated arises.

Below we illustrate the development of the three benchmarks on the OSE during the last ten years. This is done by indexing all three indices from the starting date 31/12/2005. When the financial crisis hit, we can see that all three indices decrease severely. The evolvements of the four indices are quite similar in general, showing that the different benchmark depends on the evolvement in the global economy.

Figure 5.1: Development in benchmarks (2005 – 2015), Source: Own creation based on Thomsen Reuters Datastream data



5.7 Risk-free rate of return

The tests conducted in the consecutive sections will be on returns in excess of the risk-free rate of return. The risk-free rate represents the return required for investing money in a security over a period, i.e. the expected return on an investment with zero risks (Bodie et al., 2009). Since these strict conditions of zero risk are impossible to fulfill for empirical studies, in reality, the risk-free rate is defined estimated by a proxy that is considered as little risky as possible. Conventionally, this has been the 3-month Treasury bill yield of the country in question, which is also the choice we have made. The main reason for applying the 3-month rate instead of rates with longer or shorter time horizons is the fact that the 3-month Treasury bill is most frequently traded. Therefore, it should provide more accurate results than if we would have used interest rates with longer time horizons (Gruber, 2003).

We collected the T-bill data from Norges Bank[18], quoted in yearly figures. The rates were then converted into monthly continuous rates by the following equation:

$$Monthly\ continuous\ rf_t = \frac{\ln(1 + r_t^{3M})}{12}$$

In our sample period between December 2005 and December 2015, the average continuous risk-free rate of return on a yearly basis was 2.3623%.

[18] Norway's central bank

5.8 Fund expenses

It is essential to distinguish between gross returns and net returns when evaluating mutual fund performance. Gross return, which is the rate of return before the deduction of any management fees, can be explained as the total return the fund manager can create. Net returns, on the other hand, are the returns of investments after deduction of management fees. Naturally, investors are most interested in a fund's net returns, as they represent the actual gains from their investment. However, by calling attention to both gross and net returns, this study can analyze two different dimensions. While the regression on net returns indicates whether the fund manager can add value for the customer, it does not indicate if the manager can beat the market. Hence, we will run regressions on gross returns to look at fund performance from a market efficiency point of view.

If net returns only evaluated the fund managers' performance, it would not be clear if the abnormal returns were in reality erased by the expenses. Since the Total Expense-Ratio (TER) of the different funds varies considerably across the sample, the abnormal return of a good (bad) performing fund could in truth be a result of a low (high) TER. Hence, unless fund performance of both net and gross returns is taken into consideration, we cannot investigate if the funds' abnormal returns are significant both before and after expense deduction.
In order to define what a TER incorporates, expenses related to funds are divided into three main categories:

- ***Bank fees***

  Fees paid every year as a percentage of the fund's NAV to the bank
- ***Management fees***

  Fees paid every year as a percentage of the fund' NAV to the management company, including incentive fees, i.e. an additional fee paid to the management depending on the performance of the fund to the given benchmark.
- ***Trading costs***

  These costs include stamp duty, brokerage fees, as well as bid-ask spreads paid on securities transactions.

In addition, TER accounts for entry and exit costs. It is important for an investor to note that a high-expense fund does not guarantee superior performance, even though the most expensive fund managers should, in theory, show evidence of superior skills or/and a higher active share. Moreover, in the world of finance, compensation and risk are related. The more expensive funds should, in theory, take on more risk and thereby have a potential for higher returns, and should be compensated for doing so.

The TERs used in this study captures all annual expenses. However, it should be pointed out that trading costs are difficult to measure as these continuously vary and are expressed as a percentage of the funds' NAV. The Morningstar database was not able to provide us with the historical figures, and neither were the Bloomberg database nor the individual funds' prospectus. Thus, the TERs of the different funds are assumed to be constant over the sample period and equal to the TERs as of 01.01.2016. We consider this as a fair assumption as the TERs are a relative measure based on the NAV. The TERs in our data sample differ from 0.28 % to 2.50 %. Across our sample of 47 equity funds, the annual average TER is 1.39 %.

The data we collected from Thomsen Reuters DataStream were reported as net asset values, that is, expenses were already deducted. Additional information about the funds' costs was obtained from the Morningstar database. To convert the returns from the net to gross, we simply added the funds' expenses to their respective computed net returns.

5.9 Information Variables for Conditional Models

When applying Ferson & Schadt's conditional model, also known as the conditional Treynor- Mazuy, discussed in section 4.4, we require a set of information variables to obtain time-varying beta estimations. As mentioned in the theory section, two of the five original information variables included in their model were proven statistically insignificant. Hence, we will only add the three statistically significant information variables in our conditional models. That is, we will include the lagged risk-free rate of return, the lagged measure of the slope of the term structure, and the lagged dividend yield.

For the lagged risk-free rate of return, we will lag our risk-free rate by one month. Furthermore, for the slope of the term structure, we will use the difference between the continuous monthly yield of the Norwegian ten-year government bond and the monthly continuous yield of the three month NIBOR, which is the same approach as Ferson & Schadt used in their original study. Moreover, the slope variable will be lagged one month. Finally, for the dividend yield, we will lag the dividend yield of the OSEFX by one month. The reasoning behind the choice of OSEFX is discussed in greater detail in section 5.4.

5.10 Survivorship Bias

As mentioned in section 4.5, there is a risk of survivorship bias being prominent in our data sample. Hence, creating an undesirable upward bias of our results, and should, therefore, be taken into account in our study. With this in mind, we used the same procedure as Dahlquist et al. (2000) used on the Swedish mutual fund market to measure the survivorship bias:

We will create three different portfolios to find a direct measure of the survivorship bias. The first portfolio will consist of a time-series of returns on an equally weighted portfolio of all of the funds in our sample, including the dead funds. By default, this portfolio should experience the same survivorship bias as the entire sample. The second portfolio will consist of a time-series of returns of an equally weighted portfolio of the funds alive at the end of our sample period.

In addition, we will construct a third portfolio consisting of only dead funds. By performing a t-test on the difference in the means of the “portfolio alive” and the “dead portfolio”, we can identify whether the difference between the two portfolios is statistically significant. That is, if the survivorship bias in our sample is statistically significant, it has to be taken into account.

5.11 Testing robustness

In line with Jensen (1967), the regressions in this study were conducted by the use of ordinary least square (OLS) to estimate the unknown coefficients in the different models. OLS minimizes the sum of squared vertical differences between the observed returns and those predicted by the linear regression. Several assumptions must be fulfilled to get unbiased results. Best linear unbiased estimator (BLUE) contains ten assumptions for use in OLS. However, these assumptions are not equally crucial for performance measurement, whereas homoscedasticity, the absence of autocorrelation and absence of multicollinearity are the only assumptions tested in this study. The consequences are similar if autocorrelation and heteroscedasticity (opposite of homoscedasticity) are present. The coefficients of the regression remain unbiased, but the standard errors estimates will be incorrect (Dahlquist et al., 2000). Incorrect estimates of standard error have a direct impact on the t-statistic, which is used to test the statistical significance of the results generated. Similarly, the presence of multicollinearity creates artificially high standard errors, which will affect the t-statistics.

The occurrence of positive autocorrelation will typically imply OLS regressions to compute artificially small standard error. Thus, the t-statistic will be inflated, which could result in statistical significance and falsely rejection of the null hypothesis (type 1 error). Hence, an essential element in understanding the significance of the regression outputs is to test for autocorrelation and heteroscedasticity. The test is also highly necessary for the validity of the alpha estimates.

5.11.1 Autocorrelation test

Autocorrelation is the similarity between observations as a function of the time lag between them. An example of autocorrelation could be a series of stock returns that shows a pattern of moving up in successive periods. This pattern is not uncommon. There exist traders willing to bet on an up-moving stock as its returns have been identified as positively autocorrelated. Hence, the traders see an increased probability of another successive upwards move.

Mutual fund returns are generated from a time-series of stock returns, thus, there is a certain probability that autocorrelation may occur in the dataset. This study considers returns on a monthly basis, which counts against the likelihood of identifying autocorrelation. Hence, correlated succession in stock price moves is most often seen on a daily basis. However, as we know the assumption of no autocorrelation often is violated when analyzing stock or stock index returns, it is important to test for it. For this assumption to be upheld, the Durbin-Watson test is applied. The d-statistics, which the test is based on, is described below:

$$d = \frac{\sum_{t=2}^{T}\left(e_t - e_{t-1}\right)^2}{\sum_{t=2}^{T} e_t^2}$$

Where:

T is the number of observations

e_t is the residual associated with the observation at time t.

The d-statistic always lies between 0 and 4, where 0 indicates a high degree of positive autocorrelation, and 4 indicates a high level of negative autocorrelation. To decide whether the d-statistic is a cause for concern, an upper and lower threshold is defined through a Durbin-Watson statistics table, based on the number of variables, the number of observations and required significance. In this study, there are 120 monthly observations, one explanatory variable and the desired significance level of 5%. Hence, our upper-level threshold will be 1.720 and our lower level threshold will be 1.747.

The Durbin-Watson test involves the following assumptions: The explanatory variables are nonstochastic, implying that random phenomena are not present. Error terms are assumed to be normally distributed and the regression models do not include the lagged values of the regression.

Testing autocorrelation in the Durbin-Watson method is separated into positive and negative autocorrelation. Each test has three possible outcomes: The presence of autocorrelation can be confirmed, rejected or the test can be inconclusive.

To test for positive autocorrelation d is compared to lower and upper critical value ($d_{L,\alpha}$ and $d_{U,\alpha}$), at the given significance level, α.

If $d < d_{L,\alpha}$, there is statistical evidence that the error terms are positively autocorrelated.

If $d > d_{U,\alpha}$, there is no statistical evidence that the error terms are positively autocorrelated.

If $d_{L,\alpha} < d < d_{U,\alpha}$, the test is inconclusive.

To test for negative autocorrelation (4 - d) is compared to lower and upper critical values ($d_{L,\alpha}$ and $d_{U\alpha,}$), at the given significance level, α.

If $(4 - d) < d_{L,\alpha}$, there is statistical evidence that the error terms are negatively autocorrelated.

If $(4 - d) > d_{U,\alpha,}$ there is no statistical evidence that the error terms are negatively autocorrelated.

If $d_{L,\alpha} < (4 - d) < d_{U,\alpha}$, the test is inconclusive.

Table 5.3: Durbin-Watson test for autocorrelation, Source: Own creation

			Evidence of no positive autocorrelation	Evidence of no negative autocorrelation	Evidence of positive autocorrelation	Evidence of negative autocorrelation
	d-stat	**4 – d**	**$d > d_U$**	**$4 - d > d_U$**	**$d < d_L$**	**$4 - d < d_L$**
Alfred Berg Aktiv	1.5026	2.4974		✔	✔	
Alfred Berg Gambak	1.5563	2.4437		✔	✔	
Alfred Berg Human	1.9192	2.0808	✔	✔		
Alfred Berg Classic	1.6257	2.3743		✔	✔	
Carnegie Aksje Nor.	2.0017	1.9983	✔	✔		
Danske Invest Inst I	2.1608	1.8392	✔	✔		
Danske Invest Inst II	2.1079	1.8921	✔	✔		
Danske Invest Nor. I	2.2181	1.7819	✔	✔		
Danske Invest Nor.II	2.1990	1.8010	✔	✔		
Danske Invest Vekst	2.0597	1.9403	✔	✔		
Delphi Norge	2.0498	1.9502	✔	✔		
DNB Norge	2.7817	1.2183	✔			✔

DNB Norge III	2.7786	1.2214	✔			✔
DNB Norge IV	2.7758	1.2242	✔			✔
DNB Selektiv I	2.5520	1.4480	✔			✔
DNB Selektiv II	2.5398	1.4602	✔			✔
DNB Selektiv III	2.5421	1.4579	✔			✔
DNB SMB	1.8499	2.1501	✔	✔		
Eika Norge	2.0818	1.9182	✔	✔		
Fondsfinans Norge	2.2591	1.7409	✔	✔		
Forte Norge	2.4639	1.5361	✔			✔
Forte Tronder	2.4727	1.5273	✔			✔
Handelsbanken	1.5538	2.4462		✔	✔	
Holberg Norge	1.7569	2.2431	✔	✔		
KLP Aksje Norge	2.3070	1.6930	✔			✔
Landkreditt Norge	2.0474	1.9526	✔	✔		
Landkreditt Utbytte	2.3903	1.6097	✔			✔
Nordea Avkastning	2.1074	1.8926	✔	✔		
Nordea Kapital	2.1838	1.8162	✔	✔		
Nordea Pluss	2.1089	1.8911	✔	✔		
Nordea Verdi	2.0204	1.9796	✔	✔		
Odin Norge C	1.7211	2.2789	✔	✔		
Pareto Norge A	1.9973	2.0027	✔	✔		
Pareto Norge B	1.9900	2.0100	✔	✔		
Pareto Norge I	2.0069	1.9931	✔	✔		
Pareto Inv. Fund C	1.5559	2.4441		✔	✔	
Pareto Inv. Fund A	1.7199	2.2801	✔	✔		
Pareto Inv. Fund B	1.5563	2.4437		✔	✔	
Pluss Aksje	2.3505	1.6495	✔			✔
Pluss Markedsverdi	1.9021	2.0979	✔	✔		
Storebrand Innland	1.8623	2.1377	✔	✔		
Storebrand Norge I	1.8191	2.1809	✔	✔		
Storebrand Norge	2.2470	1.7530	✔			
Storebrand Optima	1.9633	2.0367	✔	✔		
Storebrand Vekst	1.8712	2.1288	✔	✔		
Storebrand Verdi	1.8276	2.1724	✔	✔		
Swedbank Gener.	2.3299	1.6701	✔			✔

As can be seen in Table 5.3 above, we find no evidence of autocorrelation for 29 of the funds in our sample. However, we find signs of positive autocorrelation for six funds. Positive autocorrelation tends to make the estimate of error variance too small. Hence, the t-statistic becomes artificially large which implies an increased probability of rejecting a true null hypothesis, known as a “type 1 error”. The table also shows that 12 of the funds have significant evidence of negative autocorrelation. As opposed to positive autocorrelation, negative autocorrelation tends to make the estimate of the error variance too large. Thus, the regression generates a smaller t-statistic, and the standard errors might be biased. Negative autocorrelation implies that if a particular observation is below the average value, the next observation has increased the probability of being above the average value.

5.11.2 Homoscedasticity

The second of the two main assumptions that need to be fulfilled for the OLS regression to be BLUE is the assumption of constant variance of the residuals (Stock & Watson, 2009), known as homoscedasticity. If the variance turns out not to be constant, or homogenous, the errors are said to be heteroscedastic. The consequence of heteroscedasticity is the same as with autocorrelation, namely biased standard errors. These can be above or below the true population variance. Hence, inferences from the standard errors, such as rejecting a null hypothesis due to a high t-stat, may be misleading.

To control for the presence of heteroscedasticity, the White test is applied. The test does not build on normality assumptions. The test value is prob > chi-square which should be greater than 0.05 to confirm that there is no heteroscedasticity present. If the test value is lower than 0.05 the conclusion is that heteroscedasticity is present, which means the assumption of homoscedasticity must be rejected, and the OLS regression is not BLUE (Stock & Watson, 2009).

The White test for heteroscedasticity in our sample reveals no significant issues with the Norwegian mutual funds. Only two funds had an observed chi-square value below 0.1, and those funds were *Nordea Norge Verdi* and *Danske Invest Norske Aksjer Institusjon I*. However, it should be mentioned that Nordea Norge Verdi had a chi-square value equal to 0.0505. Hence, the fund had a value just above the limit of heteroscedasticity being present. Nevertheless, Stock & Watson (2009) state that it is important not to overreact to heteroscedasticity and that it is not a reason to dismiss a regression with the OLS method. The same authors state that it is only worth to correct for heteroscedasticity if the problems are severe. In this case, there are no problems regarding deviance from the cut-off value of 0.05 with most values far above the limit. Due to this observation, and the fact that the coefficients estimated will never be entirely unaffected by heteroscedasticity, it has been chosen to proceed with the data without further adjustments.

5.11.3 Newey-West HAC standard errors

As we discussed in section 5.10.1, the Durbin-Watson test yielded evidence of both positive and negative autocorrelation in our dataset. In order to deal with the autocorrelation, we decided to adopt the procedure of Newey-West (Newey & West, 1994) which produces standard errors that are heteroscedasticity and autocorrelation consistent (HAC). This procedure has been prevalent in recent literature on mutual fund performance, and was adopted by Dahlquist et al. (2000) and Blake & Timmermann (2002) amongst other researchers.

By the use of the statistical software SAS 9.4, we ran ARIMA regressions on each fund to determine the optimal lag order to include in the Newey-West. SAS reports the Akaike's Information Criterion (AIC), which is a measure of the relative quality of statistical models; the lower the AIC, the better quality of the statistical model. After looking at the AIC outputs from the ARIMA regressions, it became evident that one lag-order for every fund was optimal, as they yielded the lowest AIC. All regressions in this study are performed with Newey-West HAC standard errors to optimize the validity of our findings.

5.11.4 Multicollinearity

To make sure our OLS regression is BLUE (Stock & Watson, 2009), we have tested for multicollinearity in our dataset. Multicollinearity appears in a dataset when two or more independent variables in a multiple regression are highly correlated. If this is the case, then one of the variables can be linearly predicted from the others with a high degree of certainty. The major consequence of multicollinearity is that the coefficient estimates may change erratically in response to small variations in the model. Despite this, multicollinearity does not affect the explanatory power or reliability of the model. Multicollinearity only affects the coefficient estimates through artificially high standard errors, and thus wider confidence intervals.

In our Treynor-Mazuy regressions (see section 4.3.4), the excess market returns is present twice, even though it is squared in the third term of the model. Including the same variable twice could lead to multicollinearity, and to make sure our OLS regressions are BLUE, we will check for this. Moreover, the same applies for our pooled performance persistence regression (see section 6.6), where the excess market return is paired with the binary variable, and thus included twice in the model. Intuitively, it is not unlikely for variables that are included twice in the same regression model to be highly correlated with each other, even though the variables differ slightly. Despite the fact that the above-mentioned regression models are frequently used in research and literature on the field, we would like to test for multicollinearity to rule out any doubt.

We have applied the *Variance Inflation Factor (VIF)* in our statistical software SAS 9.4 to all of the regressions used in this study to check for multicollinearity. The VIF is a widely applied test to check if multicollinearity is present within datasets. If the regression output indicates a VIF above 5, a problem with multicollinearity is detected. However, none of our regressions indicated a VIF above the critical value of 5, and we are confident that our datasets are free of multicollinearity.

5.12 Hypothesis testing

To investigate whether the various fund managers possess selection skills and/or market timing abilities, the respective alpha and gamma estimates have to be tested to see whether they are different from zero or not. If they are not equal to zero, we have two distinct outcomes: they will be greater or less than zero, i.e. the trials in the study are two-sided. Furthermore, the null hypothesis is written such that the coefficient being tested is equal to zero, while the alternative hypothesis is that the coefficient is different from zero. If the coefficient in question is statistically insignificant, the null hypothesis will not be rejected. However, if the coefficient is significantly different from zero, the null hypothesis is rejected, and the alternative hypothesis is seen as more feasible.

The 5%-significance level is used as a general threshold for all tests, with a two-sided test leaving 2.5% in each tail of the distribution as the rejection area. It should be mentioned that the significance level is equal to the probability of committing a type 1 error, i.e. rejecting a true null hypothesis (Gujarati & Porter, 2009). Thus, with the sample in this study consisting of 47 funds, more than 2 out of the 47 funds could appear significant by chance. Thus, this constitutes a consideration when results are being interpreted.

6.0 Empirical findings

In this section, we present the hypotheses and the results of our empirical tests. We will begin by presenting a summary of the descriptive statistics. Furthermore, the funds are ranked by different relative performance measures. The rest of the section involves other performance measures and regression outputs. Stock picking skills and market timing ability are being analyzed, and we try to identify performance persistence and distinguish skills from luck. Ultimately, we apply the Active Share Measure on our sample funds, to conduct analyses based on the actual level of activity of each fund. The practical implications of our findings will be analyzed deeper in section 7.

6.1 General findings

In Table 6.1 below, the descriptive statistics and TER for the Norwegian mutual funds are shown. As described earlier, all funds are tested against the same benchmark (OSEFX). Using several different benchmarks would make it practically impossible to comment on relative differences in performance.

Table 6.1: Descriptive statistics of our sample funds. Source: Own creation

Fund name	Mean		Excess return	Standard deviation	Minimum return	Maximum return	Skewness	Kurtosis	Expense ratio
ALFRED BERG AKTIV	0.6472%		0.4503%	6.64%	-31.54%	15.94%	-1.88	6.79	1.50%
ALFRED BERG GAMBAK	0.7790%	**	0.5822%	6.63%	-31.99%	15.18%	-2.13	8.03	1.80%
ALFRED BERG HUMANFOND	0.3810%		0.1841%	6.48%	-29.95%	14.94%	-1.86	7.00	1.80%
ALFRED BERG NORGE (CLASSIC)	0.6695%		0.4727%	6.59%	-31.48%	15.78%	-2.01	7.85	1.20%
CARNEGIE AKSJE NORGE	0.5987%		0.4019%	6.60%	-32.18%	14.78%	-1.85	6.89	1.20%
DANSKE INVEST NORSKE AKSJER INSTITUSJON I	0.7595%	**	0.5626%	6.29%	-25.94%	14.38%	-1.56	5.05	0.90%
DANSKE INVEST NORSKE AKSJER INSTITUSJON I	0.6406%		0.4437%	6.42%	-25.78%	14.02%	-1.46	4.49	0.90%
DANSKE INVEST NORGE I	0.6613%		0.4644%	6.27%	-27.25%	13.85%	-1.60	5.46	2.00%
DANSKE INVEST NORGE II	0.7275%	**	0.5307%	6.21%	-26.51%	13.89%	-1.55	5.22	1.25%
DANSKE INVEST NORGE VEKST	0.3542%		0.1573%	6.09%	-29.68%	14.75%	-1.62	6.52	1.75%
DELPHI FONDENE NORGE	0.8003%	**	0.6034%	4.23%	-11.00%	10.96%	-0.55	1.56	2.00%
DNB NORGE	0.3594%		0.1625%	3.94%	-9.97%	9.86%	-0.39	0.75	1.80%
DNB NORGE III	0.4232%		0.2263%	3.94%	-9.88%	9.92%	-0.39	0.75	1.09%
DNB NORGE IV	0.4431%		0.2463%	3.95%	-9.90%	9.96%	-0.39	0.74	0.75%
DNB NORGE SELEKTIV I	0.3317%		0.1349%	4.15%	-10.33%	12.87%	-0.05	1.13	2.01%
DNB NORGE SELEKTIV II	0.4095%		0.2127%	4.14%	-10.24%	12.92%	-0.05	1.11	1.01%
DNB NORGE SELEKTIV III	0.4260%		0.2291%	4.16%	-10.25%	12.99%	-0.04	1.12	0.80%
DNB SMB	0.1344%		-0.0624%	5.37%	-14.16%	14.43%	-0.03	0.60	2.01%
EIKA NORGE	0.5073%		0.3104%	6.51%	-30.96%	16.89%	-1.72	6.40	2.00%
FONDSFINANS NORGE	0.7468%	**	0.5500%	6.42%	-29.75%	15.12%	-1.40	5.13	1.00%
FORTE NORGE	0.2490%		0.0522%	4.37%	-12.33%	13.53%	-0.04	1.95	2.00%
FORTE TRONDER	1.0358%	**	0.8389%	2.73%	-4.04%	9.05%	0.53	0.84	1.00%
HANDELSBANKEN NORGE	0.7811%	*	0.5843%	7.02%	-34.00%	16.34%	-2.15	8.60	2.00%
HOLBERG NORGE	0.2138%		0.0169%	5.68%	-27.31%	13.79%	-1.30	5.08	1.50%
KLP AKSJE NORGE	0.5556%		0.3587%	6.56%	-35.34%	16.2%	-1.78	7.75	0.75%
LANDKREDITT NORGE	0.4117%		0.2148%	6.14%	-23.19%	15.81%	-1.07	3.00	1.75%
LANDKREDITT UTBYTTE	0.7893%	**	0.5924%	3.02%	-9.55%	4.55%	-1.91	4.19	1.50%
NORDEA AVKASTNING	0.4962%		0.2994%	6.58%	-30.35%	15.39%	-1.76	6.42	1.50%
NORDEA KAPITAL	0.5799%		0.3830%	6.51%	-29.73%	15.44%	-1.73	6.26	1.00%
NORDEA NORGE PLUSS	0.5431%		0.3462%	4.17%	-11.75%	11.42%	-0.57	1.57	1.00%
NORDEA NORGE VERDI	0.6006%		0.4037%	5.52%	-28.05%	14.13%	-1.76	7.34	1.50%
ODIN NORGE C	0.0000%		-0.1972%	5.79%	-27.56%	12.59%	-1.64	5.57	2.00%
PARETO AKSJE NORGE A	0.3086%		0.1117%	5.69%	-30.20%	13.11%	-1.73	7.74	2.50%
PARETO AKSJE NORGE B	0.2496%		0.0527%	5.82%	-30.03%	13.10%	-1.64	6.92	2.01%
PARETO AKSJE NORGE I	0.4128%		0.2159%	5.85%	-30.23%	13.24%	-1.68	7.10	0.50%
PARETO INVESTMENT FUND C	1.5549%	**	1.3580%	1.79%	-1.60%	4.35%	0.08	-1.07	0.50%
PARETO INVESTMENT FUND A	0.6892%	**	0.4923%	6.70%	-34.04%	17.18%	-1.98	8.11	1.80%
PARETO INVESTMENT FUND B	1.5185%	**	1.3216%	1.79%	-1.64%	4.31%	0.08	-1.07	0.95%
PLUSS AKSJE	0.6501%		0.4532%	5.83%	-25.98%	13.47%	-1.36	4.48	1.20%
PLUSS MARKEDSVERDI	0.641%		0.4441%	6.30%	-28.81%	14.80%	-1.62	5.87	0.90%
STOREBRAND AKSJE INNLAND	0.4158%		0.2189%	3.87%	-9.72%	9.76%	-0.55	0.84	0.60%
STOREBRAND NORGE I	0.4117%		0.2149%	3.90%	-10.17%	9.57%	-0.68	1.04	0.28%
STOREBRAND NORGE	0.7634%	**	0.5665%	4.11%	-11.23%	10.77%	-0.54	1.75	1.50%
STOREBRAND OPTIMA NORGE	0.5371%		0.3402%	4.27%	-10.66%	9.56%	-0.79	0.70	1.00%
STOREBRAND VEKST	1.1760%	**	0.9791%	4.70%	-10.98%	12.17%	-0.34	0.83	2.00%
STOREBRAND VERDI	0.5891%		0.3923%	3.91%	-10.24%	10.6%	-0.46	1.01	2.00%
SWEDBANK GENERATOR	1.1252%	**	0.9283%	5.11%	-15.58%	11.14%	-0.78	1.18	1.50%
Average	0.5979%		0.4010%	5.21%	-20.70%	12.74%	-1.10	3.97	1.39%
OSEFX	0.4814%		0.2845%	6.85%	-0.317%	0.153%	-1.968	7.60	
Risk free return	0.1969%								

* = Higher excess return than OSEFX.
** = Higher excess return and lower standard deviation than OSEFX.

Firstly, we notice that the average monthly means for the 47 funds are larger or equal to zero over the ten year period for all equity mutual funds. When computing the excess return, two of the funds, *DNB SMB* and *Odin Norge C*, yields negative excess returns. However, we notice that the two funds have standard deviation almost equal to the average of the sample, not in correspondence with the basic financial theory where investors should be compensated for adding higher risk to their portfolios. On the other hand, *Pareto Investment Fund C* and *Pareto Investment Fund B* have the greatest excess returns with the monthly mean above 1.3 %. Also, these two funds also have significantly lower standard deviation than the rest of the funds in the sample. Nevertheless, according to the TER, *DNB SMB*, and *Odin Norge C* are not among the cheapest funds both demanding fees significantly higher than the average. On the contrary, *Pareto Investment Fund C and B* are not among the most expensive funds with fees lower than the average. Thus, the results presented in Table 6.1 above indicate that expenses do not necessarily correlate with performance. The relationship between fund performance and related expenses is further investigated in section 6.4.

Furthermore, 13 out of the total sample of 47 mutual funds have both a greater excess return and a lower standard deviation compared to the benchmark. Fulfilling these two conditions is a good indicator of the funds' ability to create value, and one might think that such funds are heavily sought after by investors. However, it is important to notice that returns may not be the most important factor. Albeit 13 funds have a greater return, as well as lower standard deviation than the benchmark, a lower standard deviation may be a measurement worth mentioning in itself. For several investors who may be risk-averse, the benchmark can be viewed as too volatile. Such clients would favor mutual funds with low volatility. It is also worth to highlight the fact that only four of the funds have a minimum return lower than the benchmark. Our interpretation of this result is that fund manager investing in the Norwegian market can eliminate the biggest losers in the benchmark portfolio from their portfolios.

Regarding skewness, all the Norwegian mutual funds, as well as the benchmark, have negative skewness. The only exceptions are *Pareto investment fund C and B*. Skewness quantifies how symmetrical the distribution is. Negative skewness entails a long left tail in the distribution, which in turn entails an increased probability of extreme negative returns. A reasonable explanation for the negative skewness is the financial crisis from 2007 to 2009. Additionally, we have computed kurtosis, which quantifies whether the shape of the data distribution matches the normal distribution. Again *Pareto Investment Fund C and B* show opposite results compared to rest of the sample and the benchmark. An interesting point to note for these two funds is that they require a minimum deposit of 50 and 10 million NOK respectively. In other words, these two funds target corporate investors and high net worth individuals.

For the rest of the sample, the majority of the funds have a positive kurtosis, entailing a more peaked distribution, while the minority has a negative kurtosis, causing a flatter distribution. A kurtosis larger than 3 indicates fat tails and more peaked distribution. Hence, there is an increased probability of extreme returns and returns close to the mean compared to fund with a normal distribution. Thus, using a normal distribution will undervalue risk when the fund has a kurtosis greater than 3.

6.2 Relative performance measures

Relative performance measures involve many factors that might be of importance to different investors in asset management. At the same time, each measure has some shortages and does not consider every factor of interest. Hence, it is important to bear these deficiencies in mind when the results and ultimate rankings of the measures are considered. In addition, to being used as a ranking tool, the relative performance measures can provide useful analytical insight. The different actions take risk into consideration to varying extent, and thus the rankings are probably to exemplify different strategies.

As both the Sharpe ratio and the Treynor ratio are derived from the CAPM formula, they are expected to generate similar results. The two measures differ in how the risk of the portfolio is accounted for. The Sharpe ratio is based on the total risk as measured by the standard deviation of returns while the Treynor ratio is based on the risk relative to the market portfolio. As the Treynor ratio only accounts for the beta (undiversifiable risk), it tends to over-estimate funds with an over-/underweight sector strategy. Hence, the beta will not be “diversified” and will have a relatively higher undiversifiable risk. Thus, these funds will obtain a higher beta, but a lower standard deviation than that of the benchmark.

In the ranking of the Norwegian mutual funds, the M^2 measure is used as the main relative performance measure. As described in section 4.3.3, M^2 quantifies the excess return an investor gets from holding the investment fund as opposed to the benchmark index. Hence, the measure can be used to analyze how well the fund performs in itself, not just how well it performs in comparison to other funds. This is, in essence, the exact thing we would like to investigate in this study. The Sortino ratio is considered the second best-ranking measure, as it measures the probability of negative returns. Simply put, one could assert that the measures presented a choice on whether to take the risk on the beta level or in the volatility. In a small stock exchange as OSE, the different measures will not create as much of an impact as one could expect in larger markets.

Table 6.2: Relative performance measures: Norwegian mutual funds. Source: Own creation

Ranking	Fund	M^2	Treynor	Sortino	Sharpe
1	Pareto Investment Fund C	1	1	1	1
2	Pareto Investment Fund B	2	2	2	2
3	Forte Tronder	3	3	5	3
4	Storebrand Vekst	4	4	3	4
5	Landkreditt Utbytte	5	5	7	5
6	Swedbank Generator	6	6	4	6
7	Delphi Fondene Norge	7	7	6	7
8	Storebrand Norge	8	11	10	8
9	Storebrand Verdi	9	22	23	9
10	Danske Invest Norske Aksjer Inst.	10	9	11	10
11	Alfred Berg Gambak	11	8	9	11
12	Fondsfinans Norge	12	10	12	12
13	Danske Invest Norge II	13	12	13	13
14	Nordea Norge Pluss	14	27	26	14
15	Handelsbanken Norge	15	13	8	15
16	Storebrand Optima Norge	16	26	27	16
17	Pluss Aksje	17	14	17	17
18	Danske Invest Norge I	18	17	16	18
19	Nordea Norge Verdi	19	15	21	19
20	Pareto Investment Fund A	20	16	14	20
21	Alfred Berg Norge (Classic)	21	18	15	21
22	Pluss Markedsverdi	22	20	19	22
23	Danske Invest Norske Aksjer Inst.	23	19	20	23
24	Alfred Berg Aktiv	24	21	18	24
25	DNB Norge IV	25	32	31	25
26	Carnegie Aksje Norge	26	23	22	26
27	Nordea Kapital	27	24	24	27
28	DNB Norge III	28	34	33	28
29	Storebrand Aksje Innland	29	35	34	29
30	Storebrand Norge I	30	37	36	30
31	DNB Norge Selektiv III	31	36	32	31
32	KLP Aksje Norge	32	25	25	32
33	DNB Norge Selektiv II	33	38	38	33
34	Eika Norge	34	28	28	34
35	Nordea Avkastning	35	29	29	35
36	DNB Norge	36	41	40	36
37	OSEFX	37	30	30	37
38	Pareto Aksje Norge I	38	31	35	37
39	Landkreditt Norge	39	33	37	38
40	DNB Norge Selektiv I	40	43	42	39
41	Alfred Berg Humanfond	41	39	39	40
42	Danske Invest Norge Vekst	42	40	41	41
43	Pareto Aksje Norge A	43	42	43	42
44	Forte Norge	44	45	45	43
45	Pareto Aksje Norge B	45	44	44	44
46	Holberg Norge	46	46	46	45
47	DNB SMB	47	47	47	46
48	ODIN NORGE C	48	48	48	47

Firstly, the initial impression of the Norwegian domestic funds is that the sample contains two funds which, again, seem to perform significantly better than the others. Regardless of the measure chosen, *Pareto Investment Fund C and B* deliver best amongst the sample. Secondly, without a few exceptions, the M^2 measure, and the Sharpe ratio generates the same ranking. This observation is not strange as the M^2 measure is based on the Sharpe ratio. In agreement with expectations, there are also significant deviations between the different measures in several funds. The deviations are most severe in *Storebrand Verdi, Nordea Norge Pluss*, and *Storebrand Optima Norge*, all of which perform significantly worse according to the Treynor Ratio and Sortino compared to the Sharpe ratio and M^2. The three mutual funds have in common that they have a relatively low excess return. However, as the excess return is used as the numerator in both computations, the risk is the main reason for the difference in ranking. The standard deviations are approximately equal to the average of all funds while the betas are above the average. Thus, the rankings become worse according to the Treynor ratio as the funds' undiversifiable risks are higher.

In addition, another aspect worth mentioning is that the bottom five of mutual funds in the ranking seem to be the worst performers across all relative performance measures.

6.3 Stock picking skills / managerial skills (value added)

To investigate whether the funds' managers add value or not for the investors, we have conducted several well-known and widely applied analyses. All of these are described in the theory section, and the regressions are carried out both with net and gross returns to test the stock picking ability both from an investor's perspective and from a market efficiency perspective, as referred to in section 5.8.

6.3.1 Jensen's alpha – Unconditional model

The first regression analysis conducted is the unconditional version of Jensen's alpha with the following null hypothesis and alternative hypothesis:

Hypothesis 1: $H_0: \alpha_i = 0$ $H_1: \alpha_i \neq 0$

Rejecting the null hypothesis implies that the fund manager indeed possesses superior stock picking skills. That is, the fund manager has statistically significantly abilities in picking the right underpriced stocks to maximize portfolio returns and add value for investors. Both the regressions on net and gross return have been run with OSEFX as the market proxy/benchmark. Intuitively, this implies that the results of the regression can be interpreted in two dimensions; first, the regression output provides insights to whether the mutual fund as investment vehicles significantly outperforms the benchmark. Second, it provides clarity of whether investors receive significant excess returns that justify the mutual funds' fees. The summary of the regression findings on gross monthly return and monthly net return results for the Norwegian funds are presented in the table below. For a full overview of the output from the unconditional Jensen's Alpha regression, we refer to Appendix 1.

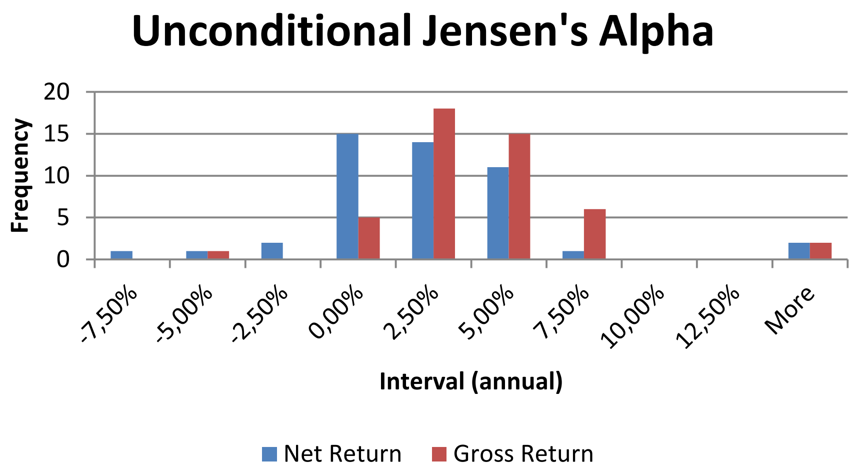


Table 6.3: Summary of Jensen's alpha Unconditional Model, gross and net returns. Source: Own creation

Market	No of funds	Return Series	Benchmark	Annual Alpha	Significantly positive (negative)
Norway	47	Net Returns	OSEFX	1.05%	8(0)
Norway	47	Gross Returns	OSEFX	2.60%	17(0)

This table presents the results from the unconditional Jensen's alpha regression using both net and gross returns. Column 2 shows the total number of funds in our data sample, and column 3 shows the return series being analysed. Column 4 reports the benchmark used as a reference point. Column 5 reports the annualized average alpha value of the sample, while column 6 reports the number of funds significantly outperforming/underperforming relative to the benchmark.

As mentioned in section 5.11.3, we have used Newey-West corrected standard errors in our regression to eliminate any problems with autocorrelation and heteroscedasticity in the sample. Moreover, in order to detect significant stock picking skills, we have used a 95% confidence interval in the statistical software SAS 9.4 to reject the null hypothesis. That is, a t-value above the absolute value of 1.96 will reject the null hypothesis stated above.

6.3.1.1 Net Returns

Looking at net returns, table 6.3 above illustrates that the average annual alpha value for the entire data sample is positive, which indicates that the average fund manager is outperforming the benchmark. However, only eight funds in the sample have an alpha value that is statistically significantly positive, with five of these funds being significant at a 1% level. Hence, there is a strong indication that fund managers of these funds are displaying significant superior stock picking skills. It is especially worth mentioning that we find no evidence of significant negative stock picking skills in our unconditional sample, which can serve as a sign of quality towards the fund managers within this sample.

Table 6.4: Funds with significant unconditional net alpha. Source: Own creation

Fund name	Net Returns			β	Obs.	R^2 adj.
	Monthly α	Yearly α	t-stat			
Pareto Investment Fund C	**0.01218****	**0.1462****	**(4.27)**	0.42191	25	0.3767
Pareto Investment Fund B	**0.01182****	**0.1418****	**(4.20)**	0.42220	25	0.3770
Danske Invest Inst. I	**0.00314****	**0.0377****	**(3.02)**	0.91189	120	0.9680
Danske Invest Inst. II	**0.00309****	**0.0371****	**(2.97)**	0.91004	120	0.9647
Danske Invest Norge II	**0.00281****	**0.0337****	**(2.66)**	0.89666	120	0.9654
Danske Invest Norge I	**0.00210***	**0.0252***	**(2.01)**	0.90527	120	0.9667
Pluss Markedsverdi	**0.00189***	**0.0227***	**(2.39)**	0.91458	120	0.9821
Alfred Berg Norge (Classic)	**0.00180***	**0.0216***	**(2.21)**	0.95141	120	0.9819

As we can see from the individual funds' estimated alpha and beta values in Table 6.4 above, *Pareto Investment Fund C and B* have the highest unconditional monthly alpha in our sample with 1.22% and 1.18% respectively. That is, 14.62% and 14.18% in annual terms, both significant at the 1% level. Because we can reject the null, the outperformance is due to the fund managers being able to pick continuously the correct underpriced stocks, which means superior stock picking skills. If we compare the alpha estimates with the average annual alpha from Table 6.3 above, we see that they outperform the average fund in excess of 13% per year, which is a remarkable result. With this in mind, *Pareto Investment Fund C and B's* performance severely increases the average alpha for our sample. This becomes even more prominent when we note that the third best performing fund, *Danske Invest Norske Aksjer Institusjon I*, only obtains a monthly alpha of 0.31% or 3.77% in annual terms. The remarkably good performance by the *Pareto* funds is perhaps best illustrated by looking at the histogram above table 6.3, where one clearly sees how skewed they are to the right, which emphasizes how well they have performed in comparison to the other funds in our sample. However, as we will discuss in the next paragraph, the two funds' remarkable performance needs to be interpreted with caution.

From table 6.1 (descriptive statistics), we know that *Pareto Investment Fund C and B* has the highest excess returns amongst our sample with a monthly excess return of 1.358% and 1.322% respectively. The regression estimated a beta of 0.4219 for *Pareto Investment Fund C* and a beta of 0.4222 for *Pareto Investment Fund B*, which in practice means that, on average, a 1% increase in OSEFX will result in a 0.4219 and 0.4222 percent increase in the two funds. Alternatively, a low beta can indicate that the price movements of the funds are not highly correlated with the benchmark. This matter occurs when the portfolio of stocks held by the mutual fund differs to a large extent from the stocks in the benchmark portfolio. Unfortunately, *Pareto Investment Fund C and B* are two of the few funds for which we were unable to find a full portfolio. However, we did find the full portfolio for *Pareto Investment Fund A*, which has the same fund manager.

Pareto Investment Fund A has an Active Share above 70%, as referred to in Appendix 9, which indicates large differences between its portfolio and the benchmark portfolio. Given the fact that there are usually minor differences between the holdings of funds with the same fund manager, it is not farfetched to assume that *Pareto Investment Fund B and C* most likely have a high Active Share as well. The high Active Share could very well serve as a natural explanation to the low beta estimate. However, these two funds are the youngest in our sample, with just 25 months of data. During this period, the overall market has been booming, implying that they have few negative returns, severely increasing the alpha value. Looking at the adjusted R^2, we get further confirmation of this problem; other factors can explain more than 60% of the variation in the two funds' excess returns than the variation in the benchmark's excess returns. From a research perspective, this means that we need to take caution when interpreting the statistical estimates of the two Pareto funds.

On the other hand, *Alfred Berg Norge (Classic)* is the fund with the lowest significantly positive alpha, with a yearly estimated alpha of 2.14%. From the descriptive statistics, we know that this fund delivers an excess return of 0.4727% per month, which is just above the sample average of 0.4010%. The beta values of the funds vary to quite a large extent, ranging from 0.4219 to 1.0884. However, the outliers are the funds with the least observations and the lowest adjusted R^2, which implies that other factors not captured by the model can explain the variation in their excess returns. The funds with more observations tend to have a higher adjusted R^2 and a stable beta value ranging from 0.75 to 0.97, which is in accordance with previous research.

6.3.1.2 Gross Returns

After adding the expenses to the net returns, we see that a total of 17 funds achieve a significant positive alpha. Compared with the eight funds in our net return sample, it is evident that while the 17 funds do in fact display vital stock picking skills before deduction of fees, nine of them are not attractive to investors because the funds' fees erase the benefits from the skill. An overview of the funds that becomes unattractive from an investors' point of view after fees, but display stock picking skills before fees, is presented in Table 6.5 below. It is important to note that these funds are actually outperforming the benchmark, due to their positive alpha value, but after fees, we find no evidence of stock picking skills. Hence, investors are not able to enjoy benefits from the fund managers skills in the funds presented in Table 6.5.

Table 6.5: Funds w/ stock picking skills before fees, but are unattractive to investors. Source: Own creation

	Gross Returns					
Fund name	Monthly α	Yearly α	t-stat	β	Obs.	R^2 adj.
Handelsbanken Norge	**0.00410****	**0.0492****	**(2.95)**	0.9533	120	0.9533
Alfred Berg Gambak	**0.00386***	**0.0463***	**(2.13)**	0.9106	120	0.9106
Fondsfinans Norge	**0.00368***	**0.0442***	**(2.23)**	0.9246	120	0.9246
Pareto Investment Fund A	**0.00342***	**0.0410***	**(2.10)**	0.9327	120	0.9327
Pluss Aksje	**0.00322****	**0.0386****	**(2.81)**	0.9594	120	0.9594
Alfred Berg Aktiv	**0.00261***	**0.0313***	**(2.01)**	0.9543	120	0.9543
Carnegie Aksje Norge	**0.00228***	**0.0274***	**(2.55)**	0.9802	120	0.9802
Nordea Kapital	**0.00197****	**0.0236***	**(2.89)**	0.9875	120	0.9875
Nordea Avkastning	**0.00148***	**0.0178***	**(2.24)**	0.9884	120	0.9884

As expected due to the way calculated gross returns are calculated, the average annual alpha of our sample is higher for the gross returns than for the net returns. The average gross alpha is 2.60% per year, which is 1.55 percentage points higher than the average net alpha.

6.3.2 Jensens's alpha – Conditional Beta Model

The second regression analysis conducted is the conditional beta model. In this analysis, a second hypothesis is posited to examine if the conditional model is an improvement of the unconditional model. The first hypothesis is the same as in the unconditional model, where we test if alpha is significantly different from zero or not. The interpretation of a significant alpha is the same as before; a significant alpha value implies superior/inferior stock picking skills, dependent on whether we achieve a positive or negative alpha estimate. The second hypothesis tests if the explanatory variables have any impact on the dependent variable by testing all the slopes coefficients simultaneously

Hypothesis 2:	$H_0 : \alpha = 0$	$H_1 : \alpha \neq 0$
Hypothesis 3:	$H_0 : \beta_2 = \beta_3 = \beta_4 = 0$	$H1: \beta 2 \neq 0, and/or\ \beta 3 \neq 0, and/or\ \beta 4 \neq 0$

To determine whether the conditional model adds explanatory power to the unconditional model, the following test has been employed:

$$F = \frac{\frac{SSE_{Unconditional} - SSE_{Conditional}}{No. of\ extra\ terms}}{MSE_{Conditional}}$$

That is, we are investigating whether adding the three lagged information variables improves the model. The hypothesis is tested using the F test of statistics, according to the formula above. If the computed F-value is above its critical value (5.6581 for 100 observation given our model), the null hypothesis is rejected. Hence, at least one of the explanatory variables is statistically significantly different from zero. Thus, the conditional model adds explanatory power to the unconditional model, and accordingly the conditional model is preferred. However, if we cannot reject the null hypothesis, the unconditional Jensen's alpha will be preferred.

Table 6.6 below shows the overall results for the Norwegian mutual funds, computed by the conditional beta model.

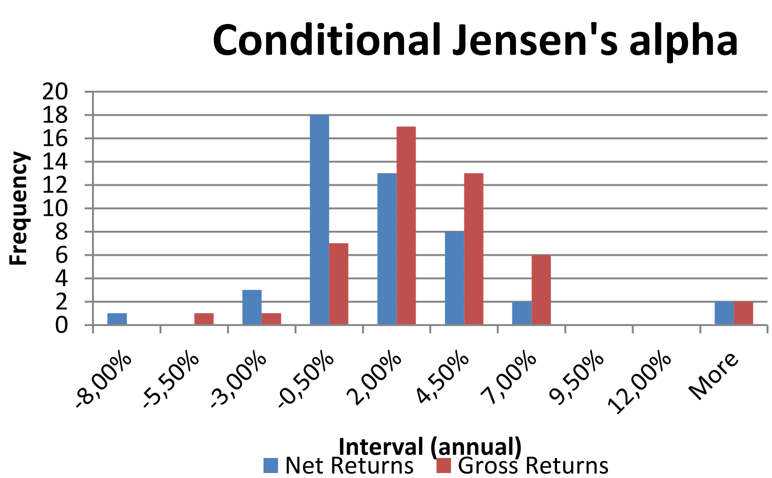


Table 6.6: Summary of Jensen's alpha Conditional Model, gross and net returns. Source: Own creation

Market	No of funds	Return Series	Benchmark	Annual Alpha	Significantly positive (negative)	Percentage of significant F
Norway	47	Net	OSEFX	0.60%	5(1)	25.53%
Norway	47	Gross	OSEFX	2.00%	13(0)	25.53%

This table presents the results from the conditional Jensen's alpha regression using both net and gross returns. Column 2 shows the total number of funds in our data sample, and column 3 shows the return series being analyzed. Column 4 reports the benchmark used as a reference point. Column 5 reports the annualized average alpha value of the sample, while column 6 reports the number of funds significantly outperforming/ underperforming relative to the benchmark. Column 7 indicates the percentage of funds for which the F-test of the information variables was not jointly zero. That is, the model illustrates the percentage of funds where the conditional model adds significant explanatory power to the unconditional model.

6.3.2.1 Net Returns

Looking at the overall results from the conditional model, it becomes evident that adding the lagged information variables, and thus introducing a time-varying beta, reduces the average annual alpha by 43% compared to the unconditional model. We add the time-varying beta for several reasons; first of all, it controls for omitted variable bias in the traditional unconditional models, thus improving the overall fit of the models[19]. Second, it provides a more realistic estimate of the beta. Traditional performance models assume a stable beta, which implies stable risk-levels. In the real world, such a thing would be extremely unlikely as the micro- and macroeconomic environment is constantly changing. Thus, from an investor perspective, a time-varying beta provides a more realistic estimate of the undiversifiable risk of each fund.

The average annual alpha is estimated to 0.60% across our sample. That is, the average fund manager is still outperforming the market, but to a much lower extent than previously estimated. Interestingly, if we exclude the statistically significant outperforming/underperforming funds, the average annual alpha is -0.064%. Thus, among the fund managers *not* displaying superior or inferior stock picking skills, the average fund manager is actually underperforming relative to the benchmark.

Moreover, Table 6.6 above illustrates that the conditional model improved 25.53% of the models in our sample. In regards to *hypothesis 3* mentioned above, this means that in 25.53% of the cases, we reject H_0, which implies that the conditional model adds some explanatory power to our regression models. Hence, we need to take the results of both the unconditional and the conditional model into account

[19] Ferson & Schadt, *Measuring Fund Strategy and Performance in Changing Economic Conditions,* 1996

when we interpret the results. Not surprisingly, bearing in consideration that funds are regressed against the same benchmark in both the net and gross scenario, the conditional model improves the same amount of models in both scenarios.

Even though the conditional model only improves one-quarter of our models, there are a couple of interesting differences one should note. First, the number of significant outperforming funds is reduced from eight to five. Second, we now observe a significantly underperforming fund. Looking at the individual alpha and beta estimates in Appendix 2, we can see that *Holberg Norge* is significantly underperforming relative to the market with a monthly alpha of -0.429 %, or -5.15% in annual terms. These figures are much lower than the annual sample average of 0.60%. In view of the model, this means that *Holberg Norge's* fund manager is consistently displaying inferior stock picking skills. The funds with significant alpha estimates are presented in Table 6.7 below, ranked by outperformance relative to the benchmark index.

Table 6.7: Summary of funds with a significant net alpha estimate. Source: Own creation

	Net Returns						
Fund name	Monthly α	Yearly α	t-stat	β	Obs.	R^2 adj.	F-Value
Pareto Inv Fund C	**0.01199****	**0.1439****	**(3.94)**	0.38237	25	0.3487	0.111
Pareto Inv Fund B	**0.01163****	**0.1396****	**(3.87)**	0.38236	25	0.3490	0.167
Danske Invest Inst. I	**0.00243***	**0.0292***	**(2.21)**	0.90642	120	0.9694	6.723*
Danske Invest Inst. II	**0.00222****	**0.0266****	**(3.07)**	0.90812	109	0.9685	6.723*
Alfred B Nor (Classic)	**0.00188***	**0.0226***	**(2.20)**	0.94797	120	0.9818	0.128
Holberg Norge	**-0.00429***	**-0.0515***	**(-2.61)**	0.86421	120	0.9021	25.080*

Among the significantly outperforming funds, *Pareto Investment Fund C and B* are still dominating, with an estimated monthly alpha of 0.01199 and 0.01163 respectively. These figures correspond to a yearly outperformance relative to the benchmark of 14.39% and 13.96%. This is a remarkable result, keeping in mind that the average outperformance is 0.60% per year. Comparing with the third best performing fund, *Danske Invest Norske Aksjer Institusjon I*, which has an estimated yearly alpha of 2.92%, they deliver an annual outperformance which is 11.47% and 11.04% higher respectively. Of course, this severely increases the average alpha of the sample. In fact, due to the same reasons we discussed in section 6.3.1.1, we need to be careful when interpreting the estimates of these two funds. If we exclude *Pareto Investment Fund C and B* from our sample, the average annual alpha of the total sample drops to 0.001%, which in practice implies neutral performance among the fund managers in our sample. An overview of the mentioned scenarios is presented in table 6.8 below.

Danske Invest has two of the three remaining significantly outperforming funds. *Danske Invest Norske Aksjer Institusjon I and II* have an estimated monthly alpha of 0.00243 and 0.0222 respectively, which in annual terms represent an outperformance relative to the benchmark of 2.91% and 2.66% respectively. *Danske Invest Norske Aksjer Institusjon II's* estimated alpha is, in fact, significant at a 1% level, which is a strong indication of superior stock picking skills among their fund managers. Moreover, we have 120 and 109 monthly observations of the two funds, yielding an estimated beta of 0.90642 and 0.90812 along with an adjusted R^2 of 0.9694 and 0.9685 respectively. This implies that the problems regarding *Pareto Investment Fund C and B* are avoided, and our confidence regarding the results is further enhanced.

As identified using the unconditional model, *Alfred Berg Norge (Classic)* is the significantly outperforming fund with the lowest estimated alpha. According to our regression output in Appendix 2, *Alfred Berg Norge (Classic)* has an estimated monthly alpha of 0.00188, which in annual term equals a yearly outperformance of 2.26% compared to the benchmark. This finding is slightly higher than the 2.14% identified under the unconditional model. If we check the F-value from our significance test in regards to *hypothesis 2*, we see that the conditional model does not add explanatory power to our model on *Alfred Berg Norge (Classic).* Thus, we rely more on the estimates from the unconditional model for this particular fund.

Table 6.8: Overview of conditional net alpha scenarios. Source: Own creation

Sample	Average Yearly Estimated Alpha	Interpretation
Total Sample Average	0.600%	Outperformance
Excluding significantly outperforming/underperforming funds	-0.064%	Underperformance
Excluding *Pareto Investment Fund C and B*	0.001%	Neutral Performance

This table presents the average estimated alphas for our sample for two different scenarios, along with the practical interpretation of the alpha value. The first row presents the total sample average. The second row presents the sample average when the significantly outperforming/underperforming funds are excluded while the third row presents the results when the two "troubled" funds are removed from the sample.

6.3.2.2 Gross Returns

Once again after adding the fund expenses to net return to obtain results for the funds' gross return, we identify major differences between gross and net returns. The conditional gross return is 1.40% higher than the conditional net return, which is approximately equal to the average TER of our sample, estimated to 1.39%. Moreover, our regression output identifies 13 significantly outperforming funds when regressing gross returns, where nine is significant at a 1%-level. In other words, 13 out of the 47 funds in our sample are significantly outperforming the benchmark before the deduction of expenses. Compared with the net returns in section 6.3.2.1, this means that eight of the funds in our sample are beating the benchmark, but are unattractive to investors because the expenses erase the benefits from the stock picking skills. Another interesting aspect one should note is that none of the funds are significantly underperforming before deduction of fees. Thus, from a market efficiency point of view, none of the funds are underperforming relative to the benchmark.

However, as discussed in section 6.3.2.1, *Holberg Norge* is underperforming after deduction of fees. In practice, this implies that from an investor's point of view, *Holberg Norge* is a very unattractive fund and its fees completely eradicate its performance. A summary of the funds with a significant alpha estimate ranked by outperformance relative to the benchmark is presented in Table 6.9 below.

Comparing the results to the unconditional model, we observe the same trend as for net returns, namely that the conditional model drags the alpha estimates down. It seems that including a time-varying beta to our model consistently reduces the estimated outperformance of the funds. In fact, the average conditional gross alpha is 23% lower than the average unconditional gross alpha.

Table 6.9: Summary of funds with a significant gross alpha estimate. Source: Own creation

	Gross Returns						
Fund name	Monthly α	Yearly α	t-stat	β	Obs.	R^2 adj.	F-Value
Pareto Investment Fund C	**0.01239****	**0.1487****	**(4.02)**	0.38237	25	0.3487	0.111
Pareto Investment Fund B	**0.01239****	**0.1487****	**(4.02)**	0.38236	25	0.3490	0.167
Handelsbanken Norge	**0.00438****	**0.0526****	**(2.96)**	0.97861	120	0.9531	0.441
Alfred Berg Gambak	**0.00435***	**0.0522***	**(2.26)**	0.89109	120	0.9105	1.036
Danske Invest Inst. I	**0.00320****	**0.0384****	**(2.91)**	0.90642	120	0.9694	**6.723***
Danske Invest Inst. II	**0.00312****	**0.0374****	**(2.88)**	0.90812	109	0.9685	**6.723***
Danske Invest Norge I	**0.00291****	**0.0349****	**(2.73)**	0.94254	120	0.9690	**10.000***
Danske Invest Norge II	**0.00289****	**0.0347****	**(2.69)**	0.93803	120	0.9683	**12.500***
Alfred Berg Norge (Classic)	**0.00287****	**0.0344****	**(3.35)**	0.94797	120	0.9818	0.128
Pluss Markedsverdi	**0.00206****	**0.0247****	**(2.76)**	0.93896	120	0.9831	**7.879***
Pluss Aksje	**0.00193***	**0.0232***	**(2.12)**	0.89024	120	0.9652	**21.552***
Carnegie Aksje Norge	**0.00181***	**0.0217***	**(2.26)**	0.97684	120	0.9806	4.096
Nordea Kapital	**0.00146***	**0.0175***	**(2.14)**	0.96988	120	0.9882	**7.959***

On a general basis, with only 13 out of 47 funds displaying superior stock picking skills, our results must be deemed disappointing for the Norwegian fund industry. One of the major selling points with active management is that they actively search for underpriced stocks to deliver abnormal returns to their investors, and charge their investors for doing so. In practice, our results point towards only 28% of Norwegian funds displaying positive benefits of active management. In other words, in 72% of the cases, passive management should be preferred in the Norwegian fund market.

6.4 Fund expenses and performance

To examine the impact of fund expenses on performance, we conduct another series of trials. The funds are ranked ascendingly according to their TER. Next, the sample is divided into groups, to compare the alphas of the funds in the low expense group to the funds in the high expense group. The alphas are given in yearly numbers. The ranking is presented in Table 6.10 below. To have a comparable number of funds within each group, a threshold of 0.90% or lower indicates a low TER and a threshold of 2.00% or higher indicates a high TER.

Table 6.10 Funds ranked according to TER, alphas are computed for net returns. Source: Own creation

Group	Fund name	Uncond. α	Cond. α	TER
Low expense	STOREBRAND NORGE I	-1.39%	-1.51%	0.28%
Low expense	PARETO AKSJE NORGE I	-0.12%	-1.24%	0.50%
Low expense	PARETO INVESTMENT FUND C	14.62%	14.39%	0.50%
Low expense	STOREBRAND AKSJE INNLAND	-1.22%	-1.27%	0.60%
Low expense	DNB NORGE IV	-0.48%	-0.59%	0.75%
Low expense	KLP AKSJE NORGE	0.94%	-0.97%	0.75%
Low expense	DNB NORGE SELEKTIV III	-0.58%	-0.84%	0.80%
Low expense	DANSKE INVEST NORSKE AKSJER	3.77%	2.92%	0.90%
Low expense	DANSKE INVEST NORSKE AKSJER	3.71%	2.66%	0.90%
Low expense	PLUSS MARKEDSVERDI	2.27%	1.56%	0.90%
Low expense	**Mean**	**2.15%**	**1.51%**	**0.69%**
High expense	DANSKE INVEST NORGE I	2.52%	1.46%	2.00%
High expense	DELPHI FONDENE NORGE	1.19%	0.98%	2.00%
High expense	EIKA NORGE	0.43%	-0.47%	2.00%
High expense	FORTE NORGE	-2.81%	-3.64%	2.00%
High expense	HANDELSBANKEN NORGE	3.00%	3.31%	2.00%
High expense	ODIN NORGE C	-2.68%	-4.06%	2.00%
High expense	STOREBRAND VEKST	3.42%	2.86%	2.00%
High expense	STOREBRAND VERDI	-1.50%	-1.32%	2.00%
High expense	DNB NORGE SELEKTIV I	-1.79%	-2.04%	2.01%
High expense	DNB SMB	-7.18%	-8.10%	2.01%
High expense	PARETO AKSJE NORGE B	-1.58%	-2.70%	2.01%
High expense	PARETO AKSJE NORGE A	1.25%	-2.30%	2.50%
High expense	**Mean**	**-0.69%**	**-1.33%**	**2.04%**

Table 6.10 displays the key figures for the low expense and high expense groups. Column 1 and 2 indicates which group, and which fund is considered. Column 3 and 4 reports the unconditional and conditional annual alphas respectively. Column 5 is the annual total expense ratios of the fund in question.

The table above shows unambiguous results for the unconditional and conditional model. The mean alpha for the "high expense" group is severely lower than the mean alpha for the "low expense" group independent of the model applied. However, it is important to pinpoint that there are several outliers in the two groups, both for the unconditional and conditional model. *Pareto investment fund C, Danske Invest Norge I, Eika Norge* and *DNB SMB* all have substantial differences between the unconditional and conditional estimates. Thus, the mean alphas will be affected by this difference. For the further analysis, we will use the original numbers, but to show how the outliers affect the mean alphas, we have computed the mean alpha values without outliers below.

Group	Uncond. α	Cond. α	TER
Low expense	0.77%	0.08%	0.71%
High expense	-0.09%	-0.72%	2.05%

The mean alpha values without outliers are still surprising as there are certain differences between the unconditional and conditional model, as well as the negative correlation between alpha and TER. Hence, a higher TER implies a lower alpha. In practice, this entails worse performance for a higher expense.

From Figure 6.1 below, we can also observe that there is a certain correlation between TER and alpha in the original sample. Hence, a higher TER yields a lower alpha. The graph is based on the unconditional alpha. This observation is not in line with theory as a higher expense should yield an investor a higher alpha.

Figure 6.1: Relationship between fund expenses and performance. Source: Own creation

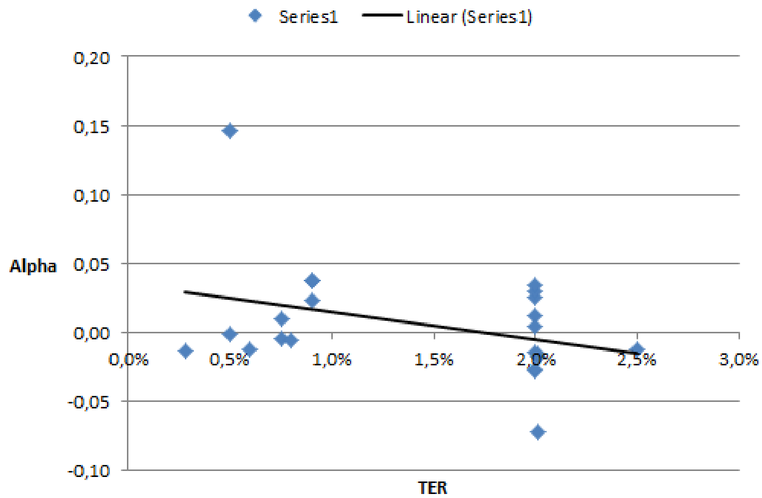


Figure 6.1 displays the statistics from Table 6.10 graphically

6.4.1 Normal distribution of alphas

To perform a meaningful analysis of the relationship between fund expenses and performance, we have to verify whether the allocation of alphas is normal or not. The most appropriate tests to conduct are the Kilmogorov-Smirnov test and the Shapiro-Wilk test. However, The Shapiro-Wilk test (S-W test) is more suitable for small sample sizes (< 50 samples), and thus will be used as the numerical means of assessing normality in this study. Additionally, the values of skewness and kurtosis are examined.

The null hypothesis of the Shapiro-Wilk test is that the distribution is normal. Correspondingly, the alternative hypothesis is that the sample is not normally distributed. Hence, if the null hypothesis is rejected, the computed alphas are following a non-normal distribution. The results can be seen in Table 6.11 below. Both the unconditional and conditional models were tested.

Table 6.11: Tests of normality in net return alpha distributions. Source: Own creation

	Number of funds	Mean alpha	Kurtosis	Skewness	S-W
Unconditional	47	1.05%	5.04923	1.3429	0.905
p-value					**(<0,01)**
Conditional	47	0.60%	5.43266	1.6188	0.911
p-value					**(<0,01)**

Table 6.11 reports the statistics from the tests of normality in the distribution of alphas. Column 1 indicates which model is considered. Column 2 is the number of funds in the sample. Column 3 presents the annual mean alpha from both the unconditional and conditional model when using net returns. Column 4 and 5 report the kurtosis and skewness of the mean alpha distribution. Column 6 presents the output of the Shapiro-Wilk test. The relevant p-values are given in parentheses.

As described above, the null hypothesis of the S-W test of normality is that the distribution is normal. From the output of Table 6.11, we can see that the null hypothesis is rejected both for the unconditional and conditional model on every level of significance. Hence, the computed alphas are following a non-linear distribution. This finding is supported by the skewness and kurtosis measures. A skewness equal to zero and kurtosis equal to 3 indicates perfect normal distribution. As the reported values are quite different from these numbers, our confidence regarding our findings is amplified. Conducting the S-W test is motivated by the assumption of the alphas following a normal distribution or not. Thus, we can assume that the alphas are following a non-normal distribution.

6.4.2 The unconditional model

Based on the data from the unconditional model, the mean yearly alpha estimates, the mean standard errors, and deviations for both low and high expense groups are computed and presented in Table 6.12:

Table 6.12: Summary statistics for the low and high groups, unconditional model. Source: Own creation

Group	Number of funds	Mean alpha	St Error	St dev
Low expense	10	2.15%	0.0151	4.7769%
High expense	12	-0.69%	0.0087	3.0010%
Combined	22	0.60%	0.0087	4.0725%
Difference		2.84%	0,0054	

Table 6.12 presents summary statistics for the low expense and high expense groups utilizing the unconditional model with net returns. Column 1 indicates the group in question. Column 2 represents the number of funds in the group. Column 3 presents the mean alphas of the group. Column 4 and 5 report the standard error and standard deviation of each group.

Table 6.12 provides output specifying a mean alpha of the low expense group equal to 2.15% and a mean alpha of the high expense group equal to -0.69%. Thus, the difference between the two groups' mean alpha is equal to 2.84%. Moreover, we want to investigate whether the difference is statistically significant or not.

As the t-test cannot be used for non-normally distributed alphas, we need to make use of a non-parametric test. A well-suited test taking account of the abovementioned requirements is the Wilcoxon rank-sum test. This implies that the test can analyze two independent samples following a non-normal distribution. Another advantage with this test is that it is less sensitive to outliers. Moreover, the funds are still ranked by their TER. Hence, the low expense and high expense groups remain the same, and the new hypothesis states a null hypothesis implying no difference in the populations between the low and high expense groups. Accordingly, the alternative hypothesis states that there exists a difference between the two populations of alphas.

Hypothesis 4: H_0: $Population_{low-expense} = Population_{high-expense}$

H_1: $Population_{low-expense} \neq Population_{high-expense}$

The test is conducted by ranking all funds in the low and high expense groups by their alpha values. Furthermore, the sum of the rankings of each of the groups is computed. This sum is called the rank sum. We also calculate the expected rank sum which is a theoretical value based on the number of funds in each group.

$$Exp\ rank\ sum_{Low} = \frac{No.of\ funds_{Low} * (No.of\ funds_{Low} + No.of\ funds_{High} + 1)}{2}$$

Finally, the Z-value is computed by taking the difference between theoretical and actual rank sum and divide by the standard error.

$$z - value = \frac{Rank\ sum - Exp.rank\ sum}{Standard\ error}$$

The results for the unconditional model can be seen in the table below. Returns are given in net returns.

Table 6.13: Wilcoxon Rank-Sum test, unconditional model. Source: Own creation

Group	Number of funds	Rank sum	Expected rank sum
Low expense	10	117	115
High expense	12	136	138
Combined	**22**	**253**	253
z	**1.78033**		
p-value	0.07502		

Table 6.13 presents the output of the Wilcoxon rank-sum test. Column 1 and 2 indicate the group and the number of funds in question. Column 3 presents the rank sum of the group while column 4 presents the expected rank sum of each group. The lower part of the table contains the z-value and p-value of each group.

The test shows that the low expense group has a higher rank sum than expected, whereas the high expense group has a lower rank sum than expected. Moreover, as we can see in the table, the z-score is not statistically significant at the 5% level, and thus, we cannot reject the null hypothesis of the two populations not being different. That is, there does not seem to exist a difference between the two populations of alphas.

6.4.3 The conditional model

As with the unconditional model, the mean yearly alpha estimates, the mean standard errors and deviations for both low and high expense groups are computed for the conditional model. The results are presented below.

Table 6.14: Summary statistics for the low and high groups, conditional model

Group	Number of funds	Mean alpha	St Error	St dev
Low expense	10	1.51%	0.0153	4.8264%
High expense	12	-1.33%	0.0093	3.2317%
Combined	22	-0.04%	0.0089	4.1900%
Difference		2.84%	0.0055	

Table 6.14 presents summary statistics for the low expense and high expense groups utilizing the conditional model with net returns. Column 1 indicates the group in question. Column 2 represents the number of funds in the group Column 3 presents the mean alphas of the group. Column 4 and 5 report the standard error and standard deviation of each group.

As with the unconditional model, Table 6.14 provides output specifying a mean alpha of the low expense group and the high expense group using the conditional model. The average alpha of the low expense group, in this case, is equal to 1.51% and a mean alpha of the high expense group equal to -1.33 %.With a difference of mean alpha equal to 2.84%, we once again want to investigate whether the difference is statistically significant or not. As computed earlier, the conditional model is non-normally distributed. Hence, we make use of the Wilcoxon rank test and thus the same hypothesis as for the unconditional model. Once again net returns are being used:

Table 6.15: Wilcoxon Rank-Sum test, conditional model.

Group	Number of funds	Rank sum	Expected Rank sum
Low expense	10	112	115
High expense	12	141	138
Combined	**22**	**253**	**253**
z	**1.58251**		
p-value	0.11353		

Table 6.15 presents the output of the Wilcoxon rank-sum test. Column 1 and 2 indicate the group and the number of funds in question. Column 3 presents the rank sum of the group, while column 4 presents the expected rank sum of each group. The lower part of the table contains the z-value and p-value of each group.

The Wilcoxon rank-test for the conditional model generates opposite results compared to that of the unconditional model. In this particular test, the low expense group has a lower rank sum than expected, whereas the high expense group has a higher rank sum than expected. The z-value is not statistically significant on the 5% level. Thus, we are left with the same conclusions for the unconditional and the conditional model; the mean alphas of the low expense and high expense groups are different in both models. Nevertheless looking at the p-values, they are close to being significant. Thus, there seems to be some evidence that the low expense group outperforms the high expense group.

6.5 Market timing ability

In addition to stock picking skills, it would be of investors' interest to know which fund managers can time the market successfully. That is, successfully invest with regards to macro-movements. To investigate the funds managers' market timing ability, we apply the Treynor-Mazuy (1966) model. The model comprises OLS regressions, and as the regressions are on individual funds, the standard errors have been Newey-West corrected. Similar to the previous tests conducted, the model will be tested based on both net and gross returns. Furthermore, the information variables are implied to observe how the sample behaves in a conditional as well as the unconditional setting of the model.

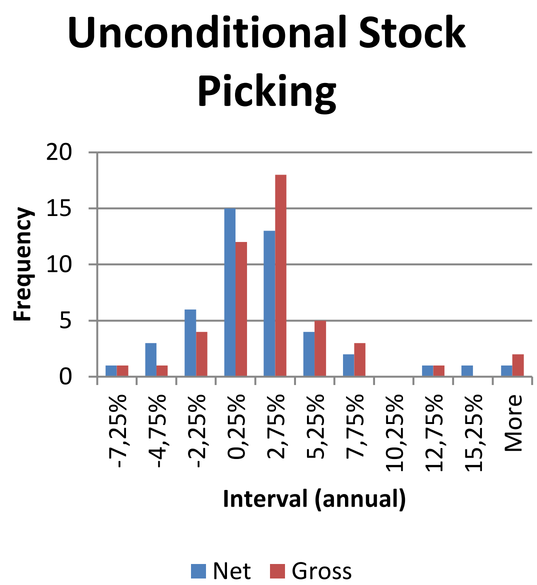
6.5.1 Treynor-Mazuy model – unconditional model

The Treynor-Mazuy model delivers estimates for both stock picking skills and market timing ability. Hence, it describes the excess return obtained by the manager not explained by current risk positions. To control for both skills, two separate hypotheses are needed. Similar to Jensen's regression, the intercept is still measuring the stock picking skills. Thus, *hypothesis 1* is reiterated. The null hypothesis is still that alpha is equal to zero, and failing to reject the null hypothesis implies that the fund manager does not possess any stock picking skills.

To control for the manager's market timing ability, the gamma coefficient of the model is tested. Furthermore, we conduct a two-sided test when measuring the significance of the gamma estimate as the market as the market can be forecasted for better and for worse. Thus, the new hypothesis is composed such that the null hypothesis is that gamma is equal to zero, whereas the alternative hypothesis is that gamma is different from zero.

Hypothesis 5:	$H_0: \alpha = 0$	$H_1: \alpha \neq 0$
Hypothesis 6:	$H_0: \gamma = 0$	$H_1: \gamma \neq 0$

The summary statistics of the net return and gross return results for our sample funds are presented in Table 6.16 below:



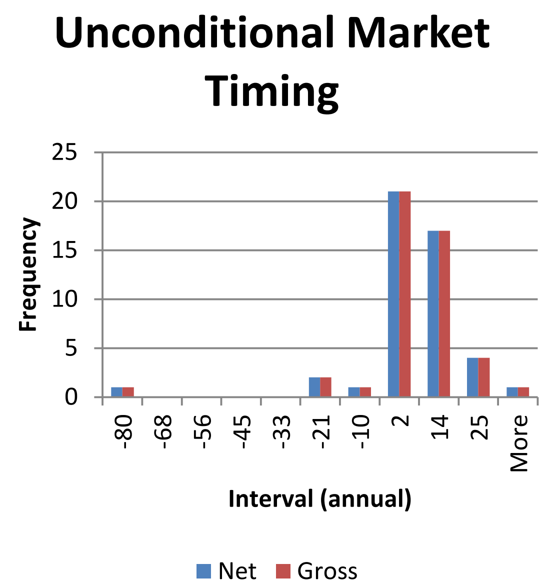


Table 6.16 Treynor-Mazuy Unconditional model, net and gross returns. Source: Own creation

Return Series	Number of funds	Average Annual Alpha	Significantly positive (negative)	Average Annual Gamma	Significantly positive (negative)
Net	47	0.78%	5(3)	0.51	12(3)
Gross	47	1.95%	11(0)	0.51	12(3)

Table 6.16 presents the summary statistics for the unconditional Treynor-Mazuy model. Column 1 and 2 indicates which return series we are looking at, along with the number of funds. Column 3 and 4 reports the estimated average annual alpha with the number of significantly outperforming (underperforming) funds. Column 5 and 6 reports the estimated average annual gamma with the number of funds with significantly positive (negative) market timing abilities.

When looking at the histograms above, it becomes evident that the alpha estimates are skewed to the left. That is, to the left tail which indicate lower performance. The summary statistics in Table 6.16 reports an annual average alpha of 0.78% for the net returns, and an annual average alpha of 1.95% for the gross return. The interpretation is identical to that of the Jensen regression; namely that the average fund manager tend to outperform the benchmark. In fact, for the gross returns, we can reject the null at a 5% level in *hypothesis 5* for 11 funds. As expected this number drops when fund expenses are deducted. After expenses we reject the null for only eight funds, where three obtain a significantly negative alpha estimate, indicating inferior stock picking abilities. However, as this section emphasizes market timing skills, we will not analyze stock picking any deeper by itself, but rather examine it together with market timing. An in-depth analysis of stock picking abilities was performed in section 6.3.

On average the gamma estimate is 0.51 for the entire sample. We can reject the null at a 5% level in *hypothesis 6* for 15 funds, where 12 displayed significantly positive market timing abilities and three displayed significantly negative market timing abilities. These funds are presented in Table 6.17 below, where they are ranked from highest to lowest. Please see Appendix 3 for a complete overview of the coefficient estimates.

Table 6.17: Unconditional significant gamma estimates, ranked from highest to lowest. Source: Own creation

	Stock-Picking Ability			Market Timing Ability		
Fund name	**Net α**	**t-stat**	**Obs.**	**γ**	**t-stat**	**R^2 adj.**
Forte Norge	**-0.00614***	**(-2.08)**	57	**2.11689***	**(2.10)**	0.7711
DNB Norge Selektiv II	-0.00348	(-1.75)	60	**1.68048***	**(2.45)**	0.8875
DNB Norge Selektiv III	-0.00331	(-1.67)	60	**1.68039***	**(2.44)**	0.8877
DNB Norge Selektiv I	**-0.00432***	**(-2.17)**	60	**1.67134***	**(2.43)**	0.8884
Landkreditt Norge	-0.00269	(-1.52)	114	**0.60455****	**(4.02)**	0.9083
Pluss Aksje	-0.00039	(-0.36)	120	**0.49318****	**(2.87)**	0.9676
Danske Invest Norge II	0.00138	(1.29)	120	**0.27377***	**(2.62)**	0.9672
Danske Invest Inst. I	0.00174	(1.66)	120	**0.26352****	**(2.81)**	0.9698
Danske Invest Inst. II	0.00174	(1.66)	120	**0.26352****	**(2.81)**	0.9698
Pluss Markedsverdi	0.00051	(0.64)	120	**0.26316****	**(2.64)**	0.9840
Danske Invest Norge I	0.00090	(0.86)	120	**0.22702***	**(2.01)**	0.9680
Nordea Kapital	0.00020	(0.24)	120	**0.18051***	**(2.10)**	0.9883
Handelsbanken Norge	**0.00368***	**(2.33)**	120	**-0.22513***	**(-2.41)**	0.9541
Alfred Berg Gambak	0.00408	(1.97)	120	**-0.31694***	**(-2.28)**	0.9126
Landkreditt Utbytte	**0.00952***	**(2.21)**	35	**-6.65588***	**(-2.34)**	0.5015

Forte Norge has the highest estimated gamma in our sample with an estimated gamma of 2.1169. However, as Table 6.17 illustrates, *Forte Norge's* fund manager displays significantly negative stock picking abilities through the negative net alpha estimate, which is a very unattractive trait for potential investors. Displaying *significant positive* market timing abilities, while displaying *significant negative* stock picking abilities, is also the case for *DNB Norge Selektiv I.* Which of the two abilities should be preferred over the other is difficult to pinpoint, as this would be pure speculations based on our data set. However, picking the wrong stocks should make it difficult to outperform a benchmark, even if the fund manager is able to time his trades correctly with macro movements. It could be an interesting study to investigate which of the two abilities have the most impact, but is outside the scope of this study.

Another interesting observation is that *Danske Invest* can display significant positive market timing skills for 4 out of their 5 funds in our data sample. *Pluss* and *DNB* are also well represented with 2 out of 2 funds, and 3 out of 8 funds in our data sample respectively seeming to be able to predict future market movements successfully. Further investigation shows that the four significant *Danske Invest's* funds have the same fund managers, and the same applies for the three significant *DNB* funds. Unfortunately, *Pluss* does not disclose the names of their fund managers, but our results might indicate that market timing is a trait that is fund manager specific and not shared among fund managers within the same company.

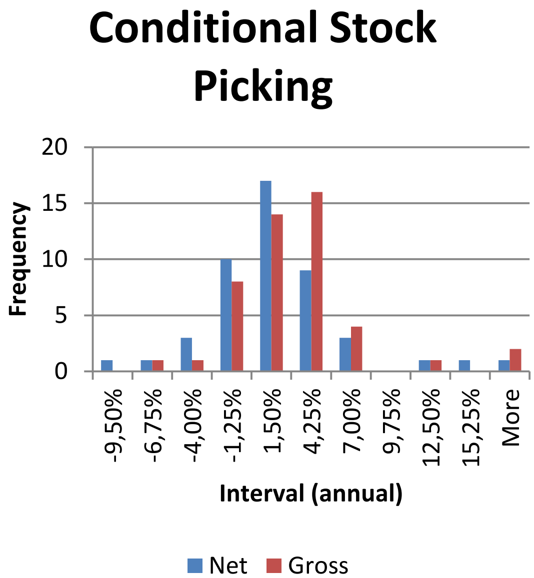
Landkreditt Utbytte is the fund with the lowest significant gamma in our sample, with an estimate of -6.6559. This is actually 21 times lower than the second lowest significant gamma estimate, which is *Alfred Berg Gambak* with -0.31694. At first glance, this is a devastating result, and it is difficult to comprehend how a fund can survive with such poor market timing abilities. However, looking at the adjusted R^2, we see that other factors explain approximately 50% of the variation in market timing abilities than the factors included in our regression. Hence, we should be careful when interpreting *Landkreditt Utbytte's* coefficients as our model suffers from a low fit.

Moreover, *Landkreditt Utbytte* displays *significant positive* stock picking abilities, while displaying *significant negative* market timing abilities, which is the opposite of the phenomenon discussed above. Looking at table 6.17, it is evident that the same is true for *Handelsbanken Norge.* Once again we cannot conclude on which of the two abilities is preferable, as this would be pure speculations. Interestingly, we do not identify any funds with significant positive stock picking skills *and* significant positive market timing abilities. These funds would be the ones that are heavily sought after by investors. Our results could serve as criticism towards active management as none are able to successfully pick the right stocks and successfully time the market.

6.5.2 Treynor-Mazuy model – conditional model

Once again we have chosen to include the information variables proposed by Ferson & Schadt. Hence, we have to state a hypothesis to investigate whether the Treynor-Mazuy model in a conditional setting is to be preferred over the model in an unconditional setting. The null hypothesis will be that the information variables are jointly zero while the alternative hypothesis is that at least one of the information variables is different from zero. This is the same hypothesis as *hypothesis 2,* and the same F-test we conducted under the conditional Jensen regression has been applied here.

Hypothesis 7: $H_0: \beta_2 = \beta_3 = \beta_4 = 0$ $H_1: \beta_1 \neq 0, and/or\ \beta_2 \neq 0, and/or\ \beta_3 \neq 0$



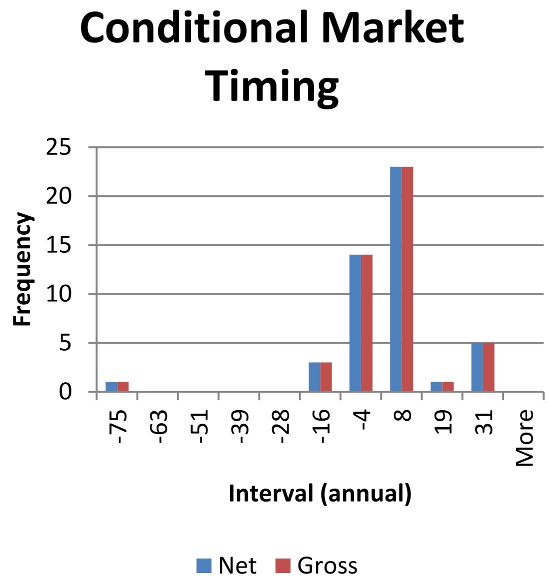


Table 6.18 Treynor-Mazuy Conditional model, net and gross returns. Source: Own creation

Return Series	Number of funds	Average Annual Alpha	Significantly positive (negative)	Average Annual Gamma	Significantly positive (negative)	Percentage of significant F
Net	47	0.88%	7(2)	-1.59	3(7)	23.40%
Gross	47	2.27%	12(0)	-1.59	3(7)	23.40%

Table 6.18 presents the summary statistics for the conditional Treynor-Mazuy model. Column 1 and 2 indicates which return series we are looking at, along with the number of funds. Column 3 and 4 reports the estimated average annual alpha with the number of significantly outperforming (underperforming) funds. Column 5 and 6 reports the estimated average annual gamma with the number of funds with significantly positive (negative) market timing abilities. Finally, Column 7 presents the result of the F-test, and illustrates how many of the unconditional models were improved by including the lagged information variables.

From Table 6.18 above, it is clear that the F-test improved 23.40% of the unconditional models. Hence, we need to take both the conditional and unconditional models into consideration when interpreting the results. When the lagged information variables are added, and thus a time-varying beta is introduced, the average alpha estimates increase. More interestingly, the conditional model estimates average negative gamma, compared to the previous positive average gamma from the unconditional model.

In regards to *hypothesis 6* above (market timing), we are now able to reject the null for 10 funds, where the majority suddenly display significant negative market timing abilities. In fact, seven of the significant funds demonstrate negative market timing skills, and only three funds can successfully predict future market movements. A summary of the significant funds is presented in Table 6.19 below. Please see Appendix 4 for a complete overview of the conditional Treynor-Mazuy estimates.

Table 6.19: Significant conditional gamma estimates, ranked from highest to lowest. Source: Own creation

	Stock-Picking Ability			Market-Timing Ability		
Fund name	**Net α**	**t-stat**	**Obs.**	**γ**	**t-stat**	**R^2 adj.**
DNB Norge Selektiv II	-0.00346	(-1.76)	60	**1.62145***	**(2.23)**	0.8856
DNB Norge Selektiv III	-0.00329	(-1.67)	60	**1.62072***	**(2.23)**	0.8859
DNB Norge Selektiv I	**-0.00430***	**(-2.18)**	60	**1.61297***	**(2.22)**	0.8866
Alfred Berg Aktiv	0.00193	(1.35)	120	**-0.39340***	**(-2.23)**	0.9558
Handelsbanken Norge	**0.00407***	**(2.59)**	120	**-0.46804****	**(-2.63)**	0.9544
Alfred Berg Gambak	**0.00448***	**(2.17)**	120	**-0.56621****	**(-2.90)**	0.9127
Pareto Investment Fund A	**0.00332***	**(1.99)**	120	**-0.63058****	**(-2.87)**	0.9355
Pareto Aksje Norge I	0.00110	(0.49)	120	**-0.78229***	**(-1.99)**	0.8428
Pareto Aksje Norge A	0.00029	(0.14)	120	**-0.81281***	**(-2.03)**	0.8596
Odin Norge C	-0.00088	(-0.38)	107	**-0.89105***	**(-2.09)**	0.8577

Table 6.19 identifies *DNB Norge Selektiv I, II, and III* as the only funds with positive market timing abilities. These funds were also identified as positive market timing funds under our unconditional scenario, discussed in section 6.5.1, which strengthens our confidence in our findings for these funds. Moreover, *Handelsbanken Norge* and *Alfred Berg Gambak* still display significant negative market timing, just like in the unconditional scenario, with an estimated gamma of -0.4680 and -0.5662 respectively, both significant at a 1% level. *Landkreditt Utbytte*, which by far had the lowest estimated gamma in the unconditional scenario, is no longer deemed significant - further supporting our suspicions to its coefficients due to the low adjusted R^2.

DNB Norge Selektiv I is still displaying *positive* market timing abilities but *negative* stock picking ability, with an estimated alpha of 0.0043 and an estimated gamma of 1.1613, both significant at a 5% level. On the contrary, *Handelsbanken Norge* is still displaying *negative* market timing abilities but *positive* stock picking abilities, which is identical to the results from our unconditional scenario. Furthermore, *Alfred Berg Gambak* is now displaying similar tendencies, with an estimated alpha of 0.0045 and the already mentioned gamma estimate of -0.5662.

Interestingly, we are still not able to identify the most attractive funds from an investor’s perspective, namely funds with both significantly positive alphas and significantly positive gammas. This further strengthens the critique towards active management as mentioned in the unconditional scenario.

6.6 Performance persistence

As we pointed out in the problem statement, we find it intriguing to investigate if Norwegian fund managers have the ability to repeat performance over successive periods. It would be in any investor's interest to know whether performance tends to repeat itself. Hence, we seek to unveil if the fund managers' performance is arbitrary when it comes to stock picking skills and market timing ability, or if they possess the potential to outperform the market over time. Theoretically, historic returns are no guarantee of future returns, and asset managers often stress this matter to their clients. However, in many instances, the clients have little else to go by. The following approaches are widely regarded as effective. However, one should consider the results carefully as they are quite exposed to changes in criteria and variations in calculations (Otten & Bams, 2002).

To unveil to what extent performance persistence is present in our sample we make use of two different models with two different criteria. Nevertheless, they have certain elements in common. Based on the previous work of Malkiel (1995), Goetzmann & Ibbotson (1994, 1998), Otten & Bams (2002) and Blake & Timmerman (1998), the results are ranked based on the absolute performance in the previous twelve months. This period is known as the "selection period". The sample is then divided into quartiles, with the best performing quarter in one portfolio, and the worst performing quarter in another. Furthermore, each of the returns is given equal weight, and then the respective portfolios are held for twelve months, often referred to as the "performance period". After one year has passed, the two portfolios are rebalanced according to their new selection period, and held for yet another performance period. The process is then repeated consecutively throughout the sample period.

The result is two portfolios with 108 observations each. One portfolio consists of returns from prior "well" performing funds, and one portfolio consists of prior "bad" performing funds. Testing the two portfolios together leaves us with a total time series of 216 observations. To investigate the presence of performance persistence, we use a binary variable which equals 1 for "well" performing funds and equals zero for "bad" performing funds. Pairing the new term with the same indicator variable together with the excess market return, a new equation is assembled:

$$r_{i,} - r_{f,t} = \alpha_i + \beta_0\,(r_{m,t} - r_{f,t}) + cDgood + \beta_1\,(r_{m,t} - r_{f,t})\;Dgood + \varepsilon_{i,t}$$

The above equation can easily be extended with our information variables. Thus, we get a conditional model:

$$r_{i,t} - \mathrm{r}_{f,t} = \alpha_i + \beta_0\,(r_{m,t} - r_{f,t}) + cDgood + \beta_1(\,_{m,t} - r_{f,t})\,Dgood + \beta_i{}'Z_{t-1}\,(r_{m,t} - r_{f,t}) + \varepsilon_{i,t}$$

Evidence of performance persistence will be present if the prior "well" performing portfolio generates significantly different results than that of the prior "bad" performing portfolio. The evidence is denoted by the indicator variable being significant. If the coefficient is significantly positive, the "well" performing funds have outperformed the "bad" performing funds. If the indicator variable is statistically negative, the opposite is true, and the "bad" funds perform better. If the coefficient is not statistically significant, there is no evidence of performance persistence. Hence, the null hypothesis is that the estimate of the indicator variable is equal to zero, while the alternative hypothesis is that it is different from zero.

Hypothesis 8: $H_0\!: Indicator\ effect = 0$ $\quad H_1\!: Indicator\ effect\ \neq 0$

Table 6.20: Summary statistics for the perf. pers. model, net and gross – conditional model. Source: Own creation

	Number of obs.	Annual Alpha	P-Value	Indicator	P-Value	F-Prob.
Net	216	0.25%	0.8555	-0.03%	0.9834	< 0.0001
Gross	216	1.88%	0.2332	0.06%	0.7547	< 0.0001

Table 6.20 presents the summary statistics of our pooled regression from the conditional model with net and gross returns. Column 1 and 2 indicates whether net or gross returns are considered, and how many observations the regression was ran with. Column 3 and 4 illustrates the annual alpha along with the pertaining p-value. Column 5 and 6 indicates the coefficient on our indicator variable, along with its p-value. Column 7 illustrates the probability of our conditional information variables being jointly zero.

As we discussed in section 6.3.2, the conditional model improved 25% of the unconditional models. In table 6.20 above, we have only reported the results from the conditional model along with the results from an F-test to test whether the regression variables are jointly zero. The results of the F-tests, illustrated by the "F-Prob"-column, are highly significant, and thus, the conditional model is preferred.

As we can see from the summary statistics in Table 6.20 above, the estimates of the indicator are highly insignificant for both the net and gross returns. The estimate for the net returns is -0.03%, which in practice means that "well" performing funds actually tend to perform worse in the subsequent period compared to the prior "bad" performing funds. However, the p-value is 0.9834 which indicates a highly insignificant result.

In the case of the gross returns, the estimate of the indicator is 0.06%, which in practice means that "well" performing funds tend to continue to perform better in the subsequent period compared to the prior "bad" performing funds. Looking at the p-value, however, we see that the same story applies for the gross returns; a p-value of 0.7547 indicates a highly insignificant result. Hence, we are not able to reject the null in *hypothesis 8* above, and it seems that the performance of prior "well" performing funds is no different than the performance of prior "bad" performing funds. That is, we found no evidence of performance persistence in our sample.

At first glance, it might be difficult to comprehend the findings of such few funds delivering significant outperformance over a 10-year period as described in section 6.3 and 6.5, but no evidence of performance persistence is identified in the sample. However, the performance persistence is regressed by altering our portfolio of "well" performing funds for each subsequent year. For example, if a fund is delivering superior performance in year 1, 5, 7, and 10, it could obtain a positive significant alpha, yet not be classified as persistence because the performance is not repeated in successive periods. In other words, if a fund delivered superior performance in year 1, 2, and 3, it would be classified as performance persistence. Hence, based on the results of our study, we conclude that mutual fund performance is arbitrary, rather than fund managers being able to beat the market in successive periods.

The method used above for *hypothesis 8* focuses on the performance of the two constructed portfolios together. However, as we make use of one common benchmark in this study, we would like to test each of the portfolios against the market, as the previous method shed little light on this. Thus, we want to investigate whether the portfolios outperform the market or if they are outperformed by the market over time. The two-time series from *hypothesis 8* are disconnected and separately tested against the market. To conduct this test, the Jensen's alpha is utilized once more and past winners and previous losers are investigated both in an unconditional and conditional setting. Accordingly, two new hypotheses are required, one for the "well" performing funds and one for the "bad" performing funds. As in previous tests, the null hypothesis is that the alpha is equal to zero, whereas the alternative hypothesis is that alpha is different from zero.

Hypothesis 9: $H_0: \alpha_{Well} = 0$ $H_1: \alpha_{Well} \neq 0$

Hypothesis 10: $H_0: \alpha_{Bad} = 0$ $H_1: \alpha_{Bad} \neq 0$

Both portfolios have been examined based on both net and gross returns. The results can be seen below:

Table 6.21: Summary statistics of separate regressions, net and gross for conditional model. Source: Own creation

Portfolio	Number of obs.	Annual Alpha	P-Value	F-Prob
Net – Well	108	0.74%	0.4934	< 0.0001
Net – Bad	108	-0.29%	0.8575	< 0.0001
Gross – Well	108	2.64%	0.0997	< 0.0001
Gross – Bad	108	1.82%	0.2635	< 0.0001

Table 6.21 presents the summary statistics of the Jensen regression taking the separate portfolios into consideration in a conditional setting. Column 1 and 2 illustrates which portfolio is considered along with the number of observations. Column 3 and 4 indicates the estimated yearly alpha with the relevant p-value. Column 5 illustrates the probability of our information variables being jointly zero.

Once again the conditional model adds explanatory power, so the results presented in Table 6.21 above are from the conditional model. When looking at the alpha values for the net returns, it appears to be evidence of the "well" performing funds outperforming the benchmark, as the estimate is positive with an annual alpha of 0.74%. We experience the same issue with *Pareto Investment Fund C and B* as before, with the two funds severely driving up the overall alpha estimate because of their tremendous outperformance during the last two years. Once again we stress that this result must be interpreted with caution, as the alpha estimate is artificially high. Moreover, the "bad" performing funds tend to underperform relative to the benchmark, with an estimated negative alpha of -0.29%. However, both the p-value shows that the estimates are insignificant. Thus, we cannot reject the null in *hypothesis 9 and 10* for the net return alphas at a 5%-level.

As expected, the alpha estimates for the gross returns are positive, which means that both the "well" performing funds and the "bad" performing funds outperform the benchmark before the deduction of costs. Nonetheless, the estimates have p-values of 0.0997 and 0.2635 respectively, which makes them insignificant at a 95% confidence level, and the null hypothesis is not rejected. Furthermore, the results suggest that the fund expenses erase any abnormal return, as the net return alphas are very low, and even negative for the "bad" performing funds.

6.7 Survivorship bias

As mentioned in previous sections, we strive to keep our study free of any survivorship bias. To avoid these biases, we examine whether the difference in mean returns between dead and alive funds in our sample are significant. Moreover, the percentage of funds leaving the sample during the sample period is 14.9%. As a matter of fact, only seven funds have become defunct during the sample period between December 2005 and December 2015. These funds are Norwegian equity funds that have at least 80% of their assets in domestic businesses. Hence, it seems justifiable to assert the survivorship bias in the sample to be negligible. Descriptive statistics of the dead funds are presented in the table below.

Table 6.22: Descriptive statistics for dead funds. Source: Own creation

Fund name	Mean	Excess return	Standard deviation	Minimum return	Maximum return	Skewness	Kurtosis
ALFRED BERG NORGE	0.5801% *	0.3833%	7.15%	-31.35%	15.82%	-1.87	6.47
EIKA SMB	0.2303%	0.0334%	6.64%	-25.19%	15.75%	-1.22	3.66
EIKA VEKST	0.1204%	-0.0765%	6.41%	-26.53%	12.50%	-1.80	5.05
NORDEA SMB	-0.1885%	-0.3853%	6.38%	-26.44%	14.23%	-0.97	2.81
NORDEA VEKST	0.3857%	0.1889%	6.83%	-30.41%	15.53%	-1.64	5.62
STOREBRAND FORSIKTIG ALLOKERING	0.345%	0.1482%	1.56%	-6.52%	3.80%	-1.66	5.71
STOREBRAND OFFENSIV ALLOKERING	0.4707%	0.2738%	4.47%	19.25%	11.24%	-1.75	6.11
Average	0.2780%	0.0808%	5.63%	-23.67%	15.29%	-1.56	5.06
OSEFX	0.4810%	0.2845%	6.85%	-31.69%	15.29%	-1.97	7.61
Risk-free	0.1970%						

* = Higher excess return than OSEFX.

Comparing the descriptive statistics to that of the surviving funds, we can see that the dead funds have an average excess return as low as 0.0808%, compared to the surviving funds' 0.4010%. Hence, the return is substantially below the OSEFX excess return of 0.2845%. Moreover, the dead funds also have a higher average standard deviation than the surviving funds. However, the volatility is lower than that of the OSEFX.

Nevertheless, we have calculated the mean return over the entire sample period for all funds in the sample, as well as the return of only surviving funds and only dead funds to analyze whether these seven funds are inducing survivorship bias or not. The results are reported in the table below:

Table 6.23: Summary statistics of survivorship bias. Source: Own creation

Funds	Observations	Mean	Std. Error	Std. Deviation
All	120	6.35%	0.0054	20.42%
Surviving	120	7.00%	0.0056	21.15%
Dead	113	3.50%	0.0049	17.97%
Surviving - All		0.65%	0.0007	
Surviving - Dead		2.86%	0.0007	

Table 6.23 reports the survivorship bias in our sample. Column 1 and 2 indicates which funds are being considered, together with the number of observations. Column 3 displays the mean returns. Column 4 and 5 report the standard error as well as the standard deviation of the mean return estimates.

When we construct three portfolios, in which all funds have equal weights, we can unveil the difference between all funds, surviving fund, and dead funds. Before the specific differences are interpreted, we present some thresholds based on other studies. Grinblatt & Titman (1989) found survivorship bias of 0.5%, while Brown & Goetzman (1995) and Dahlquist et al. (2000) found 0.8% and 0.7% respectively. Hence, our findings are quite high with a difference between surviving and all funds equal to 0.65% and a difference between surviving and dead funds equal to 2.86%.

With such substantial differences, it is a prerequisite to investigating whether these figures are statistically significant or not. However, the difference between surviving and all funds occurs because of the dead funds. Hence, we test the difference between surviving and dead funds. Thus, a new hypothesis is required. The null of this hypothesis is that the mean of the surviving funds is not different from that of the dead funds. The alternative hypothesis is that the two means are different.

Hypothesis 11: $H_0 : r_{Surviving} = r_{Dead}$ $H_1 : r_{Surviving} \neq r_{Dead}$

To verify the hypothesis, we have employed an independent sample t-test, assuming both equal and unequal variance. The results are reported in Table 6.24 below:

Table 6.24: Independent samples t-test of mean return differences between surviving and dead funds.

	Df	t-stat	p-value	Mean difference	SE differences
Equal variances assumed	231	-0.375	0.354	0.00279	0.0007
Unequal variances assumed	229	-0.377	0.353	0.00279	0.0007

Table 6.24 contains the output of the independent samples t-test when testing for equality of the mean returns of the two groups. Column 1 indicates if the variance is considered to be equal or unequal. Column 2 is the degrees of freedom being used in the regression. Column 3 and 4 reports the t-stats and related p-values. Column 5 displays the differences between the mean returns of the two groups. Finally, column 6 indicates the standard errors of the differences in the mean returns.

The results generated in the independent samples t-test of mean return difference, shows that the t-stats are nowhere near statistically significant. Hence, we are not able to reject the null hypothesis of the mean return of the surviving funds being equal to the mean return of the dead funds. We will be explaining the effect of this in detail under the analysis in section 7.

6.8 Performance across different time horizons

So far our findings must be deemed disappointing for active management; any significant outperformance tends to be erased by fund expenses, and we are only able to identify a few funds with significant positive net outperformance looking at a 10-year horizon. In addition, we find mixed evidence for market timing abilities. The unconditional model identifies positive market timing abilities on average, whereas the conditional model identifies negative market timing skills on average. Thus, as a long-term investment opportunity, our findings are not encouraging for active fund investment in Norway. However, could active fund management prove to be a wise investment in shorter periods? In this section, we apply the Jensen regression on a 5-year horizon in order to investigate this further. The absolute majority of the funds in our sample claim that a potential investor should have at least a 2-year perspective to anticipate abnormal returns. Moreover, to ensure as many observations as possible to maintain the statistical validity, we do not test for a shorter time horizon than five years.

In addition, as our evidence points towards poor performance for active management on average, it would be of an investor's interest to know whether active management performs better in economic downturns. Hence, we look specifically at the financial crisis to investigate whether active management performs better than passive management in periods of economic downturn. As the market timing ability depends on macro movements, and these are of less importance when the investment horizon shortens, we will only be testing for stock picking ability in this section.

6.8.1 Time horizon of 5 years

In order to investigate the performance for a 5-year horizon, we have removed any funds with a shorter lifetime from the sample. This criterion removes nine funds, leaving us with 38 funds in the sample with 60 observations each. Similarly to the previous performance models, we run the regression in both an unconditional and conditional setting. It is important to note, however, that reducing the time horizon implies reducing the number of observations, which in turn affects the statistical validity of our results. Hence, the interpretation of our 5-year horizon should be interpreted with some caution. Nevertheless, comparing the number of observations in this section with other studies on the field, the number of observations is comparable. Thus, we are confident we the number of observations will generate reliable estimates.

6.8.1.1 Unconditional Model

The interpretation of the regression model is still the same, where rejecting the null in *hypothesis 12* below indicates a significant outperformance and thus presence of stock picking skills in case of a significantly positive alpha. Similarly, a significantly negative alpha indicates significant underperformance and inferior stock picking skills.

Hypothesis 12: $H_0: \alpha_i = 0$ $H_1: \alpha_i \neq 0$

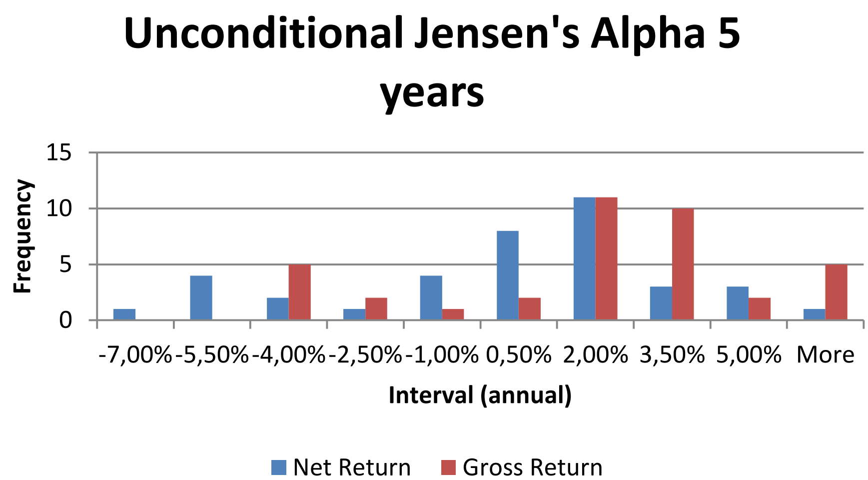


Table 6.25: Summary of the unconditional Jensen regression for a 5-year horizon. Source: Own creation

Return Series	No of funds	Average Annual Alpha	Significantly positive (negative)
Net	38	-0.64%	1(4)
Gross	38	0.83%	5(0)

Comparing the results from Table 6.25 above with the results from the unconditional 10-year Jensen's alpha regression in section 6.3.1, we see that the average annual net alpha is much lower. In fact, it is now negative, whereas the average annual 10-year net alpha was estimated to be slightly positive. By shortening the investment horizon by five years, the average net alpha estimate has decreased from 1.05% to -0.64%. Some of the drops in net alpha can be explained by the exclusion of the high-performing *Pareto Investment Fund C and B*[20]. However, the overall result is still startling; the average fund is underperforming relative to the benchmark by 0.64% annually after the deduction of fees. Of similar interest, we are now able to reject the null in *hypothesis 12* for five funds, of which four funds are significantly underperforming, whereas we did not identify any significant underperformers in the 10-year horizon. We refer to Appendix 5 for a full overview of the statistical outputs for our 5-year horizon.

[20] Removed because of the criterion of having a lifetime of minimum five years.

Apparently, shortening the investment horizon does not change our previous conclusion on active fund management. The conclusion is in fact strengthened. The fund managers in our data sample tend to perform even worse for a shorter time horizon. Looking at the average annual gross alpha further supports the conclusion; before deduction of expenses the funds outperform the benchmark by 0.83% annually. Unfortunately, the outperformance is completely erased by fund expenses, and the investors do not benefit at all.

6.8.1.2 Conditional Model

Hypothesis 13: $H_0: \alpha_i = 0$ $H_1: \alpha_i \neq 0$

Hypothesis 14: $H_0: \beta_2 = \beta_3 = \beta_4 = 0$ $H1: \beta2 \neq 0, and/or\ \beta3 \neq 0, and/or\ \beta4 \neq 0$

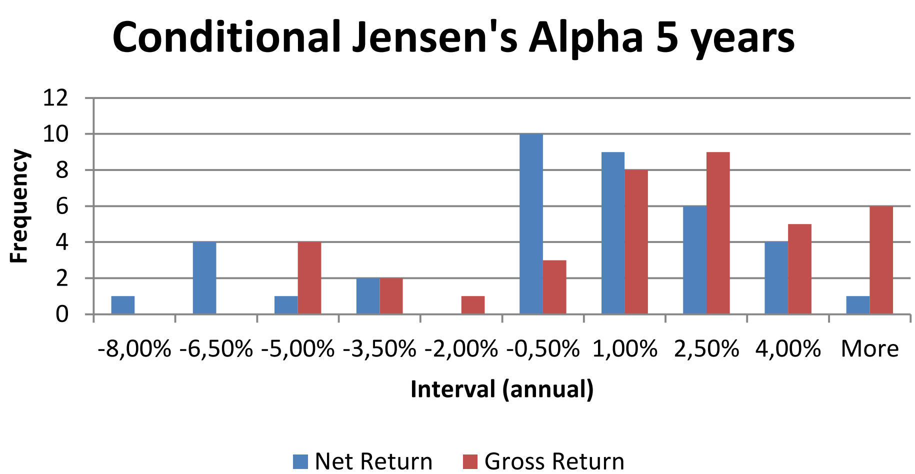


Table 6:26: Summary of the conditional Jensen regression for a 5-year horizon. Source: Own creation

Return Series	No of funds	Average Annual Alpha	Significantly positive (negative)	Percentage of Significant F
Net	38	-0.98%	0(5)	7.89%
Gross	38	0.83%	3(0)	7.89%

Similarly to the 10-year conditional Jensen's alpha, the introduction of a time-varying beta drags the overall alpha estimates downwards. However, looking at the column for "Percentage of significant F", adding the lagged information variables only allow us to reject the null in *hypothesis 14* above in 7.89% of the times. In other words, the conditional model only improves 7.89% of the unconditional models, which is a very low result. Intuitively, this is expected as shortening the time horizon also reduces the importance of having a time-varying beta. Thus, we will not put any emphasis on the conditional model, as the unconditional model evidently delivers the best alpha predictions 92.11% of the times for a 5-year horizon.

6.8.2 The Financial Crisis (2007 – 2009)

So far the results have been disappointing; we are not able to identify major benefits of using pricey active management relative to cheaper passive management. It appears as if the majority of the funds do in fact outperform the benchmark, but after deduction of fees, the outperformance is erased. Thus, investors are not able to benefit from active management, and funds are seemingly not able to defend their fees. However, it would be interesting to know if they do justify their fees, in times of severe economic downturn. Would an investor be better off by active management when the market is crumbling?

To answer this question, we will perform an analysis on the Financial Crisis, which occurred from September 2007 to June 2009. This leaves us with a dataset consisting of 26 funds that were alive during the financial crisis, with 22 observations each. Once again, we must emphasize the fact that this dataset has few observations which will affect the statistical validity of our results, and the results should be interpreted with caution. Despite the low number of observations, we still include this test, as it is the only market crash in our sample period, and would still provide an indication of fund performance in recessions.

As discussed in section 6.8.1.2 above, introducing a time-varying beta is of less importance for shorter time horizons, and we will therefore only apply an unconditional model for this section. Moreover, as we are looking at this from an investor's perspective, we are only interested in the estimated net alpha.

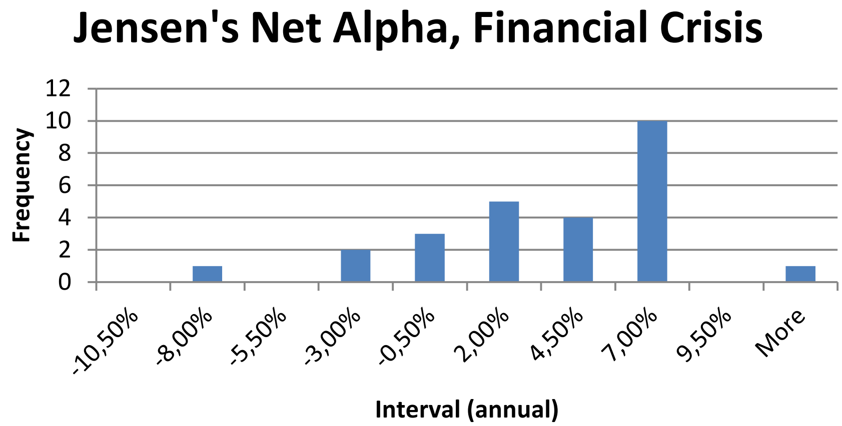


Table 6.27: Summary of the unconditional Jensen regression for the financial crisis. Source: Own creation

Return Series	No of funds	Average Annual Alpha	Significantly positive (negative)
Net	26	2.04%	2(0)

From Table 6.27 above, we see that the average annual net alpha for the 26 funds during the financial crisis was 2.04%. That is, the average fund outperformed the benchmark by 2.04% annually during the financial crisis. The histogram above illustrates this point better, where we clearly can observe a skew towards the right tail, which indicate outperformance on average. For example, we see that as many as 10 funds are located in the outperformance interval between 4.50% and 7.00%, which is an encouraging result taking into consideration the disappointing results from the previous tests in this study. Please see Appendix 7 for a full overview of the output for the financial crisis.

Moreover, two funds are found to display superior stock picking abilities through their statistically significant positive alpha estimate. As we can see from Table 6.28 below, the two funds in question are *Fondsfinans Norge* and *Pluss Markedsverdi*. In annual terms, they are outperforming the benchmark by 11.71% and 5.87% respectively, where *Fondsfinans Norge's* alpha is statistically significant at the 1% level. The two mentioned fund have been consistently able to pick the correct stocks during the financial crisis, making them able to outperform the benchmark.

All evidence from our test conducted on the financial crisis points towards active fund management being preferable in periods of severe economic downturn. The funds may not be able to justify their costs taking a full economic cycle into consideration, but at least they seem to be able to defend their costs when the markets are crashing. The result from this test can be deemed a small revenge for active fund management. However, it is important not to lose yourself in these results; even though the funds on average performed better than the benchmark during the crisis, an investor would still experience severe losses on his investment. The losses would just not be as severe as if he invested in a passive fund.

Table 6.28: Significantly outperforming funds during the financial crisis. Source: Own creation

Fund name	Net Returns			β	Obs.	R^2 adj.
	Monthly α	Yearly α	t-stat			
Fondsfinans Norge	**0.00976****	**0.11712****	**(3.14)**	0.86652	22	0.9726
Pluss Markedsverdi	**0.00489***	**0.05868***	**(2.06)**	0.89522	22	0.9888

6.8.3 General Market Downturns

Following our interesting findings from the Financial Crisis, we are interested in investigating whether Norwegian equity mutual funds perform better in general market downturns as well, or if the encouraging results are limited to the Financial Crisis. In order to investigate this matter further, we will construct a new data sample consisting of all monthly observations where the market has declined by 1.5% or more on a monthly basis. In our 10 years of data, this leaves us with 36 months of decline by 1.5% or more. In addition, we remove the funds with fewer than 22 observations to maintain the statistical validity of our test. This leaves us with a data sample consisting of 26 funds. By applying the same Jensen regression we used for the financial crisis, we are able to detect any potential outperformance. The summary of our test is presented in Table 6.29 below. For a full overview of the statistical output for this test, we refer to Appendix 8.

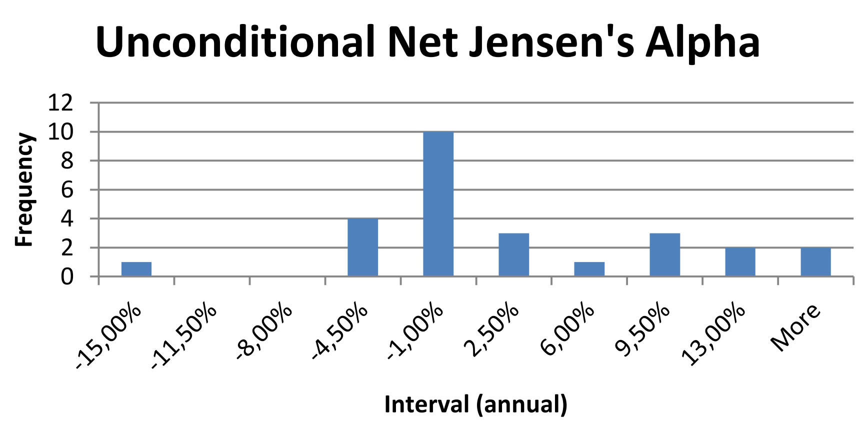


Table 6.29: Summary statistics for general market downturns. Source: Own creation

Return Series	No of funds	Average Annual Alpha	Significantly positive (negative)
Net	26	0.08%	3(1)

By comparing the results in Table 6.29 with the results from the Financial Crisis presented in section 6.8.2, it is evident that the outperformance has diminished. An average annual alpha of 0.08% can hardly be defined as outperformance, and serves more as an indication of neutral performance. By looking at the histogram above, we observe no obvious skewness to either side, indicating average neutral performance in general market downturns.

Furthermore, three funds obtain a statistically significant positive alpha, indicating superior stock picking abilities. More interesting, we now also identify a fund with significant negative stock picking abilities, which in times of general market downturn is highly unattractive from an investor's perspective. The four funds in question, along with their statistical output, are presented in Table 6.30 below, where they are ranked by performance.

Table 6.30: Significantly out- and underperforming funds in general market downturns. Source: Own creation

	Net Returns					
Fund name	Monthly α	Yearly α	t-stat	β	Obs.	R^2 adj.
Alfred Berg Gambak	**0.01336***	**0.16032***	**(2.44)**	0.99053	35	0.9090
Handelsbanken Norge	**0.01079***	**0.12948***	**(2.28)**	1.03683	35	0.9471
Alfred Berg Norge (Classic)	**0.00554***	**0.06648***	**(2.33)**	0.96592	35	0.9801
Landkreditt Norge	**-0.01272***	**-0.15264***	**(-2.14)**	0.74070	34	0.8563

As we can see *Alfred Berg Gambak* and *Handelsbanken Norge* has been able to pick the correct stocks continuously during overall market downturns, yielding them an average yearly outperformance of 16.032% and 12.948% respectively, which is impressive taking the sample average of 0.08% into consideration. On the other hand, we identify *Landkreditt Norge* as continuously picking the wrong stocks, yielding a monthly underperformance of 1.272% relative to the benchmark. This implies an average yearly underperformance of 15.26% in times of general market downturn, which is highly unattractive for investors.

In general, our test is not able to support the results from the financial crisis. On average, the funds in our sample deliver neutral performance in times of general market downturn. Despite this, we do successfully identify a few funds delivering significant outperformance, but as a whole, our test does not indicate that Norwegian equity mutual funds are able to defend their fees in times of general market downturn.

6.9 Distinguishing skill from luck

A final question that would be of interest for an investor is whether any outperformance (underperformance) is due to skill, or if the fund managers simply get lucky (unlucky). As stated in the introduction of this section, we will try to distinguish skill from luck by conducting a test. To perform the test, we have applied an adapted version of the bootstrapping technique proposed in the article by Cuthbertson et al. (2008), which was described in section 4.3.6. Like the original method, 1000 bootstrap replications are applied. For a model of equilibrium returns, we make use of the unconditional model of Jensen's alpha. The main reason for choosing this model is because of its simplicity. Additionally, Sørensen (2009) applied the Fama-French three-factor model in his study, and thus we find it interesting to use Jensen's alpha to see if our results deviate from the findings of the aforementioned study. Returns are used net of expenses as we are mainly interested in compensation to investors in order to reveal if active management is beneficial. Most importantly, this test serves as a control for our findings from Jensen's alpha in section 6.3.1; is the statistically significant alphas due to skills, like the model predicts, or are they simply due to luck?

Instead of using the 1000 bootstrap replications to create "new" alpha values, we use the replications to create new residuals, which is in line with a fixed resampling bootstrapping method. The new residuals affect the standard errors, and we obtain new t-values and confidence intervals for each fund based on the 1000 replications. The new confidence intervals constitute the tails in a "luck distribution" where it is possible to distinguish skill from luck. We follow the original theory proposed by Cuthbertson et al. and create two-sided 90% confidence intervals in order to test *hypothesis 15* below.[21] The method described is performed with the help of the statistical software "R-Studio". The null hypothesis of our skill vs. luck test is that alpha is equal to zero, and thus the alternative hypothesis is that alpha is different from zero. Naturally, if zero is located within the confidence interval, we cannot reject the null. That is, zero is located within the "luck distribution", and we find no evidence of skill. Similarly, if zero is located outside of the confidence interval, we can reject the null in *hypothesis 15,* and performance

[21] Appendix 1 is presented with a 95% confidence interval. A t-value exceeding 1.64 will entail significance in a 90% confidence interval.

seems to be due to skill. Whether it is “good” skills or “bad” skills depends on the coefficients of the confidence interval.

Hypothesis 15: $H_0: \alpha_i = 0$ $H_1: \alpha_i \neq 0$

Table 6.31 Fund performance based on skill or luck? Source: Own creation

Fund	Actual Alpha	Simulated Luck Distribution where the Left tail 5%	Simulated Luck Distribution where the Right tail 5%	Reject H_0?
Alfred Berg Aktiv	0,00139	-0,00040	0,00410	No
Alfred Berg Gambak	0,00242	-0,00010	0,00600	No
Alfred Berg Humanfond	-0,00084	-0,00240	0,00080	No
Alfred Berg Norge (Classic	0,0018	0,00060	0,00340	Yes
Carnegie Aksje Norge	0,00127	-0,00010	0,00270	No
Danske Invest Inst. I	0,00314	0,00140	0,00480	Yes
Danske Invest Inst. II	0,00309	0,00138	0,0044	Yes
Danske Invest Norge I	0,0021	0,00040	0,00380	Yes
Danske Invest Norge II	0,00281	0,00100	0,00450	Yes
Danske Invest Norge Veks	-0,00103	-0,00350	0,00170	No
Delphi Fondene Norge	0,00099	-0,00280	0,00390	No
DNB Norge	-0,00127	-0,00370	0,00110	No
DNB Norge III	-0,00061	-0,00310	0,00180	No
DNB Norge IV	-0,0004	-0,00290	0,00190	No
DNB Norge Selektiv I	-0,00149	-0,00480	0,00160	No
DNB Norge Selektiv II	-0,0064	-0,00400	0,00220	No
DNB Norge Selektiv III	-0,00048	-0,00380	0,00250	No
DNB SMB	-0,00598	-0,01120	0,00360	No
Eika Norge	0,00036	-0,00220	0,00280	No
Fondsfinans Norge	0,00284	0,00030	0,00590	Yes
Forte Norge	-0,00234	-0,00700	0,00290	No
Forte Tronder	0,00424	-0,00110	0,00930	No
Handelsbanken Norge	0,0025	0,00060	0,00530	Yes
Holberg Norge	-0,00212	-0,00510	0,00120	No
KLP Aksje Norge	0,00078	-0,00110	0,00330	No
Landkreditt Norge	0,00021	-0,00250	0,00380	No
Landkreditt Utbytte	0,00351	-0,00740	0,00910	No
Nordea Avkastning	0,00021	-0,00080	0,00120	No
Nordea Kapital	0,00112	0,00010	0,00240	Yes
Nordea Norge Pluss	-0,00019	-0,00260	0,00240	No
Nordea Norge Verdi	0,00149	-0,00070	0,00470	No
Odin Norge C	-0,00223	-0,00580	0,00160	No
Pareto Aksje Norge A	-0,00104	-0,00460	0,00220	No
Pareto Aksje Norge B	-0,00132	-0,00490	0,00180	No
Pareto Aksje Norge I	-0,0001	-0,00330	0,00360	No
Pareto Investment Fund C	0,01218	0,00850	0,01730	Yes
Pareto Investment Fund A	0,00194	-0,00030	0,00510	No
Pareto Investment Fund B	0,01182	0,00820	0,01710	Yes
Pluss Aksje	0,0022	0,00060	0,00400	Yes
Pluss Markedsverdi	0,00189	0,00060	0,00310	Yes
Storebrand Aksje Innland	-0,00102	-0,00330	0,00080	No
Storebrand Norge I	-0,00116	-0,00400	0,00100	No
Storebrand Norge	0,00027	-0,00200	0,00220	No
Storebrand Optima Norge	-0,00028	-0,00460	0,00410	No
Storebrand Vekst	0,00285	-0,00160	0,01270	No
Storebrand Verdi	-0,00125	-0,00320	0,00140	No
Swedbank Generator	0,00307	-0,00230	0,00750	No

Table 6.31 above presents the estimated alpha and the luck distribution for each fund. The test is conducted through 1000 (random) residual replications of each fund, which implies that Table 6.31 contains results from 47 000 replications. Interpreting the results reveals that we can reject the null in *hypothesis 15* for 12 funds. Thus, approximately 25% of the fund managers in the sample seem to possess some skills. All of these 12 funds have positive confidence intervals, suggesting "good" skills. Additionally, we discover that they are all statistically significant at the 10% level in our unconditional model for Jensen's alpha. That is, all of the significant findings in the Jensen regression are supported, and our confidence regarding the identified stock picking skills are further enhanced.

Finally, none of the funds in our sample are found to display "bad" skills in this test, as none of the zeros are located outside a negative confidence interval. Just like above, these results are also in line with our findings in the unconditional Jensen's alpha regression in section 6.3.1.

6.10 Active Share

This section is dedicated to the investigation of whether the funds are as active as they identify themselves as. Also, we investigate if the level of activity in a fund can be related to superior performance. For an investor, this would be of interest as active funds are more expensive.

6.10.1 Active Share Computed

As mentioned in section 4.6 and 5.5, the Active Share is a quantifiable measure that illustrates how actively managed a given fund is. By computing the absolute difference in portfolio holdings by the fund compared to the benchmark, we obtain a percentage measure of the degree of activity within a given fund. Based on the reasoning in section 5.5, we determined that an Active Share above 50% in the Norwegian market is sufficient to be classified as an actively managed fund. Funds below 50% will be classified as a passively investment fund, which is in accordance with Cremers & Petajisto's original paper on the field. Unfortunately, we have only been able to identify the portfolio holdings of 41 of the 47 funds in our sample. However, we are confident that this is a sufficient amount to be representative of our sample as a whole. Table 6.32 below illustrates the 10 most active and the 10 least active funds in our sample:

Table 6.32: Top 10/Bottom 10 actively managed funds, ranked from highest to lowest. Source: Own creation

Fund	Active Share
Top 10	
DNB SMB	91,77%
Forte Trønder	84,14%
Storebrand Vekst	78,61%
Danske Invest Norge Vekst	76,70%
Landkreditt Utbytte	76,67%
Pareto Investment Fund A	70,61%
Holberg Norge	70,36%
Pareto Aksje Norge A	67,97%
Forte Norge	65,66%
Nordea Norge Pluss	61,45%
Bottom 10	
Danske Invest Norge I	31,22%
Danske Invest Norge II	31,46%
Danske Invest Norge Aksjer Inst. I	30,95%
DNB Norge IV	30,62%
DNB Norge	30,61%
DNB Norge III	30,61%
KLP AksjeNorge	28,69%
Storebrand Norge I	25,76%
Pluss Markedsverdi	25,42%
Storebrand Aksje Innland	19,62%

For a full overview of the Active Share measure for our entire sample of funds we refer to Appendix 9.

6.10.2 Active Share and Fund Expenses

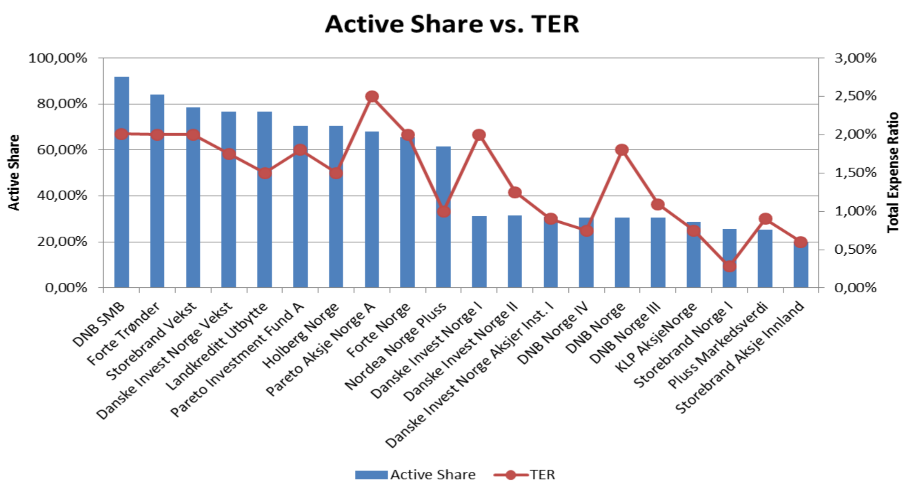
In our sample of 47 funds, only 16 have an Active Share above 50% and can be classified as an actively managed fund. The result is remarkable when we take into consideration that all of the funds in our sample consider themselves actively managed, and charge their investors accordingly. As we discussed in section 5.5 and 5.8, an active fund takes on higher risk and should, therefore, be compensated accordingly, while a less actively fund should be compensated less. That is, a fund with high Active Share should "cost" an investor more than a fund with a low Active Share. Our results indicate that only 16 funds should charge their investors fees that are fair for an actively managed fund. In other words, 31 funds might charge their investors fees that are too high relative to their level of risk.

Table 6.33 and Figure 6.2 below illustrates the Top 10/Bottom 10 Active Share funds along with their TER. From looking at the average TERs in Table 6.33, we see that the highly active funds have an average TER of 1.81% while the least active funds have an average TER of 1.03%. In line with theory, the most active funds do have the highest costs, as illustrated in Figure 6.2. However, the differences are not overwhelming, especially when you take into account that passively managed funds usually have a TER of 0.10% - 0.20%. *Danske Invest Norge I* is a good example; even though it is the 10th *least* active fund, it has the same TER as the three *most* active funds. If Cremers & Petajisto's Active Share truly gives a correct definition of active/passive funds, then the majority of Norwegian funds severely overcharge their investors.

Table 6.33: Top 10/Bottom 10 actively managed funds with Total Expense Ratio. Source: Own creation

Fund	Active Share	TER
DNB SMB	91,77%	2,01%
Forte Trønder	84,14%	2,00%
Storebrand Vekst	78,61%	2,00%
Danske Invest Norge Vekst	76,70%	1,75%
Landkreditt Utbytte	76,67%	1,50%
Pareto Investment Fund A	70,61%	1,80%
Holberg Norge	70,36%	1,50%
Pareto Aksje Norge A	67,97%	2,50%
Forte Norge	65,66%	2,00%
Nordea Norge Pluss	61,45%	1,00%
Average High Active Share		**1,81%**
Danske Invest Norge I	31,22%	2,00%
Danske Invest Norge II	31,46%	1,25%
Danske Invest Norge Aksjer Inst. I	30,95%	0,90%
DNB Norge IV	30,62%	0,75%
DNB Norge	30,61%	1,80%
DNB Norge III	30,61%	1,09%
KLP AksjeNorge	28,69%	0,75%
Storebrand Norge I	25,76%	0,28%
Pluss Markedsverdi	25,42%	0,90%
Storebrand Aksje Innland	19,62%	0,60%
Average Low Active Share		**1,03%**

Figure 6.2: Active Share vs. Total Expense Ratio, Top 10/Bottom 10. Source: Own creation



6.10.3 Active Share on Individual Performance

An absolute cornerstone of this study is to determine whether active management is preferable for potential investors. As we have used Active Share as a quantifiable measure of whether a fund truly is active or not, we have compared this with the individual funds net annual alpha from our conditional Jensen's regression from section 6.3. Hence, we can determine whether more active funds deliver better performance than less active funds. Table 6.34, along with Figure 6.3 below, presents the 10 most active and the 10 least active funds in our sample, along with their respective annual net alphas:

Table 6.34: Active Share vs. Annual Net Alpha, Top 10/Bottom 10. Source: Own creation

Fund	Active Share	Annual Net Alpha
DNB SMB	91,77%	-8,10%
Forte Trønder	84,14%	5,39%
Storebrand Vekst	78,61%	2,86%
Danske Invest Norge Vekst	76,70%	-2,30%
Landkreditt Utbytte	76,67%	4,90%
Pareto Investment Fund A	70,61%	-2,30%
Holberg Norge	70,36%	-5,15%
Pareto Aksje Norge A	67,97%	-2,30%
Forte Norge	65,66%	-3,64%
Nordea Norge Pluss	61,45%	-0,62%
Average High Active Share		**-1,13%**
Danske Invest Norge I	31,22%	1,46%
Danske Invest Norge II	31,46%	2,20%
Danske Invest Norge Aksjer Inst. I	30,95%	2,92%
DNB Norge IV	30,62%	-0,59%
DNB Norge	30,61%	-1,62%
DNB Norge III	30,61%	-0,84%
KLP AksjeNorge	28,69%	-0,97%
Storebrand Norge I	25,76%	-1,51%
Pluss Markedsverdi	25,42%	1,56%
Storebrand Aksje Innland	19,62%	-1,27%
Average Low Active Share		**0,13%**

Table 6.34 indicates that it is the least active funds in our sample that delivers the best performance. In fact, the 10 least active funds tend to outperform the benchmark by 0.13% on average per year. On the other hand, the 10 most active funds tend to underperform by 1.13% annually compared to the benchmark. Intuitively, it is not surprising that the most active funds differs the most from the benchmark, as the funds with a high Active Share have a portfolio that deviates from the benchmark portfolio to a large extent. As an example, *Pluss Markedsverdi* has a relatively low Active Share of 25.42% and a positive net return. Hence, even though 74.56% of *Pluss Markedsverdi's* portfolio does not

deviate from the benchmark, their portfolio managers are able to invest the remaining 25.42% of the portfolio in assets that do in fact outperform the benchmark. Thus, in order to outperform the benchmark the deviating shares need to generate a correspondingly high excess return. There are a limited number of highly liquid stocks in the Norwegian market, and none of the Norwegian funds can invest more than 10% of their portfolio in a single stock due to the previously mentioned UCITS regulations. Hence, it is harder to consistently outperform the benchmark in a small market such as Norway. However, the fact that the average net alpha for the highly active funds is negative must be deemed disappointing for active management, as it seems like passive management perform better on average.

Figure 6.3: Active Share vs. Net Alpha, Top 10/Bottom 10. Source: Own creation

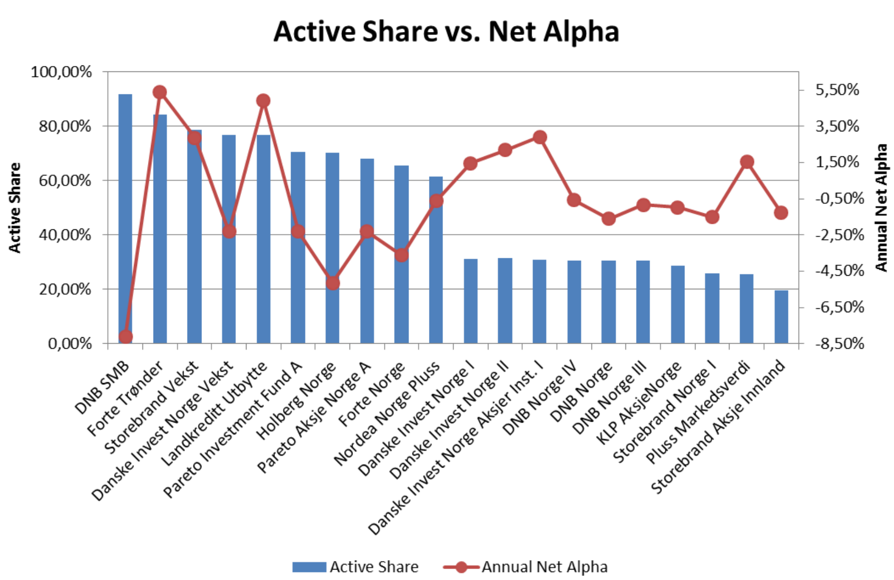


Figure 6.3 above further illustrates the points discussed; a high Active Share does not automatically imply a high net alpha. In fact, the net alphas of the highly active funds deviate to a much larger extent than the low activity funds. Hence, Active Share alone does not explain the mutual fund's performance in our sample.

6.10.4 Active Share and Tracking Error – Identifying Investment Strategies

As mentioned in section 4.6 in our study, Active Share and Tracking Error measure active management in two dimensions. In addition to being a measure of active risk, Tracking Error serves as a proxy for market timing. By combining Tracking Error with Active Share an investor can identify which strategies the fund managers are applying. Further, if we then compare the strategy with the net alphas from the

Jensen's regression, we can get an idea of which strategies have been the most successful among our sample. Looking at the formula for Tracking Error, presented in section 4.6.2, it is evident that computing the Tracking Error for each fund would be an incredibly time-consuming task. Therefore, we gathered the Tracking Errors for each fund directly from Bloomberg's database. For a complete overview of the Active Share and Tracking Error for the individual funds, we refer to Appendix 9.

Table 6.35 below presents which of the four strategies each fund's managers are utilizing. Due to the nature of the calculation of Tracking Error, an actively managed fund should have a high Tracking Error whereas the benchmark should have a Tracking Error approximately equal to zero. As explained in section 4.6.3, *Diversified Stock Picks* implies a sector weighting approximately equal to the benchmark index, but investments in individual stocks that differs widely from those in the benchmark, indicated by a high Active Share and a low Tracking Error. Hence, *Concentrated Stock Picks* implies that the fund manager's invest in few/many sectors and heavily in some stock-specific positions. That is, the fund differs from the benchmark in both when it comes to the size of the stock positions and sector weightings.

Because the Tracking Error serves as a proxy for market timing, fund managers that focus on market timing rather than stock picking tend to have a high Tracking Error but a low Active Share. Strategy-wise this is known as *Factor Bets*. Intuitively, the last strategy, *Closet Indexing*, implies a low Active Share and a low Tracking Error. That is, mimicking the benchmark indexing by not differentiating in either sector weighting or the size of the stock positions.

Table 6.35: Strategies from Active Share and Tracking Error. Source: Own creation based on Bloomberg data

Diversified Stock Picks	Concentrated Stock Picks
• Nordea Norge Pluss • Storebrand Optima Norge	• Alfred Berg Gambak • Danske Invest Norge Vekst • Delphi Norge • DNB SMB • Fondsfinans Spar • Forte Norge • Forte Tronder • Holberg Norge • Landkreditt Norge • Landkreditt Utbytte • Nordea Norge Verdi • Pareto Aksje Norge A • Pareto Investment Fund A • Storebrand Vekst
Closet Indexing	**Factor Bets**
• Alfred Berg Aktiv • Carnegie Aksje Norge • Danske Invest Norge I • Danske Invest Norge II • Danske Invest Norske Aksjer Inst. I • Danske Invest Norske Aksjer Inst. II • DNB Norge • DNB Norge III • DNB Norge IV • DNB Norge Selektiv I • DNB Norge Selektiv II • DNB Norge Selektiv III • Eika Norge • Handelsbanken Norge • KLP Aksje Norge • Nordea Avkastning • Pluss Aksje • Pluss Markedsverdi • Storebrand Aksje Innland • Storebrand Norge I • Storebrand Verdi	• Odin Norge C • Storebrand Norge

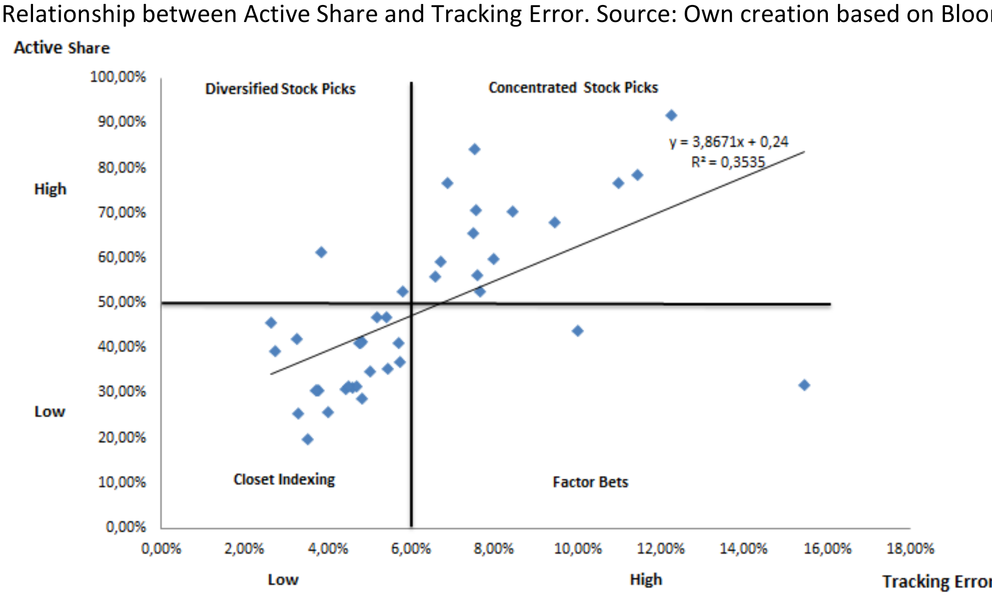
Figure 6.4 below illustrates the relationship between Active Share and Tracking Error. Cremers & Petajisto (2009) classified a Tracking Error above 6% as high, and thus an actively managed fund. Furthermore, as we mentioned in section 5.5, an Active Share above 50% also indicates an actively managed fund. Hence, the relationship between the strategies presented above.

As both Active Share and Tracking Error are measures for active risk, we expect a positive relation between the two. From the regression line in Figure 6.4 we can see that this is true. From the regression output, we can see that a 1% increase in Tracking Error implies an increase of approximately 4% in Active Share.

According to our findings in section 6.5, *Handelsbanken Norge* and *Landkreditt* Utbytte were the only funds identified with a significant positive net alpha in both the conditional and unconditional setting. Looking at the strategies presented in table 6.35 above, *Handelsbanken Norge* has a low Active Share and a low Tracking Error and falls into the" Closet Indexing" category. That is, *Handelsbanken Norge* is categorized as a passive fund according to Cremers & Petajisto's definition. These results support the findings from section 6.10.3; active management does not automatically imply a significant outperformance. On the other hand, *Landkreditt Utbytte* has a high Active Share and a high Tracking Error, and falls into the "Concentrated Stock Pick" category, which is the exact opposite of "Closet Indexing". Clearly, funds utilizing both strategies are able to deliver significant outperformance, which makes it difficult to identify a relation between significant outperformance and level of activity. The outperformance seems to be random, and independent from strategy.

DNB SMB is the most active fund in our sample with an Active Share of 91.77% and average Tracking Error of 12.25%. Despite this, *DNB SMB* is underperforming relative to the benchmark both in the conditional and unconditional setting, as referred to in appendix 1 and 2. However, the underperformance is not statistically significant. *Storebrand Aksje Innland*, on the other hand, is the least active fund in our sample, with an Active Share of 19.62% and a Tracking Error of 3.50%. Looking at Appendix 1 and 2, we see that *Storebrand Aksje Innland* also underperforms relative to the benchmark in both the conditional and unconditional setting, although not significant at a 5% level. This further strengthens our conclusion that outperformance is random and independent of strategy.

Figure 6.4: Relationship between Active Share and Tracking Error. Source: Own creation based on Bloomberg data



7.0 Analysis - Summary of findings

This section is included to provide a more practical view on the empirical findings in section 6. In addition, this section acts as a summary of the findings. Moreover, we will compare our findings with previous research on the field, which was described in our literature review in section 3.0.

7.1 Stock picking skills

In order to investigate whether Norwegian fund managers possess stock picking skills or not, we utilize the Jensen's regression model. When stock picking skills are considered on the basis of the unconditional Jensen's alpha, it seems that the performance of the Norwegian equity funds is quite neutral. When we interpret the results from the net returns, 8 out of 47 funds in the sample deliver significant alphas, all of which are positive. These findings seem reasonable if we compare them with other studies conducted, i.e. Lee and Rahman (1990). Moreover, when applying the gross returns, 17 of the funds were statistically positive. Thus, 36% of the funds have significant alphas. This number may seem high, but theoretically, the funds should have a positive alpha when related costs are not yet deducted. Otherwise, the funds are not able to outperform the benchmark from a market efficiency point of view.

The stock picking skills are also considered on the basis of the conditional Jensen's alpha. Performance still seems to be neutral. When we interpret the results from the net returns, five of the alphas were significantly positive, while one turned out to be significantly negative. These results also seem reasonable compared with previous studies. Furthermore, the conditional model is to be preferred in 25.53% of the cases, while the mean alphas between the two models differ by 1.40% points annually (due to several round-ups). This number comes as no surprise as it is exactly equal to the average annual TER of the funds in the sample.

Based on these findings, it is hard to draw a reasonable conclusion of the managerial performance. It may be tempting to assert that several fund managers possess superior stock picking skills, but that their fees exterminate the alphas. We do in fact identify a higher share of significantly positive funds than Jensen (1968) did in his original study on U.S mutual funds. More interestingly, compared to Sørensen's (2009) study on the Norwegian market, which identified no evidence of significant superior stock picking skills, we are now able to identify some funds being able to display such skills. However, on general basis our findings are in line with previous studies on the field; abnormal returns seem to be erased by the funds' fees.

Furthermore, as the TERs in our sample vary to a large degree, it is interesting to investigate if the most expensive funds outperform the funds with lower TER. When comparing the low expense group to the high expense group, we find no conclusive evidence of the high expense funds performing better. As a matter of fact, the low expense group performs better than the high expense group in both models. Randomly, the low expense group outperforms the high expense group by 2.84% points for both models. This finding is surprising as the high expense group on average has a TER of which is 1.35% points higher than that of the low expense group. The difference between the two groups appeared significant on the 10% level in the unconditional model while the difference in the conditional model appeared insignificant.

Our analysis of the stock picking abilities of Norwegian fund managers appears to substantiate the hypothesis that the average fund will not outperform an efficient market, as we make use of the 5% level as the required level of significance. Moreover, some of the fund managers actually seem to be superior forecasters, with the ability to outperform the market through selecting the right stocks. Nevertheless, it appears the expenses of the average fund in the Norwegian fund market devour most of the abnormal returns headed for the investors.

7.2 Market timing ability

To examine if Norwegian mutual fund managers possess any market timing ability, we make use of the Treynor-Mazuy model. The model indicates evidence for Norwegian fund managers indeed being able to time market fluctuations. That is, however, if the unconditional model is applied. On the contrary, when the conditional model is applied, the results are opposite to that of the unconditional model. In the unconditional setting, the Treynor-Mazuy model displays 15 significant gamma coefficients, of which 12 are positive and three are negative. The mean gamma in the unconditional model is 0.509. However, when we take the conditional information variables into account the mean gamma drops to -1.588, now displaying 10 significant gamma coefficients. Of these coefficients, three are positive, while seven are negative. Furthermore, it is difficult to make a clear choice of which model to interpret, as the F-test reveals that the conditional model is to be preferred over the unconditional model in 23.40% of the cases. Thus, we consider both models in the following.

The interpretation of a significantly negative gamma coefficient would be that the fund manager has the adverse ability to predict the market movements, but systematically in the wrong direction. This seems quite strange as any other fund manager could profit by trading against a manager with such abilities. Moreover, the manager would most likely reverse the current strategy, when the negative market timing ability comes to his attention. Furthermore, a negative gamma coefficient could be the product of derivative strategies, such as options. In such a case there should be a significantly positive alpha to offset the negative gamma. However, this is true only for 3 out of 7 funds with significantly negative gamma in the conditional model. For the unconditional model, 2 out of 3 funds with negative gamma have significantly positive alphas. We, therefore, question the reliability of the results from the conditional model and choose to evaluate the results from the unconditional model.

Furthermore, we examine the pertaining values of the Treynor-Mazuy model net of expenses. The mean alpha has decreased from 1.05% to 0.78% annually. This also results in a reduction from eight significantly positive funds to five significantly positive funds, alongside a newfound three significantly negative funds. A reduction is also observed in the gross return model, with the mean alpha decreasing from 2.60% to 1.95%. This finding implies that the positive figure from the Jensen model of 17 significantly positive alphas has been reduced to 11 significantly positive funds. This observation is in line with Grant's (1977) findings, which demonstrate that in the presence of market timing, the alphas estimates will be biased downwards.

Even if the market timing models, in an unconditional setting, emerge to display significant evidence that fund managers possess some market timing acumen, most of these gains seem to be lost again by the accompanying low alpha values. These findings are similar to those of Henriksson (1984) who identified the same tendencies for the 116 open-ended American mutual funds in his study. Thus, for an investor seeking abnormal returns, the performance of the Norwegian fund managers is not very convincing. Moreover, if we compare our results to those of Gjerde & Sættem (1991) on the Norwegian market, they also found evidence of positive market timing abilities among Norwegian mutual fund managers. However, in line with our study, they also identified accompanying negative alpha values, reducing the overall impact of the positive market timing abilities.

7.3 Performance persistence

When investigating the presence of performance persistence in our sample, we chose to employ a model based on the Otten & Bams (2002) approach. We were not able to find any significant funds repeating performance in successive periods. Hence, there is no indication of any hot- or cold-hands phenomena. It appears no evidence of the portfolio comprising of prior ”well” performing funds being different from the portfolio comprising of prior “bad” performing funds when we utilize the pooled regression. Moreover, when running the Jensen regression on the “well” performing funds as well as the “bad” performing funds, none of the portfolios produce any statistically significant alphas. This finding is independent of the use of net or gross returns. The “bad” performing portfolio generates a negative alpha when returns are considered net of expenses. Thus, it seems that the investment strategy of investing in prior winners yields no reliable profits in the Norwegian equity fund market. Our findings on performance persistence are in line with previous studies on the Norwegian mutual fund market; Sørensen (2009) was not able to identify any evidence of persistence in his data sample.

7.4 Survivorship bias

During the sample period, seven funds seized to exist. This constitutes 14.9% of the surviving funds. Hence, the survivorship bias should be relatively small. By a direct measure, the difference in means between all funds and surviving funds was 0.65% points per year. However, we found it more relevant to conduct tests investigating if the means of the surviving funds and the dead funds were significantly different from each other. The difference was 2.86% points annually, showing the evident reason for why the funds died, namely a notably lower return than rest of the sample. Nevertheless, we found no significance of the means being different. Thus, it is justifiable to argue that the survivorship bias would not have afflicted our study in any case.

7.5 Performance across different time horizons

In light of the disappointing results from our previous tests, we investigated whether investing in actively managed Norwegian equity mutual funds is preferable as a short-time investment. Moreover, we investigated whether active management is preferred in times of severe market downturns, by looking at the financial crisis specifically. After the analysis of the financial crisis was conducted, we performed the same analysis on periods of general market downturns. More specifically, we investigated if we could replicate the results from the financial crisis by estimating Jensen’s alpha on monthly returns below -1.5%.

After performing both an unconditional and conditional Jensen regression on a 5-year horizon, it became evident that the conditional model did not add a satisfactory level of explanatory power and was removed from further tests when analyzing shorter time horizons. Intuitively, this was as expected as using a time-varying beta loses its importance when the time horizon shortens. When the time horizon shortens, the risk-level will not vary to the same extent as for longer time horizons.

The results from our 5-year horizon pointed towards the same tendencies as for the 10-year horizon; the average fund does, in fact, outperform the benchmark, but the fund expenses erase the abnormal returns. Hence, an investor does not receive the benefits from active management. Moreover, we identified four funds with significant negative alpha, meaning that they continuously pick the wrong stocks, eventually yielding an underperformance. For a 10-year horizon, we were only able to detect one fund delivering significant underperformance in the unconditional setting. Despite this, we did, in fact, identify one fund displaying superior stock picking skills. Thus, as we identified in the previous tests some funds do demonstrate superior skills, but it is hard to draw a reasonable conclusion based on these results. The fact that the only fund displaying superior stock picking skills in a 5-year horizon, *Pareto Investment Fund A,* was not displaying superior stock picking skills in a 10-year horizon makes the results even more confusing for potential investors. Our results indicate that short-time significant outperformance does not automatically imply long-term significant outperformance. In fact, the average fund performs worse when we shorten the time horizon. Similarly, the significant short-time underperformance does not automatically indicate significant long-term underperformance. However, this is expected as the long-time underperformers tend to become defunct.

When looking at the financial crisis, we obtained interesting results; the estimated net alpha indicated that the average fund outperformed the benchmark by 2.04% annually, which is a lot higher than any previously estimated average net alphas. That is, Norwegian equity mutual funds seem to be able to defend their fees in times of severe market turmoil, which in practice means that an investor would lose less money if he utilized active management during the financial crisis. On the other hand, it is important to note that if an investor was investing in active management during the financial crisis, he would still incur severe losses. If the alternative was to keep his funds in a risk-free savings account, active management would be highly unattractive. However, as the purpose of this study is to conduct a comparison of active and passive management this matter is regarded outside of the study's scope and will not be discussed any further.

In light of the encouraging results from the financial crisis, we investigated whether active management performs better than a passive benchmark in times of general market downturns as well. Would an investor be better off investing in active management in months of market decline? Unfortunately, our results from the test on general market downturns do not support the findings from the financial crisis.

We were only able to identify neutral performance on average in times of general market downturn, which means that an investor would not benefit from investing in active management in times of general market downturn.

7.6 Active Share

When looking at the level of activity of the funds in our sample, we find inconsistent results. All of the 47 funds in our sample were included on the premise of being actively managed according to themselves, as the selection criteria in section 5.1 dealt with. However, according to Cremers & Petajisto's (2009) definition of actively managed funds, only 16 of the funds in our sample can be deemed truly actively managed funds. It is important to note that Cremers & Petajisto's measure activity solely based on the difference in portfolio holdings between a fund and the benchmark, which serves a proxy for the market portfolio. This implies that other factors used by investors to measure activity, e.g. trading frequency, are ignored. In practice, our results indicate that only 16 funds in our sample differentiate their holdings to such an extent that they are classified as truly active. In other words, the rest of the funds are passively managed according to our definition. Our results must be deemed discouraging from an investor's point of view; a large number of Norwegian funds that present themselves as active, are in fact the opposite. Investors who are interested in investing in active management are in danger of accidentally investing in passive management instead.

Another critical aspect for an investor in terms of the level of activity is the cost involved. According to theory, a fund with a higher Active Share takes on more risk because they differentiate themselves from the market portfolio to a larger extent, and should be compensated for doing so. That is, the more active funds should be more expensive than the less active funds. Our results do in fact indicate that the more active funds are more expensive than the less active funds. The average TER among the 10 *most* active funds is 1.81% while the average TER among the 10 *least* active funds is 1.03%. Hence, at first sight, it appears that investors wanting to invest in Norwegian mutual funds are not in danger of overpaying for less active funds. However, if we dive deeper into the analysis, we find evidence of some of the least passive funds charging their investors fees equal to those of the most active funds. *Danske Invest Norge I* is the 10th least active fund in our sample and has a TER of 2.00%, which is the same as the three most active funds. Moreover, *DNB Norge*, the 6th least active fund in our sample, has a TER of 1.80% which is approximately the same as the Top 10 average. Our results indicate that an investor must apply caution in regards to fund expenses; even though the least active funds are cheaper on average, he might accidentally end up severely overpaying for a passive fund.

The most interesting question, from an investor's point of view, is whether more active funds perform better than less active funds. Our study reveals some startling results; on average the least active funds perform better than the most active funds. By comparing the Active Share with the net alpha from our Jensen regression, we can compare performance with the level of activity. On average, the 10 most active funds tend to underperform relative to the benchmark by 1.13% annually. The 10 least active funds, on the other hand, tend to outperform the benchmark by 0.13% annually. It is important to note that the Norwegian stock market is relatively small, with few highly liquid stocks to choose from. In addition, Norwegian funds must comply with the UCITS regulations which restrict funds from holding more than 10% of their portfolio in a single stock. These factors make it difficult consistently to outperform the benchmark in a small market such as Norway. Based on the results from our study on Active Share, an investor would be better off by investing in passively managed Norwegian funds as they seem to perform better on average. Taking all the factors mentioned above into consideration, an investor investing in actively managed Norwegian equity mutual funds do not get the product he is entitled.

The final part of our study on Active Share identifies which investment strategies our sample funds are utilizing. By comparing the identified strategy with the net alpha from the Jensen regression, we are able to analyze whether some strategies are more successful than other. We are identifying the 4 different investment strategies that Cremers & Petajisto defined in their original study, where they differ from each other in sector holdings and individual stock holdings. However, we were not able to isolate a superior investment strategy, as it seems that outperformance is random and independent of strategy. We base this conclusion on the fact that both funds that are classified as "closet index funds" and "concentrated stock pickers" are able to outperform the benchmark, even though these strategies in practice are completely opposite of each other. In practice, these results imply that both funds using a strategy where the sector weighting and investments in individual stocks differs very little from the benchmark portfolio, and funds which invest in few sectors and individual stock holdings differs greatly from the benchmark portfolio, are able to outperform. In addition, there are funds within the two categories that underperform relative to the benchmark, implying that a given strategy does not automatically imply superior performance.

8.0 Conclusion

Our sample represents a minority of the total segment of actively managed funds available to investors looking to invest in the Norwegian market. The funds in our sample are mainly investing in Norwegian equities, and the funds are analyzed in the period from December 2005 to December 2015. Survivorship bias is a reoccurring issue in studies on mutual funds and needs to be considered carefully. To test for survivorship bias, we have performed a significance test on the difference between the mean returns of the dead funds and the surviving funds. The result from the test was highly conclusive; survivorship bias is not an issue in our sample.

Traditionally, the major selling point for actively managed mutual funds is that they are able to deliver abnormal returns to their investors. Hence, an investor should receive a higher return investing in active management compared to investing in passive management. The results from our tests indicate that Norwegian mutual funds mainly investing in Norwegian equities are *not* able to provide abnormal returns for their investors, which is in direct contrast to what the industry itself claims. For the majority of the funds in our sample, we find that alphas are *not* significantly different from zero. When testing for stock picking skills through the Jensen's alpha regression, we obtain varying results from the unconditional and conditional setting; we are in fact able to identify some fund managers displaying superior stock picking skills through a statistically positive net alpha. Despite this, a clear trend is prominent; when analyzing the funds' gross returns we do in fact see that the funds outperform the passive benchmark on average from a market efficiency point of view. Unfortunately from an investor's point of view, the general trend is that abnormal returns seem to be erased by the funds' fees. That is, the funds do in fact outperform the passive benchmark, but the investors do not benefit as the fees are too high relative to the funds' returns. Our findings confirm previous research, such as that of Jensen (1968), Gjerde & Sættem (1991), and Sørensen (2009).

To evaluate the funds' market timing abilities, we have utilized the Treynor-Mazuy model in both an unconditional and conditional setting. In this case, we obtain contradictory results; the unconditional model indicates positive market timing abilities on average, whereas the conditional model indicates negative market timing skills on average. Most likely, the true market timing estimate is somewhere in between the two but probably skewed towards the unconditional result, as the conditional model improves roughly a quarter of the unconditional models. Hence, we do find indications of the fund managers in our sample having the ability to time successfully macro movements, which is an uplifting result for active fund management in Norway. However, both the unconditional and the conditional model seem to be punishing the alpha values when controlling for market timing, leaving only a fraction of the funds with positive alphas. These results are in line with previous research performed by Grant (1977), where alpha estimates are biased downwards in the presence of market timing. It is close to impossible to determine whether stock picking skills or market timing abilities are most important to investors based on the results of our study, as this would be pure speculations. However, for a fund to successfully outperform a passive benchmark, positive market timing alone would probably not be sufficient as these macro movements would also be caught by the benchmark. In other words, although many Norwegian equity mutual funds are able to successfully predict market movements, the accompanying low alpha values may indicate that there are little, if even any, abnormal returns left to benefit the investors at the end of the day.

It would be of great interest for all potential investors to know if there is any performance persistence present in the Norwegian fund market. To elucidate this question, we have performed tests by making use of a pooled regression on a portfolio consisting of the best performing funds and the worst performing funds in the sample. Furthermore, the portfolio is rebalanced each year in order always to contain the best and worst performers. After running the regression, we find no significant evidence of persistence in neither the prior best performers nor the prior worst performers. That is, it seems like an investment strategy where an investor invests in prior winners will *not* yield abnormal returns in the Norwegian equity mutual fund market.

In order to investigate if investors get the product and return they are paying for, along with elucidating if Norwegian equity mutual funds are fairly priced, we have adopted the innovative Active Share measure. In this particular part of the study, we deliver a devastating blow for the active management industry; only a minority of the funds in our sample is truly active according to the Active Share. This implies that investors investing in Norwegian equity mutual funds are at risk of paying for active management, but receive passive management returns. Hence, investors do not get the product and return they are paying for. Our findings are further supported when we combine the Active Share measure with the individual funds' Total Expense Ratio and net alpha; the combination of Active Share and TER shows evidence of funds being defined as passive actually charging their investors as if they were highly active. Furthermore, the combination of Active Share and net alpha shows that a high level of activity does not automatically imply a high abnormal return and that the most passive funds on average perform better than the most active funds. Ultimately, we combined Active Share and Tracking

Error to investigate if active investment strategies perform better than passive investment strategies. Our results indicate that there is no evidence of active strategies performing better than passive strategies.

Are actively managed equity mutual funds in Norway able to outperform a passive benchmark? We find evidence that they are able to do so from a market efficiency point of view, but the investors are on average not receiving any abnormal returns due to the high costs involved with active management. That is, an investor is not better off by investing in active management.

9.0 Recommendations for future research

Our recommendations for future research are based on lowering of some of the requirements made in this study. We consider the strict selection criteria introduced as a major advantage, as it facilitates the purpose of aligning investment strategies and the use of one common benchmark index. However, lowering some of the requirements would allow us to have more funds to examine, as well as the sample, being further diversified.

Furthermore, it would be interesting to conduct a comparison of funds with an international mandate and funds with a Norwegian mandate. Thus, investors could more easily make contemplated decisions regarding their investments.

It could also be interesting to perform a study where one would obtain a direct measure of the difference in importance between stock picking skills and market timing ability as this would be a great contribution to our findings.

10.0 Bibliography

10.1 Articles

Basu, S. (1977). *Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A test of the Efficient Market Hypothesis.* The Journal of Finance, Vol. 32, No. 3., pp. 663-682.

Black, F., Jensen, M. C. & Scholes, M., (1972). *The capital asset pricing model: Some empirical tests in Studies in the theory of capital markets.* New York: Praeger. ed. Jensen, M., pp. 79-121.

Blake, D., & Timmermann, A. (1998). *Mutual fund performance: Evidence from the UK.* European Finance Review, 2(1), 57-77.

Brown, S. J., Goetzmann, W. N., Ibbotson, R. G., & Ross, S. A. (1992). *Survivorship bias in performance studies.* Review of Financial Studies 5 , pp. 553-580.

Brown, S. J., & Goetzmann, W. N. (1995). *Performance persistence*. The Journal of Finance, 50(2), 679-698.

Campanella, F. B. (1972). *The measurement of portfolio risk exposure: Use of the beta coefficient Lexington Books*.

Carhart, M. M. (1997). *On persistence in mutual fund performance.* The Journal of Finance, 52(1), 57-82.

Cesari, R., & Panetta, F. (2002). *The performance of Italian equity funds*. Journal of Banking & Finance, 26(1), 99-126

Che, L., Norli, O., & Priestley, R. (2009). *Performance persistence of individual investors*. Available at SSRN 1107795.

Chen, Z., & Knez, P. J. (1996). *Portfolio performance measurement: Theory and applications*. Review of Financial Studies, 9(2), 511-555.

Christensen, M., (2003). *Evaluating Danish mutual fund performance.* Institut for Finansiering, Handelshøjskolen i Århus.

Cremers, M. K., & Petajisto, A. (2009). *How active is your fund manager? A new measure that predicts performance.* Review of Financial Studies, 22(9), 3329-3365.

Cuthbertson, K., Nitzsche D. & O'Sullivan N. (2008). *UK mutual fund performance: Skill or luck?* Journal of Empirical Finance 15 (2008) 613–634.

Dahlquist, M., Engström, S., & Söderlind, P. (2000). *Performance and characteristics of Swedish mutual funds.* Journal of Financial and Quantitative Analysis, 409-423.

Dybvik Ø.G., Simonsen, K. (2015). *Pensjonssparing – En empirisk studie av nordmenns sparevilje til pensjon.* Norges handelshøyskole.

Elton, E. J. et al (2011): *Modern Portfolio Theory and Investment Analysis*, 8th edition, John Wiley & Sons.

Elton, E. J., Gruber, M. J., & Blake, C. R. (2012). *An examination of mutual fund timing ability using monthly holdings data*. Review of Finance, 16(3), 619-645.

Elton, E. J., Gruber, M. J., Das, S., & Hlavka, M. (1993). *Efficiency with costly information: A reinterpretation of evidence from managed portfolios*. Review of Financial Studies, 6(1), 1-22.

Engsted, T. & Larsen, B.G., (2011). *Anbefalinger om aktieinvesteringer.* September 2010, pp.1–36.

Fama, E.F. (1970). *Efficient Capital Markets: A Review of Theory and Empirical Work*. The Journal of Finance, Vol. 25, No. 2

Fama, E. F. (1972). *Components of investment performance**. The Journal of Finance, 27(3), 551-568.

Fama, E. F. (1991). *Efficient Capital Markets: II.* The Journal of Finance, Vol. XLVI, No. 5 , pp. 1575-1617.

Fama, E. F., & French, K. R. (2009). *Luck versus skill in the Cross-Section of mutual fund returns.* The Journal of Finance, 65(5), 1915-1947.

Fama, E. F. & MacBeth, J. D. (1973). *Risk, return and equilibrium: Empirical tests.* Journal of Political Economy 81 (May-June), pp. 607-36.

Ferson, W. E., & Schadt, R. W. (1996). *Measuring fund strategy and performance in changing economic conditions.* The Journal of Finance, 51(2), 425-461.

Gjerde, Ø., & Sættem, F. (1991). *Performance evaluation of Norwegian mutual funds*. Scandinavian Journal of Management, 7(4), 297-307.

Goetzmann, W. N., & Ibbotson, R. G. (1994). *Do winners repeat?* The Journal of Portfolio Management, 20(2), 9-18.

Goetzmann, W. N., Ingersoll Jr, J., & Ivković, Z. (2000). *Monthly measurement of daily timers*. Journal of Financial and Quantitative Analysis, 257-290.

Grant, D. (1977). *Portfolio performance and the "cost" of timing decisions.* The Journal of Finance, 32(3), 837-846.

Grinblatt, M., & Titman, S. (1989). *Mutual fund performance: An analysis of quarterly portfolio holdings.* Journal of Business, 393-416.

Grinblatt, M., & Titman, S. (1992). *The persistence of mutual fund performance*. The Journal of Finance, 47(5), 1977-1984.

Grossman, S. J., & Stiglitz, J. E. (1980). *On the impossibility of informationally efficient markets.* The American Economic Review, 70(3), 393-408.

Hendricks, D., Patel, J., & Zeckhauser, R. (1993). *Hot hands in mutual funds: Short-run persistence of relative performance, 1974–1988*. The Journal of Finance, 48(1), 93-130.

Henriksson, R. D. (1984). *Market timing and mutual fund performance: An empirical investigation*. Journal of Business, 73-96.

Henriksson, R. D., & Merton, R. C. (1981). *On market timing and investment performance. II. statistical procedures for evaluating forecasting skills.* Journal of Business, 513-533.

Ippolito, R. A. (1989). *Efficiency with costly information: A study of mutual fund performance, 1965–1984.* The Quarterly Journal of Economics, 104(1), 1-23.

Jagannathan, R. & McGrattan, E.R., (1995). *The CAPM Debate. Federal Reserve Bank of Minneapolis.* Quarterly Review Fall.

Jensen, M. C. (1968). *The performance of mutual funds in the period 1945–1964.* The Journal of Finance, 23(2), 389-416.

Jensen, M. C. (1969). *Risk, the pricing of capital assets, and the evaluation of investment portfolios*. The Journal of Business, 42(2), 167-247.

Kon, S. J., & Jen, F. C. (1978). *Estimation of time-varying systematic risk and performance for mutual fund portfolios: An application of switching regression*. The Journal of Finance, 33(2), 457-475.

Kosowski R. (2006). *Do Mutual Funds Perform When it Matters Most to Investors? US Mutual Fund Performance and Risk in Recessions and Expansions.* Available at SSRN

Lee, C., & Rahman, S. (1990). *Market timing, selectivity, and mutual fund performance: An empirical investigation.* Journal of Business, 261-278.

Lintner, J. (1965). *The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets.* The Review of Economics and Statistics, 47(1), 13-37.

Malkiel, B. G. (1995). *Returns from investing in equity mutual funds 1971 to 1991*. The Journal of Finance, 50(2), 549-572.

Malkiel, B. G. (2003). *The Efficient Market Hypothesis and Its Critics.* CEPS Working Paper No. 91 , pp. 1-38.

Modigliani, F., & Modigliani, L. (1997). *Risk-adjusted performance.* The Journal of Portfolio Management, 23(2), 45-54.

Mullins, D. W. J., (1982). *Does the Capital Asset Pricing Model Work.* Harward Business Review.

Newey, W. K., & West, K. D. (1994). *Automatic lag selection in covariance matrix estimation*. The Review of Economic Studies, 61(4), 631-653.

Otten, R., & Bams, D. (2002). *European mutual fund performance.* European Financial Management, 8(1), 75-101.

Rohleder, M., Scholz, H., & Wilkens, M. (2010). *Survivorship Bias and Mutual Fund Performance: Relevance, Significance, and Methodical Differences*. Review of Finance, Vol.15, Issue 2 , pp. 441-474.

Roll, R. (1978). *Ambiguity when performance is measured by the securities market line.* The Journal of Finance, 33(4), 1051-1069.

Sharpe, W. F. (1966). *Mutual fund performance.* The Journal of Business, 39(1), 119-138.

Sørensen, L. Q. (2009). *Mutual fund performance at the Oslo stock exchange.* Available at SSRN 1488745,

Treynor, J. L. (1965). *How to rate mutual fund performance.* Harvard Business Review, 43, 63-75.

Treynor, J., & Mazuy, K. (1966). *Can mutual funds outguess the market.* Harvard Business Review, 44(4), 131-136.

Wallander, J. (2012). *Does active fund management add value?* Copenhagen: Copenhagen Business School.

10.2 Books

Bodie, Z., Kane, A. & Marcus, A. (2009). *Investments*. McGraw-Hill/Irwin Series.

Stock, J.H & Watson, M.W. (2009). *Introduction to Econometrics*, 3rd ed. Addison-Wesley Series in Economics.

10.3 Non-academic references

Statistics Norway:

https://www.ssb.no

https://www.ssb.no/bank-og-finansmarked/statistikker/vpfond#vedleggsartikkel-1, - downloaded 25.01.16

https://www.ssb.no/en/bank-og-finansmarked/statistikker/vpfond/aar/2015-09-11?fane=tabell&sort=nummer&tabell=239632 – downloaded 25.01.16

The Norwegian Fund and Asset Management Association:

http://vff.no

http://vff.no/historisk-statistikk - downloaded 25.01.16

Official Journals from the European Union:

http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0091&from=EN – downloaded 27.01.16

Morningstar.no – International financial database:

http://www.morningstar.no/no/

Financial Times:

http://www.ft.com

http://www.ft.com/cms/s/0/caad1152-c97e-11e4-a2d9-00144feab7de.html#axzz3zql7Bnqd, downloaded: 11.02.2016

11.0 Appendices

Appendix 1: Unconditional Jensen's alpha, net and gross return

** $p < 0.01$ * $p < 0.05$

	Net Returns				Gross Returns		
Fund name	α	t-stat	β	Obs.	α	t-stat	R^2 adj.
Alfred Berg Aktiv	0.00139	(1.07)	0.94154	120	**0.00261***	**(2.01)**	0.9543
Alfred Berg Gambak	0.00242	(1.34)	0.91167	120	**0.00386***	**(2.13)**	0.9106
Alfred Berg Humanfond	-0.00084	(-0.88)	0.93331	120	0.00066	(0.69)	0.9735
Alfred Berg Norge (Classic)	**0.00180**	**(2.21)**	0.95141	120	**0.00279****	**(3.42)**	0.9819
Carnegie Aksje Norge	0.00127	(1.42)	0.95732	120	**0.00228***	**(2.55)**	0.9802
Danske Invest Inst. I	**0.00314****	**(3.02)**	0.91189	120	**0.00392****	**(3.77)**	0.9680
Danske Invest Inst. II	**0.00309****	**(2.97)**	0.91004	120	**0.00385****	**(3.84)**	0.9647
Danske Invest Norge I	**0.00210***	**(2.01)**	0.90527	120	**0.00380****	**(3.66)**	0.9667
Danske Invest Norge II	**0.00281****	**(2.66)**	0.89666	120	**0.00387****	**(3.68)**	0.9654
Danske Invest Norge Vekst	-0.00103	(-0.64)	0.85583	120	0.00045	(0.28)	0.9171
Delphi Fondene Norge	0.00099	(0.51)	0.93391	63	0.00266	(1.38)	0.8578
DNB Norge	-0.00127	(-0.90)	0.94264	60	0.00030	(0.22)	0.9170
DNB Norge III	-0.00061	(-0.44)	0.94212	60	0.00034	(0.25)	0.9166
DNB Norge IV	-0.00040	(-0.28)	0.94454	60	0.00026	(0.18)	0.9167
DNB Norge Selektiv I	-0.00149	(-0.83)	0.96648	60	0.00032	(0.18)	0.8788
DNB Norge Selektiv II	-0.00640	(-0.36)	0.96512	60	0.00027	(0.15)	0.8777
DNB Norge Selektiv III	-0.00048	(-0.26)	0.96839	60	0.00024	(0.14)	0.8780
DNB SMB	-0.00598	(-1.50)	1.07035	60	-0.00435	(-1.09)	0.6383
Eika Norge	0.00036	(0.23)	0.91895	120	0.00204	(1.29)	0.9270
Fondsfinans Norge	0.00284	(1.72)	0.90212	120	**0.00368***	**(2.23)**	0.9246
Forte Norge	-0.00234	(-0.77)	0.93330	56	-0.00052	(-0.17)	0.7581
Forte Tronder	0.00424	(1.32)	0.67770	36	0.00517	(1.59)	0.5025
Handelsbanken Norge	0.00250	(1.80)	0.9895	120	**0.00410****	**(2.95)**	0.9533
Holberg Norge	-0.00212	(-1.16)	0.76700	120	-0.00095	(-0.53)	0.8824
KLP Aksje Norge	0.00078	(0.54)	0.93057	120	0.00140	(0.95)	0.9521
Landkreditt Norge	0.00021	(0.11)	0.84667	114	0.00173	(0.93)	0.8973
Landkreditt Utbytte	0.00351	(0.81)	0.64376	33	0.00518	(1.26)	0.4471
Nordea Avkastning	0.00021	(0.32)	0.95913	120	**0.00148***	**(2.24)**	0.9884
Nordea Kapital	0.00112	(1.64)	0.94871	120	**0.00197****	**(2.89)**	0.9875
Nordea Norge Pluss	-0.00019	(-0.13)	0.98952	56	0.00069	(0.46)	0.9320
Nordea Norge Verdi	0.00149	(0.93)	0.75561	120	0.00268	(1.67)	0.9023
Odin Norge C	-0.00223	(-0.99)	0.73749	107	-0.00066	(-0.30)	0.8438
Pareto Aksje Norge A	-0.00104	(-0.51)	0.75098	120	0.00088	(0.43)	0.8506
Pareto Aksje Norge B	-0.00132	(-0.63)	0.76643	119	0.00024	(0.11)	0.8474
Pareto Aksje Norge I	-0.00010	(-0.05)	0.77138	120	0.00029	(0.14)	0.8485
Pareto Investment Fund C	**0.01218****	**(4.27)**	0.42191	25	**0.01258****	**(4.36)**	0.3767
Pareto Investment Fund A	0.00194	(1.20)	0.94362	120	**0.00342***	**(2.10)**	0.9327
Pareto Investment Fund B	**0.01182****	**(4.20)**	0.42220	25	**0.01259****	**(4.36)**	0.3770
Pluss Aksje	0.00220	(1.93)	0.83734	120	**0.00322****	**(2.81)**	0.9594
Pluss Markedsverdi	**0.00189***	**(2.39)**	0.91458	120	**0.00265****	**(3.35)**	0.9821
Storebrand Aksje Innland	-0.00102	(-0.84)	0.92806	57	-0.00050	(-0.42)	0.9470
Storebrand Norge I	-0.00116	(-0.82)	0.92731	57	-0.00092	(-0.65)	0.9285
Storebrand Norge	0.00027	(0.22)	0.95101	63	0.00157	(1.27)	0.9333
Storebrand Optima Norge	-0.00028	(-0.11)	0.93475	57	0.00056	(0.22)	0.7792
Storebrand Vekst	0.00285	(0.74)	0.82637	63	0.00434	(1.14)	0.5515
Storebrand Verdi	-0.00125	(-0.93)	0.89639	63	0.00038	(0.28)	0.9198
Swedbank Generator	0.00307	(1.01)	1.08839	63	0.00429	(1.41)	0.7990

Appendix 2: Conditional Jensen's Alpha, net and gross returns

** p < 0.01 * p < 0.05

Fund name	Net Returns α	Net Returns t-stat	β	Obs.	Gross Returns α	Gross Returns t-stat	R^2 adj.	F-Value
Alfred Berg Aktiv	0.00085	(0.62)	0.96483	120	0.00207	(1.52)	0.9548	2.551
Alfred Berg Gambak	0.00290	(1.51)	0.89109	120	**0.00435***	**(2.26)**	0.9105	1.036
Alfred Berg Humanfond	-0.00092	(-0.92)	0.93660	120	0.00058	(0.58)	0.9733	0.000
Alfred Berg Norge (Classic)	**0.00188***	**(2.20)**	0.94797	120	**0.00287****	**(3.35)**	0.9818	0.128
Carnegie Aksje Norge	0.0008	(1.00)	0.97684	120	**0.00181***	**(2.26)**	0.9806	4.096
Danske Invest Inst. I	**0.00243***	**(2.21)**	0.90642	120	**0.00320****	**(2.91)**	0.9694	**6.723***
Danske Invest Inst. II	**0.00222****	**(3.07)**	0.90812	109	**0.00312****	**(2.88)**	0.9685	**6.723***
Danske Invest Norge I	0.00122	(1.14)	0.94254	120	**0.00291****	**(2.73)**	0.9690	**10.000***
Danske Invest Norge II	0.00183	(1.70)	0.93803	120	**0.00289****	**(2.69)**	0.9683	**12.500***
Danske Invest Norge Vekst	-0.00192	(-1.17)	0.89447	120	-0.00044	(-0.27)	0.9193	4.068
Delphi Fondene Norge	0.00082	(0.42)	0.95237	63	0.00247	(1.27)	0.8568	0.833
DNB Norge	-0.00135	(-0.95)	0.94915	60	0.00021	(0.15)	0.9155	0.163
DNB Norge III	-0.00070	(-0.49)	0.94866	60	0.00025	(0.18)	0.9154	0.244
DNB Norge IV	-0.00049	(-0.34)	0.95109	60	0.00016	(0.12)	0.9154	0.242
DNB Norge Selektiv I	-0.00170	(-0.93)	0.98275	60	0.00009	(0.05)	0.8782	0.510
DNB Norge Selektiv II	-0.00086	(-0.47)	0.98150	60	0.00004	(0.02)	0.8772	0.505
DNB Norge Selektiv III	-0.00070	(-0.39)	0.98484	60	0.00001	(0.01)	0.8775	1.010
DNB SMB	-0.00675	(-1.75)	1.13420	60	-0.00521	(-1.39)	0.6500	3.108
Eika Norge	-0.00039	(-0.25)	0.95138	120	0.00128	(0.80)	0.9282	3.010
Fondsfinans Norge	0.00125	(0.80)	0.97098	120	0.00208	(1.33)	0.9323	**14.599***
Forte Norge	-0.00303	(-1.02)	0.98120	56	-0.00128	(-0.43)	0.7683	3.555
Forte Tronder	0.00449	(1.38)	0.87924	36	0.00539	(1.64)	0.5205	2.454
Handelsbanken Norge	0.00276	(1.87)	0.97861	120	**0.00438****	**(2.96)**	0.9531	0.441
Holberg Norge	**-0.00429***	**(-2.61)**	0.86421	120	-0.00313	(-1.91)	0.9021	**25.080***
KLP Aksje Norge	-0.00081	(-0.77)	0.99921	120	-0.00021	(-0.19)	0.9597	**23.529***
Landkreditt Norge	-0.00129	(-0.73)	0.91187	114	0.00021	(0.12)	0.9046	**9.632***
Landkreditt Utbytte	0.00408	(0.97)	0.80933	33	0.00568	(1.42)	0.4451	1.064
Nordea Avkastning	-0.00024	(-0.35)	0.97817	120	0.00103	(1.53)	0.9889	**6.809***
Nordea Kapital	0,00062	(0.90)	0.96988	120	**0.00146***	**(2.14)**	0.9882	**7.959***
Nordea Norge Pluss	-0.00052	(-0.36)	1.00853	56	0.00035	(0.24)	0.9338	2.569
Nordea Norge Verdi	0.00129	(0.83)	0.76406	120	0.00248	(1.59)	0.9017	0.000
Odin Norge C	-0.00338	(-1.46)	0.79429	107	-0.00181	(-0.79)	0.8487	4.609
Pareto Aksje Norge A	-0.00192	(-0.97)	0.79013	120	0.00000	(0.00)	0.8527	2.559
Pareto Aksje Norge B	-0.00225	(-1.08)	0.80862	119	-0.00069	(-0.33)	0.8499	3.006
Pareto Aksje Norge I	-0.00103	(-0.49)	0.81287	120	-0.00065	(-0.31)	0.8508	2.794
Pareto Investment Fund C	**0.01199****	**(3.94)**	0.38237	25	**0.01239****	**(4.02)**	0.3487	0.111
Pareto Investment Fund A	0.00155	(0.97)	0.96009	120	0.00303	(1.90)	0.9326	1.007
Pareto Investment Fund B	**0.01163****	**(3.87)**	0.38236	25	**0.01239****	**(4.02)**	0.3490	0.167
Pluss Aksje	0.00093	(1.02)	0.89024	120	**0.00193***	**(2.12)**	0.9652	**21.552***
Pluss Markedsverdi	0.00130	(1.72)	0.93896	120	**0.00206****	**(2.76)**	0.9831	**7.879***
Storebrand Aksje Innland	-0.00106	(-0.84)	0.93123	57	-0.00055	(-0.44)	0.9461	0.000
Storebrand Norge I	-0.00126	(-0.86)	0.93355	57	-0.00102	(-0.70)	0.9275	0.288
Storebrand Norge	0.00023	(0.18)	0.95652	63	0.00152	(1.24)	0.9323	0.092
Storebrand Optima Norge	-0.00046	(-0.18)	0.94587	57	0.00037	(0.15)	0.7760	0.259
Storebrand Vekst	0.00238	(0.63)	0.88005	63	0.00384	(1.02)	0.5539	1.419
Storebrand Verdi	-0.0011	(-0.82)	0.87662	63	0.00055	(0.41)	0.9203	1.391
Swedbank Generator	0.00263	(0.87)	1.14515	63	0.00384	(1.26)	0.8053	3.145

Appendix 3: Unconditional Treynor-Mazuy

** p < 0.01 * p < 0.05

Fund name	Net Returns				Obs.	Gross Returns				R^2 adj.
	α	t-stat	γ	t-stat		α	t-stat	γ	t-stat	
Alfred Berg Aktiv	0.00128	(0.86)	0.02053	(0.15)	120	0.00250	(1.69)	0.02053	(0.15)	0.9539
Alfred Berg Gambak	0.00408	(1.97)	-0.31694*	(-2.28)	120	0.00554**	(2.67)	-0.31694*	(-2.28)	0.9126
Alfred Berg Humanfond	-0.00097	(-0.90)	0.02138	(0.29)	120	0.00053	(0.50)	0.02392	(0.32)	0.9740
Alfred Berg Norge (Classic)	0.00212*	(2.27)	-0.06077	(-0.80)	120	0.00311**	(3.33)	-0.06077	(-0.80)	0.9819
Carnegie Aksje Norge	0.00083	(0.88)	0.08975	(0.54)	120	0.00183	(1.97)	0.08444	(0.51)	0.9802
Danske Invest Inst. I	0.00174	(1.66)	0.26352**	(2.81)	120	0.00251*	(2.39)	0.02635**	(2.81)	0.9698
Danske Invest Inst. II	0.00174	(1.66)	0.26352**	(2.81)	120	0.00246*	(2.36)	0.02637**	(2.81)	0.9698
Danske Invest Norge I	0.00090	(0.86)	0.22702*	(2.01)	120	0.00259*	(2.47)	0.22702*	(2.01)	0.9680
Danske Invest Norge II	0.00138	(1.29)	0.27377*	(2.62)	120	0.00247*	(2.35)	0.26403*	(2.39)	0.9672
Danske Invest Norge Vekst	-0.00159	(-0.94)	0.10890	(0.55)	120	-0.00012	(-0.07)	0.10890	(0.55)	0.9167
Delphi Fondene Norge	0.002138	(0.94)	-0.62415	(-1.20)	63	0.00381	(1.64)	-0.62415	(-1.20)	0.8574
DNB Norge	-0.00235	(-1.35)	0.63420	(1.74)	60	-0.00078	(-0.45)	0.63420	(1.74)	0.9174
DNB Norge III	-0.00169	(-0.98)	0.63706	(1.74)	60	-0.00074	(-0.43)	0.63706	(1.74)	0.9170
DNB Norge IV	-0.00148	(-0.85)	0.63726	(1.74)	60	-0.00083	(-0.48)	0.63726	(1.74)	0.9170
DNB Norge Selektiv I	-0.00432*	(-2.17)	1.67134*	(2.43)	60	-0.00249	(-1.27)	1.67134*	(2.43)	0.8884
DNB Norge Selektiv II	-0.00348	(-1.75)	1.68048*	(2.45)	60	-0.00256	(-1.30)	1.68048*	(2.45)	0.8875
DNB Norge Selektiv III	-0.00331	(-1.67)	1.68039*	(2.44)	60	-0.00259	(-1.31)	1.68039*	(2.44)	0.8877
DNB SMB	-0.00809	(-1.82)	1.24063	(0.81)	60	-0.00647	(-1.42)	1.24063	(0.81)	0.6356
Eika Norge	0.00008	(0.04)	0.05511	(0.28)	120	0.00175	(1.05)	0.05511	(0.28)	0.9264
Fondsfinans Norge	0.00069	(0.40)	0.41267	(1.64)	120	0.00152	(0.88)	0.41266	(1.64)	0.9290
Forte Norge	-0.00614*	(-2.08)	2.11689*	(2.10)	57	-0.00432	(-1.44)	2.11689*	(2.10)	0.7711
Forte Tronder	0.00300	(0.71)	1.46507	(0.46)	36	0.00394	(0.92)	1.46507	(0.46)	0.4906
Handelsbanken Norge	0.00368*	(2.33)	-0.22513*	(-2.41)	120	0.00530*	(3.34)	-0.22513*	(-2.41)	0.9541
Holberg Norge	-0.00400*	(-2.22)	0.42822	(1.89)	120	-0.00316	(-1.63)	0.42822	(1.89)	0.8883
KLP Aksje Norge	-0.00089	(-0.63)	0.32224	(0.81)	120	-0.00028	(-0.20)	0.32224	(0.81)	0.9546
Landkreditt Norge	-0.00269	(-1.52)	0.60455**	(4.02)	114	-0.00147	(-0.76)	0.60455**	(4.02)	0.9083
Landkreditt Utbytte	0.00952*	(2.21)	-6.65588*	(-2.34)	35	0.01101*	(2.70)	-6.63887*	(-2.34)	0.5015
Nordea Avkastning	-0.00054	(-0.83)	0.16087	(1.89)	120	0.00066	(0.92)	0.15622	(1.89)	0.9889
Nordea Kapital	0.00020	(0.24)	0.18051*	(2.10)	120	0.00102	(1.40)	0.18051*	(2.10)	0.9883
Nordea Norge Pluss	-0.00110	(-0.72)	0.50602	(0.79)	56	-0.00022	(-0.14)	0.50602	(0.79)	0.9318
Nordea Norge Verdi	0.00118	(0.70)	0.05869	(0.26)	120	0.00237	(1.41)	0.05870	(0.26)	0.9016
Odin Norge C	-0.00225	(-0.95)	0.00834	(0.19)	107	-0.00086	(-0.34)	0.03795	(0.19)	0.8423
Pareto Aksje Norge A	-0.00094	(-0.42)	-0.02039	(-0.08)	120	0.00098	(0.44)	-0.02039	(-0.08)	0.8493
Pareto Aksje Norge B	-0.00142	(-0.61)	0.01921	(-0.08)	119	0.00014	(0.06)	0.01921	(0.08)	0.8461
Pareto Aksje Norge I	-0.00012	(-0.05)	0.00447	(0.02)	120	0.00027	(0.11)	0.00447	(0.02)	0.8472
Pareto Investment Fund C	0.01366**	(3.32)	-1.94024	(-0.62)	25	0.01406**	(3.39)	-1.94024	(-0.62)	0.3609
Pareto Investment Fund A	0.00248	(1.43)	-0.10176	(-0.42)	120	0.00396*	(2.29)	-0.10176	(-0.42)	0.9324
Pareto Investment Fund B	0.01331**	(3.25)	-1.9384	(-0.62)	25	0.01407**	(3.39)	-1.93840	(-0.62)	0.3611
Pluss Aksje	-0.00039	(-0.36)	0.49318**	(2.87)	120	0.00060	(0.56)	0.49318**	(2.87)	0.9676
Pluss Markedsverdi	0.00051	(0.64)	0.26316**	(2.64)	120	0.00128	(1.58)	0.25951**	(2.62)	0.9840
Storebrand Aksje Innland	-0.00207	(-1.40)	0.60102	(1.51)	57	-0.00156	(-1.05)	0.60102	(1.51)	0.9478
Storebrand Norge I	-0.00152	(-0.84)	0.20424	(0.45)	57	-0.00128	(-0.71)	0.20424	(0.45)	0.9274
Storebrand Norge	0.00130	(0.99)	-0.55286	(-1.62)	63	0.00259	(1.97)	-0.55286	(-1.62)	0.9338
Storebrand Optima Norge	0.00081	(0.24)	-0.61218	(-0.73)	57	0.00164	(0.50)	-0.61218	(-0.73)	0.7765
Storebrand Vekst	0.00248	(0.55)	0.20558	(0.20)	63	0.00397	(0.88)	0.20558	(0.20)	0.5440
Storebrand Verdi	-0.00073	(-0.44)	-0.27799	(-0.80)	63	0.00090	(0.54)	-0.27799	(-0.80)	0.9189
Swedbank Generator	0.00541	(1.56)	-1.27022	(-1.30)	63	0.00663	(1.90)	-1.27022	(-1.30)	0.8013

Appendix 4: Conditional Treynor-Mazuy

** p < 0.01   * p < 0.05

	Net Returns					Gross Returns					
Fund name	α	t-stat	γ	t-stat	Obs.	α	t-stat	γ	t-stat	R^2 adj.	F-Value
Alfred Berg Aktiv	0.00193	(1.35)	-0.39340*	(-2.23)	120	0.00316	(2.20)	-0.39340*	(-2.23)	0.9558	6.316*
Alfred Berg Gambak	0.00448*	(2.17)	-0.56621**	(-2.90)	120	0.00594*	(2.86)	-0.56621**	(-2.90)	0.9127	1.072
Alfred Berg Humanfond	-0.00094	(-0.84)	0.00691	(0.04)	120	0.00056	(0.50)	0.00691	(0.04)	0.9731	0.000
Alfred Berg Norge (Classic)	0.00221*	(2.35)	-0.11597	(-1.01)	120	0.00320*	(3.39)	-0.11597	(-1.01)	0.9818	0.260
Carnegie Aksje Norge	0.00115	(1.14)	-0.12691	(-0.55)	120	0.00216*	(2.14)	-0.12691	(-0.55)	0.9806	3.780
Danske Invest Inst. I	0.00183	(1.77)	0.20963	(0.81)	120	0.0026*	(2.51)	0.20963	(0.81)	0.9696	0.855
Danske Invest Inst. II	0.00179	(1.74)	0.20047	(0.68)	109	0.0026*	(2.51)	0.20047	(0.72)	0.9707	0.855
Danske Invest Norge I	0.00134	(1.29)	-0.04241	(-0.18)	120	0.00304**	(2.93)	-0.04241	(-0.18)	0.9688	4.202
Danske Invest Norge II	0.00186	(1.79)	-0.00986	(-0.04)	120	0.00292**	(2.81)	-0.00986	(-0.04)	0.9681	4.167
Danske Invest Norge Vekst	-0.00077	(-0.46)	-0.41870	(-1.16)	120	0.00071	(0.42)	-0.41870	(-1.16)	0.9204	6.597*
Delphi Fondene Norge	0.00199	(0.88)	-0.64167	(-1.19)	63	0.00365	(1.60)	-0.64167	(-1.19)	0.8565	0.422
DNB Norge	-0.00234	(-1.35)	0.60821	(1.80)	60	-0.00077	(-0.45)	0.60821	(1.54)	0.9159	0.000
DNB Norge III	-0.00169	(-0.98)	0.61084	(1.54)	60	-0.00074	(-0.43)	0.61084	(1.54)	0.9156	0.083
DNB Norge IV	-0.00148	(-0.85)	0.61105	(1.54)	60	-0.00082	(-0.48)	0.61105	(1.54)	0.9156	0.000
DNB Norge Selektiv I	-0.00430*	(-2.18)	1.61297*	(2.22)	60	-0.00248	(-1.27)	1.61297*	(2.22)	0.8866	0.000
DNB Norge Selektiv II	-0.00346	(-1.76)	1.62145*	(2.23)	60	-0.00255	(-1.30)	1.62145*	(2.23)	0.8856	0.000
DNB Norge Selektiv III	-0.00329	(-1.67)	1.62072*	(2.23)	60	-0.00257	(-1.31)	1.62072*	(2.23)	0.8859	0.000
DNB SMB	-0.00793	(-1.81)	0.72063	(0.62)	60	-0.00639	(-1.46)	0.72063	(0.62)	0.6448	2.691
Eika Norge	0.00091	(0.56)	-0.46994	(-1.58)	120	0.00259	(1.59)	-0.46994	(-1.58)	0.9296	6.529*
Fondsfinans Norge	0.00145	(0.88)	-0.07199	(-0.28)	120	0.00228	(1.38)	-0.07199	(-0.28)	0.9318	5.861*
Forte Norge	-0.00600*	(-2.11)	1.73991	(1.82)	56	-0.00423	(-1.47)	1.73991	(1.82)	0.7750	1.995
Forte Tronder	0.00236	(0.58)	2.58130	(0.85)	36	0.00325	(0.79)	2.58130	(0.85)	0.5170	3.155
Handelsbanken Norge	0.00407*	(2.59)	-0.46804**	(-2.63)	120	0.00569**	(3.62)	-0.46804**	(-2.63)	0.9544	1.826
Holberg Norge	-0.00278	(-1.60)	-0.55837	(-1.61)	120	-0.00161	(-0.93)	-0.55837	(-1.61)	0.9051	22.408*
KLP Aksje Norge	0.00015	(0.10)	-0.34909	(-0.72)	120	0.00075	(0.52)	-0.34909	(-0.72)	0.9605	18.788*
Landkreditt Norge	-0.00293	(-1.45)	0.58420	(1.95)	114	-0.00144	(-0.72)	0.58420	(1.95)	0.9075	0.000
Landkreditt Utbytte	0.00937*	(2.17)	-6.21433	(-2.00)	33	0.01085*	(2.63)	-6.21433	(-2.00)	0.4876	0.238
Nordea Avkastning	-0.00051	(-0.70)	0.09753	(0.79)	120	0.00076	(1.04)	0.09753	(0.79)	0.9889	0.638
Nordea Kapital	0.00026	(0.35)	0.12935	(1.04)	120	0.00110	(1.51)	0.12935	(1.04)	0.9883	0.417
Nordea Norge Pluss	-0.00105	(-0.72)	0.31406	(0.52)	56	-0.00018	(-0.12)	0.31406	(0.52)	0.9329	2.037
Nordea Norge Verdi	0.00126	(0.68)	0.01139	(0.03)	120	0.00244	(1.33)	0.01139	(0.03)	0.9008	0.000
Odin Norge C	-0.00088	(-0.38)	-0.89105*	(-2.09)	107	0.00071	(0.31)	-0.89105*	(-2.09)	0.8577	12.688*
Pareto Aksje Norge A	0.00029	(0.14)	-0.81281*	(-2.03)	120	0.00221	(1.05)	-0.81281*	(-2.03)	0.8596	9.707*
Pareto Aksje Norge B	-0.00022	(-0.10)	-0.74569	(-1.93)	119	0.00135	(0.60)	-0.74569	(-1.94)	0.8552	8.595*
Pareto Aksje Norge I	0.00110	(0.49)	-0.78229*	(-1.99)	120	0.00149	(0.66)	-0.78229*	(-1.99)	0.8428	9.015*
Pareto Investment Fund C	0.01347**	(3.34)	-1.95461	(-0.65)	25	0.01387**	(3.41)	-1.95461	(-0.65)	0.3309	0.114
Pareto Investment Fund A	0.00332*	(1.99)	-0.63058*	(-2.87)	120	0.00481**	(2.89)	-0.63058*	(-2.87)	0.9355	6.738*
Pareto Investment Fund B	0.01312**	(3.28)	-1.95289	(-0.65)	25	0.01388**	(3.41)	-1.95289	(-0.65)	0.3312	0.114
Pluss Aksje	-0.00033	(-0.27)	0.45368	(1.47)	120	0.00067	(0.54)	0.45368	(1.47)	0.9673	0.000
Pluss Markedsverdi	0.00046	(0.53)	0.30201	(1.59)	120	0.00121	(1.41)	0.30201	(1.59)	0.9839	0.161
Storebrand Aksje Innland	-0.00208	(-1.41)	0.60509	(1.50)	57	-0.00156	(-1.06)	0.60509	(1.50)	0.9468	0.000
Storebrand Norge I	-0.00151	(-0.85)	0.14873	(0.33)	57	-0.00127	(-0.71)	0.14873	(0.33)	0.9262	0.192
Storebrand Norge	0.00126	(0.96)	-0.55786	(-1.62)	63	0.00255	(1.94)	-0.55786	(-1.62)	0.9328	0.189
Storebrand Optima Norge	0.00084	(0.26)	-0.77675	(-0.91)	57	0.00167	(0.51)	-0.77675	(-0.91)	0.7740	0.524
Storebrand Vekst	0.00212	(0.47)	0.14149	(0.15)	63	0.00359	(0.79)	0.14149	(0.15)	0.8838	1.311
Storebrand Verdi	-0.00060	(-0.36)	-0.26593	(-0.86)	63	0.00104	(0.63)	-0.26593	(-0.86)	0.9193	1.391
Swedbank Generator	0.00507	(1.47)	-1.33334	(-1.44)	63	0.00628	(1.80)	-1.33334	(-1.44)	0.8084	3.680

Appendix 5: Unconditional Net Jensen's Alpha, 5-year horizon

**** p < 0.01** *** p < 0.05**

Fund name	Net Returns α	Net Returns t-stat	β	Obs.	Gross Returns α	Gross Returns t-stat	R^2 adj.
Alfred Berg Aktiv	0.00125	(0.76)	0.95243	60	0.00247	(1.51)	0.8977
Alfred Berg Gambak	0.00311	(1.56)	0.83002	60	**0.00458***	**(2.33)**	0.8041
Alfred Berg Humanfond	0.00027	(0.21)	0.91418	60	0.00183	(1.46)	0.9300
Alfred Berg Norge (Classic)	0.00171	(1.68)	0.92432	60	**0.00271***	**(2.66)**	0.9545
Carnegie Aksje Norge	0.00084	(0.74)	0.97784	60	0.00185	(1.65)	0.9481
Danske Invest Inst. I	0.00098	(1.07)	0.98460	60	0.00175	(1.91)	0.9671
Danske Invest Inst. II	0.00090	(1.02)	0.97989	60	0.00174	(1.90)	0.9668
Danske Invest Norge I	0.00003	(0.03)	0.99767	60	0.00173	(1.83)	0.9660
Danske Invest Norge II	0.00066	(0.69)	0.99378	60	0.00172	(1.82)	0.9659
Danske Invest Norge Vekst	-0.00080	(-0.33)	0.94483	60	0.00081	(0.33)	0.8221
Delphi Fondene Norge	0.00057	(0.28)	0.93250	60	0.00227	(1.14)	0.8426
DNB Norge	-0.00127	(-0.90)	0.94264	60	0.00030	(0.22)	0.9170
DNB Norge III	-0.00061	(-0.44)	0.94212	60	0.00034	(0.25)	0.9166
DNB Norge IV	-0.00040	(-0.28)	0.94454	60	0.00026	(0.18)	0.9167
DNB Norge Selektiv I	-0.00149	(-0.83)	0.96648	60	0.00032	(0.18)	0.8788
DNB Norge Selektiv II	-0.00064	(-0.36)	0.96512	60	0.00027	(0.15)	0.8777
DNB Norge Selektiv III	-0.00048	(-0.26)	0.96839	60	0.00024	(0.14)	0.8780
DNB SMB	-0.00598	(-1.50)	1.07935	60	-0.00435	(-1.09)	0.6383
Eika Norge	-0.00292	(-1.38)	0.99260	60	-0.00120	(-0.58)	0.8561
Fondsfinans Norge	-0.00087	(-0.38)	0.95727	60	0.00000	(0.00)	0.8058
Handelsbanken Norge	0.00307	(1.39)	0.96061	60	**0.00461***	**(2.09)**	0.8376
Holberg Norge	**-0.00536***	**(-2.17)**	0.85000	60	-0.00417	(-1.72)	0.7584
KLP Aksje Norge	-0.00136	(-1.30)	0.97397	60	-0.00074	(-0.71)	0.9533
Landkreditt Norge	**-0.00530***	**(-2.14)**	0.93059	60	-0.00390	(-1.59)	0.7839
Nordea Avkastning	-0.00052	(-0.59)	1.00746	60	0.00077	(0.86)	0.9714
Nordea Kapital	0.00037	(0.41)	0.99854	60	0.00123	(1.38)	0.9700
Nordea Norge Verdi	0.00227	(1.26)	0.84150	60	**0.00360***	**(2.00)**	0.8370
Odin Norge C	-0.00391	(-1.89)	0.90447	60	-0.00236	(-1.17)	0.8474
Pareto Aksje Norge A	**-0.00514***	**(-2.02)**	0.81972	60	-0.00309	(-1.25)	0.7333
Pareto Aksje Norge B	**-0.00562***	**(-2.08)**	0.84510	60	-0.00396	(-1.50)	0.7223
Pareto Aksje Norge I	-0.00438	(-1.65)	0.84428	60	-0.00397	(-1.50)	0.7212
Pareto Investment Fund A	**0.00490***	**(2.08)**	0.88353	60	**0.00641****	**(2.69)**	0.7890
Pluss Aksje	0.00086	(0.78)	0.88639	60	0.00188	(1.72)	0.9415
Pluss Markedsverdi	0.00024	(0.28)	0.93642	60	0.00010	(1.19)	0.9687
Storebrand Norge	0.00011	(0.08)	0.94747	60	0.00141	(1.08)	0.9231
Storebrand Vekst	0.00236	(0.61)	0.83791	60	0.00389	(1.00)	0.5322
Storebrand Verdi	-0.00117	(-0.85)	0.88653	60	0.00043	(0.31)	0.9094
Swedbank Generator	0.00333	(1.09)	1.13237	60	0.00457	(1.49)	0.7952

Appendix 6: Conditional Net Jensen's Alpha, 5-year Horizon

**** $p < 0.01$** *** $p < 0.05$**

	Net Returns				Gross Returns			
Fund name	α	t-stat	β	Obs.	α	t-stat	R^2 adj.	F-Value
Alfred Berg Aktiv	0.00108	(0.64)	0.96166	60	0.00230	(1.37)	0.8967	0,5063
Alfred Berg Gambak	0.00273	(1.35)	0.84648	60	**0.00416***	**(2.09)**	0.8041	1,1858
Alfred Berg Humanfond	0.00032	(0.25)	0.91049	60	0.00189	(1.48)	0.9289	0,2105
Alfred Berg Norge (Classic)	0.00155	(1.50)	0.93433	60	**0.00254***	**(2.46)**	0.9547	1,3115
Carnegie Aksje Norge	0.00086	(0.77)	0.97638	60	0.00188	(1.68)	0.9471	0,1250
Danske Invest Inst. I	0.00071	(0.78)	1.00329	60	0.00146	(1.62)	0.9695	5,6522
Danske Invest Inst. II	0.00059	(0.73)	1.00015	60	0.00137	(1.58)	0.9620	5,6522
Danske Invest Norge I	-0.00030	(-0.33)	1.02094	60	0.00138	(1.53)	0.9697	**8,5106**
Danske Invest Norge II	0.00032	(0.36)	1.01685	60	0.00137	(1.52)	0.9696	**8,2979**
Danske Invest Norge Vekst	-0.00143	(-0.65)	0.99088	60	0.00013	(0.06)	0.8341	5,1852
Delphi Fondene Norge	0.00034	(0.16)	0.94686	60	0.00202	(0.99)	0.8415	0,8230
DNB Norge	-0.00135	(-0.95)	0.94915	60	0.00021	(0.15)	0.9158	0,1626
DNB Norge III	-0.00070	(-0.49)	0.94866	60	0.00025	(0.18)	0.9154	0,2439
DNB Norge IV	-0.00049	(-0.34)	0.95109	60	0.00016	(0.12)	0.9154	0,2419
DNB Norge Selektiv I	-0.00170	(-0.93)	0.98275	60	0.00009	(0.05)	0.8782	0,5102
DNB Norge Selektiv II	-0.00086	(-0.47)	0.98150	60	0.00004	(0.02)	0.8772	0,5051
DNB Norge Selektiv III	-0.00070	(-0.39)	0.98484	60	0.00001	(0.01)	0.8775	1,0101
DNB SMB	-0.00675	(-1.79)	1.13420	60	-0.00521	(-1.39)	0.6500	3,1083
Eika Norge	-0.00322	(-1.53)	1.01484	60	-0.00154	(-0.74)	0.8575	1,6461
Fondsfinans Norge	-0.00165	(-0.79)	1.01092	60	-0.00082	(-0.39)	0.8238	**7,0707**
Handelsbanken Norge	0.00276	(1.21)	0.97666	60	0.00427	(1.87)	0.8365	0,7273
Holberg Norge	**-0.00557***	**(-2.31)**	0.86985	60	-0.00440	(-1.84)	0.7575	0,8621
KLP Aksje Norge	-0.00140	(-1.38)	0.97716	60	-0.00078	(-0.77)	0.9526	0,1408
Landkreditt Norge	**-0.00557***	**(-2.25)**	0.94635	60	-0.00409	(-1.70)	0.7818	0,5540
Nordea Avkastning	-0.00072	(-0.84)	1.02125	60	0.00056	(0.65)	0.9723	3,2558
Nordea Kapital	0.00015	(0.17)	1.01309	60	0.00101	(1.17)	0.9711	3,6364
Nordea Norge Verdi	0.00198	(1.17)	0.85903	60	0.00329	(1.96)	0.8370	0,9756
Odin Norge C	**-0.00423***	**(-2.08)**	0.92980	60	-0.00273	(-1.36)	0.8504	0,2262
Pareto Aksje Norge A	**-0.00555***	**(-2.26)**	0.86082	60	-0.00360	(-1.50)	0.7431	3,4188
Pareto Aksje Norge B	**-0.00598***	**(-2.28)**	0.88195	60	-0.00437	(-1.69)	0.7284	2,5063
Pareto Aksje Norge I	-0.00480	(-1.85)	0.88180	60	-0.00440	(-1.70)	0.7276	2,7500
Pareto Investment Fund A	0.00428	(1.83)	0.91568	60	**0.00575***	**(2.43)**	0.7944	2,6403
Pluss Aksje	0.00066	(0.60)	0.90033	60	0.00167	(1.51)	0.9423	1,9444
Pluss Markedsverdi	0.00005	(0.06)	0.94989	60	0.00080	(0.96)	0.9697	3,1707
Storebrand Norge	0.00003	(0.02)	0.95287	60	0.00133	(1.01)	0.9220	0,1770
Storebrand Vekst	0.00168	(0.44)	0.87982	60	0.00317	(0.83)	0.5347	1,4085
Storebrand Verdi	-0.00101	(-0.72)	0.87454	60	0.00062	(0.44)	0.9091	0,8475
Swedbank Generator	0.00286	(0.92)	1.16586	60	0.00408	(1.32)	0.7975	1,6393

Appendix 7: Unconditional Jensen's alpha – Financial crisis of 2007 – 2009

**** p < 0.01** *** p < 0.05**

Fund name	Net Returns α	Net Returns t-stat	β	Obs.	R^2 adj.
Alfred Berg Aktiv	-0.00131	(-0.47)	0.92677	22	0.9850
Alfred Berg Gambak	-0.00270	(-0.72)	0.93092	22	0.9735
Alfred Berg Humanfond	-0.00093	(-0.33)	0.93106	22	0.9877
Alfred Berg Norge (Classic)	0.00192	(1.03)	0.95441	22	0.9942
Carnegie Aksje Norge	0.00114	(0.55)	0.93707	22	0.9881
Danske Invest Inst. I	0.00547	(1.35)	0.89313	22	0.9747
Danske Invest Inst. II	0.00532	(1.31)	0.89168	22	0.9732
Danske Invest Norge I	0.00428	(0.99)	0.87673	22	0.9717
Danske Invest Norge II	0.00503	(1.16)	0.86502	22	0.9704
Danske Invest Norge Vekst	-0.00445	(-0.91)	0.80873	22	0.9562
Eika Norge	0.00149	(0.29)	0.89527	22	0.9632
Fondsfinans Norge	**0.00976****	**(3.14)**	0.86652	22	0.9726
Handelsbanken Norge	0.00419	(1.63)	1.01595	22	0.9911
Holberg Norge	0.00302	(0.57)	0.70385	22	0.9303
KLP Aksje Norge	0.00421	(1.04)	0.90015	22	0.9455
Landkreditt Norge	0.00485	(0.90)	0.82380	22	0.9533
Nordea Avkastning	0.00080	(0.43)	0.94303	22	0.9938
Nordea Kapital	0.00171	(0.89)	0.93302	22	0.9931
Nordea Norge Verdi	-0.00448	(-0.83)	0.74327	22	0.9356
Odin Norge C	-0.00899	(-1.33)	0.67954	22	0.8889
Pareto Aksje Norge A	-0.00006	(-0.01)	0.73156	22	0.9001
Pareto Aksje Norge B	-0.00061	(-0.10)	0.74213	22	0.9014
Pareto Aksje Norge I	-0.00004	(-0.01)	0.74588	22	0.8991
Pareto Investment Fund A	0.00549	(1.89)	0.96081	22	0.9802
Pluss Aksje	0.00423	(1.31)	0.79968	22	0.9704
Pluss Markedsverdi	**0.00489***	**(2.06)**	0.89522	22	0.9888

Appendix 8: Net Jensen's Alpha, General Market Downturns

** $p < 0.01$ * $p < 0.05$

Fund name	Net Returns α	Net Returns t-stat	β	Obs.	R^2 adj.
Alfred Berg Aktiv	0.00374	(0.93)	0.93580	35	0.9445
Alfred Berg Gambak	**0.01336***	**(2.44)**	0.99053	35	0.9090
Alfred Berg Humanfond	0.00040	(0.17)	0.94224	35	0.9725
Alfred Berg Norge (Classic)	**0.00554***	**(2.33)**	0.96592	35	0.9801
Carnegie Aksje Norge	0.00125	(0.40)	0.93269	35	0.9739
Danske Invest Norske Aksjer Inst. I	-0.00337	(-1.14)	0.88563	35	0.9633
Danske Invest Norske Aksjer Inst. II	-0.00351	(-1.10)	0.88372	35	0.9602
Danske Invest Norge I	-0.00376	(-1.33)	0.89464	35	0.9662
Danske Invest Norge II	-0.00375	(-1.31)	0.88020	35	0.9640
Danske Invest Norge Vekst	-0.00168	(-0.39)	0.79657	35	0.9226
Eika Norge	-0.00170	(-0.41)	0.91065	35	0.9314
Fondsfinans Norge	-0.00578	(-1.03)	0.82141	35	0.8981
Handelsbanken Norge	**0.01079***	**(2.28)**	1.03683	35	0.9471
Holberg Norge	-0.00643	(-1.06)	0.68901	35	0.8409
KLP Aksje Norge	-0.00543	(-0.75)	0.86226	35	0.9045
Landkreditt Norge	**-0.01272***	**(-2.14)**	0.74070	34	0.8563
Nordea Avkastning	-0.00349	(-1.68)	0.92812	35	0.9826
Nordea Kapital	-0.00283	(-1.32)	0.91585	35	0.9807
Nordea Norge Verdi	0.00022	(0.04)	0.77550	35	0.8875
Odin Norge C	-0.00307	(-0.38)	0.72987	33	0.7797
Pareto Aksje Norge A	0.00764	(1.20)	0.77255	35	0.8589
Pareto Aksje Norge B	0.00610	(0.94)	0.77036	35	0.8496
Pareto Aksje Norge I	0.00733	(1.13)	0.77770	35	0.8510
Pareto Investment Fund A	0.00946	(1.79)	0.99326	35	0.9325
Pluss Aksje	-0.00449	(-1.17)	0.77108	35	0.9349
Pluss Markedsverdi	-0.00208	(-0.94)	0.86732	35	0.9810

Appendix 9: Active Share w/ managers, Tracking Error & Total Expense Ratio

Mutual Fund	Fund Manager	Active Share	Tracking Error	TER
Alfred Berg Aktiv	Eriksrød	47,00%	5,18%	1,50%
Alfred Berg Gambak	Eriksrød	56,35%	7,58%	1,80%
Carnegie Aksje Norge	Christensen & Abrahamsen	42,05%	3,24%	1,20%
Danske Invest Norge I	Søderstrøm & Moen	31,22%	4,58%	2,00%
Danske Invest Norge II	Søderstrøm & Moen	31,46%	4,67%	1,25%
Danske Invest Norge Vekst	Moen	76,70%	10,97%	1,75%
Danske Invest Norske Aksjer Inst. I	Søderstrøm & Moen	30,95%	4,43%	0,90%
Danske Invest Norske Aksjer Inst. II	Søderstrøm & Moen	31,61%	4,49%	0,90%
Delphi Norge	Sætre	56,05%	6,58%	2,00%
DNB Norge	Vogt & Hammer	30,61%	3,76%	1,80%
DNB Norge III	Vogt & Hammer	30,61%	3,74%	1,09%
DNB Norge IV	Vogt & Hammer	30,62%	3,72%	0,75%
DNB Norge Selektiv	Vogt & Hammer	41,02%	4,76%	2,01%
DNB Norge Selektiv II	Vogt & Hammer	41,52%	4,81%	1,01%
DNB Norge Selektiv III	Vogt & Hammer	41,08%	4,77%	0,80%
DNB SMB	Hammer	91,77%	12,25%	2,01%
Eika Norge	Gjellestad	36,87%	5,73%	2,00%
Fondsfinans Norge	Hellem & Simensen	59,20%	6,70%	1,00%
Forte Norge	Kilnes	65,66%	7,48%	2,00%
Forte Trønder	Kilnes	84,14%	7,53%	2,00%
Handelsbanken Norge	Dahl	41,24%	5,68%	2,00%
Holberg Norge	Tyssøy & Molnes	70,36%	8,42%	1,50%
KLP AksjeNorge	Henriksen & Hallberg	28,69%	4,82%	0,75%
Landkreditt Norge	Hopsdal & Klev	52,70%	7,66%	1,75%
Landkreditt Utbytte	Hopsdal & Klev	76,67%	6,88%	1,50%
Nordea Avkastning	Vossgård	45,62%	2,63%	1,50%
Nordea Kapital	Vossgård	39,29%	2,73%	1,00%
Nordea Norge Pluss	Hille-Walle & Vossgård	61,45%	3,85%	1,00%
Nordea Norge Verdi	Næss	59,95%	7,99%	1,50%
Odin Norge C	Selmar & Nielsen	43,99%	10,00%	2,00%
Pareto Aksje Norge - Andelsklasse A	Løvoll & Frønningen	67,97%	9,45%	2,50%
Pareto Investment Fund A	Været	70,61%	7,56%	1,80%
Pluss Aksje	-	34,69%	5,00%	1,20%
Pluss Markedsverdi	-	25,42%	3,29%	0,90%
Storebrand Aksje Innland	Gjerde	19,62%	3,50%	0,60%
Storebrand Norge	Opedal	31,71%	15,45%	1,50%
Storebrand Norge I	Nilelsen	25,76%	3,99%	0,28%
Storebrand Optima Norge	Lorentzen	52,53%	5,80%	1,00%
Storebrand Vekst	Lorentzen	78,61%	11,42%	2,00%
Storebrand Verdi	Gjerde	46,91%	5,39%	2,00%

Appendix 10: F-test Information Variabel for Jensen's Alpha

*** F-Value > Critical Value**

Fund	$SSE_{Conditional}$	$SSE_{Unconditional}$	Extra Terms	$MSE_{Conditional}$	F-Value	Obs	Critical Value
Alfred Berg Aktiv	0,0233	0,0238	1	0,000196	2,551020408	120	5,6581
Alfred Berg Gambak	0,0459	0,0463	1	0,000386	1,03626943	120	5,6581
Alfred Berg Humanfond	0,0131	0,0131	1	0,00011	0	120	5,6581
Alfred Berg Norge (Classic)	0,00925	0,00926	1	0,000078	0,128205128	120	5,6581
Carnegie Aksje Norge	0,00986	0,0102	1	0,000083	4,096385542	120	5,6581
Danske Invest Inst. I*	0,0141	0,0149	1	0,000119	6,722689076	120	5,6581
Danske Invest Inst. II*	0,0141	0,0149	1	0,000119	6,722689076	109	5,6581
Danske Invest Norge I*	0,0142	0,0154	1	0,00012	10	120	5,6581
Danske Invest Norge II*	0,0143	0,0158	1	0,00012	12,5	120	5,6581
Danske Invest Norge Vekst	0,0351	0,0363	1	0,000295	4,06779661	120	5,6581
Delphi Fondene Norge	0,0149	0,0151	1	0,00024	0,833333333	63	5,6877
DNB Norge	0,00726	0,00728	1	0,000123	0,162601626	60	5,6877
DNB Norge III	0,00728	0,00731	1	0,000123	0,243902439	60	5,6877
DNB Norge IV	0,00732	0,00735	1	0,000124	0,241935484	60	5,6877
DNB Norge Selektiv I	0,0116	0,0117	1	0,000196	0,510204082	60	5,6877
DNB Norge Selektiv II	0,0117	0,0118	1	0,000198	0,505050505	60	5,6877
DNB Norge Selektiv III	0,0117	0,0119	1	0,000198	1,01010101	60	5,6877
DNB SMB	0,055	0,0579	1	0,000933	3,108252947	60	5,6877
Eika Norge	0,0356	0,0365	1	0,000299	3,010033445	120	5,6581
Fondsfinans Norge*	0,0326	0,0366	1	0,000274	14,59854015	120	5,6581
Forte Norge	0,0232	0,0247	1	0,000422	3,55450237	57	5,6877
Forte Tronder	0,0114	0,0122	1	0,000326	2,45398773	36	5,7170
Handelsbanken Norge	0,027	0,0271	1	0,000227	0,440528634	120	5,6581
Holberg Norge*	0,037	0,0448	1	0,000311	25,08038585	120	5,6581
KLP Aksje Norge*	0,0203	0,0243	1	0,00017	23,52941176	120	5,6581
Landkreditt Norge*	0,0398	0,0432	1	0,000353	9,631728045	114	5,6581
Landkreditt Utbytte	0,015	0,0155	1	0,00047	1,063829787	35	5,7459
Nordea Avkastning*	0,00562	0,00594	1	0,000047	6,808510638	120	5,6581
Nordea Kapital*	0,00584	0,00623	1	0,000049	7,959183673	120	5,6581
Nordea Norge Pluss	0,006	0,00628	1	0,000109	2,568807339	56	5,6877
Nordea Norge Verdi	0,0352	0,0352	1	0,000295	0	120	5,6581
Odin Norge C	0,0529	0,0552	1	0,000499	4,609218437	107	5,6581
Pareto Aksje Norge A	0,0558	0,057	1	0,000469	2,558635394	120	5,6581
Pareto Aksje Norge B	0,0589	0,0604	1	0,000499	3,006012024	119	5,6581
Pareto Aksje Norge I	0,0596	0,061	1	0,000501	2,794411178	120	5,6581
Pareto Investment Fund C	0,00432	0,00434	1	0,00018	0,111111111	25	5,8025
Pareto Investment Fund A	0,0354	0,0357	1	0,000298	1,006711409	120	5,6581
Pareto Investment Fund B	0,00432	0,00435	1	0,00018	0,166666667	25	5,8025
Pluss Aksje*	0,0138	0,0163	1	0,000116	21,55172414	120	5,6581
Pluss Markedsverdi*	0,00784	0,00836	1	0,000066	7,878787879	120	5,6581
Storebrand Aksje Innland	0,00426	0,00426	1	0,000076	0	57	5,6877
Storebrand Norge I	0,00582	0,00585	1	0,000104	0,288461538	57	5,6877
Storebrand Norge	0,00674	0,00675	1	0,000109	0,091743119	63	5,6877
Storebrand Optima Norge	0,0216	0,0217	1	0,000386	0,259067358	57	5,6877
Storebrand Vekst	0,0568	0,0581	1	0,000916	1,419213974	63	5,6877
Storebrand Verdi	0,00715	0,00731	1	0,000115	1,391304348	63	5,6877
Swedbank Generator	0,0296	0,0311	1	0,000477	3,144654088	63	5,6877

Proportion of Significant F	25,53%

Appendix 11: F-test Information Variable for Treynor-Mazuy

*** F-Value > Critical Value**

Fund	$SSE_{Conditional}$	$SSE_{Unconditional}$	Extra Terms	$MSE_{Conditional}$	F-Value	Obs	Critical value
Alfred Berg Aktiv*	0,0226	0,0238	1	0,00019	6,3158	120	4,3985
Alfred Berg Gambak	0,0444	0,0448	1	0,000373	1,0724	120	4,3985
Alfred Berg Humanfond	0,0131	0,0131	1	0,00011	0	120	4,3985
Alfred Berg Norge (Classic)	0,00919	0,00921	1	0,000077	0,2597	120	4,3985
Carnegie Aksje Norge	0,00979	0,0101	1	0,000082	3,7805	120	4,3985
Danske Invest Inst. I	0,0139	0,014	1	0,000117	0,8547	120	4,3985
Danske Invest Inst. II	0,0139	0,014	1	0,000117	0,8547	109	4,3985
Danske Invest Norge I	0,0142	0,0147	1	0,000119	4,2017	120	4,3985
Danske Invest Norge II*	0,0143	0,0148	1	0,00012	4,1667	120	4,3985
Danske Invest Norge Vekst	0,0343	0,0362	1	0,000288	6,5972	120	4,3985
Delphi Fondene Norge	0,0147	0,0148	1	0,000237	0,4219	63	4,4314
DNB Norge	0,00712	0,00712	1	0,000121	0	60	4,4314
DNB Norge III	0,00714	0,00715	1	0,000121	0,0826	60	4,4314
DNB Norge IV	0,00718	0,00718	1	0,000122	0	60	4,4314
DNB Norge Selektiv I	0,0106	0,0106	1	0,00018	0	60	4,4314
DNB Norge Selektiv II	0,0107	0,0107	1	0,000181	0	60	4,4314
DNB Norge Selektiv III	0,0107	0,0107	1	0,000182	0	60	4,4314
DNB SMB*	0,0548	0,0573	1	0,000929	2,6911	60	4,4314
Eika Norge*	0,0346	0,0365	1	0,000291	6,5292	120	4,3985
Fondsfinans Norge	0,0325	0,0341	1	0,000273	5,8608	120	4,3985
Forte Norge	0,0221	0,0229	1	0,000401	1,9950	57	4,4314
Forte Tronder	0,0111	0,0121	1	0,000317	3,1546	36	4,4638
Handelsbanken Norge	0,026	0,0264	1	0,000219	1,8265	120	4,3985
Holberg Norge*	0,0355	0,0422	1	0,000299	22,4080	120	4,3985
KLP Aksje Norge*	0,0197	0,0228	1	0,000165	18,7879	120	4,3985
Landkreditt Norge	0,0383	0,0383	1	0,000339	0	114	4,3985
Landkreditt Utbytte	0,0135	0,0136	1	0,000421	0,2375	35	4,4638
Nordea Avkastning	0,00557	0,0056	1	0,000047	0,6383	120	4,3985
Nordea Kapital	0,00576	0,00578	1	0,000048	0,4167	120	4,3985
Nordea Norge Pluss	0,00596	0,00618	1	0,000108	2,0370	56	4,4314
Nordea Norge Verdi	0,0352	0,0352	1	0,000295	0	120	4,3985
Odin Norge C*	0,0493	0,0552	1	0,000465	12,6882	107	4,3985
Pareto Aksje Norge A*	0,0527	0,057	1	0,000443	9,7065	120	4,3985
Pareto Aksje Norge B*	0,0563	0,0604	1	0,000477	8,5954	119	4,3985
Pareto Aksje Norge I*	0,0567	0,061	1	0,000477	9,0147	120	4,3985
Pareto Investment Fund C	0,00422	0,00424	1	0,000176	0,1136	25	4,4957
Pareto Investment Fund A*	0,0336	0,0355	1	0,000282	6,7376	120	4,3985
Pareto Investment Fund B	0,00422	0,00424	1	0,000176	0,1136	25	4,4957
Pluss Aksje	0,0129	0,0129	1	0,000108	0	120	4,3985
Pluss Markedsverdi	0,00742	0,00743	1	0,000062	0,1613	120	4,3985
Storebrand Aksje Innland	0,00412	0,00412	1	0,000074	0	57	4,4314
Storebrand Norge I	0,00581	0,00583	1	0,000104	0,1923	57	4,4314
Storebrand Norge	0,00657	0,00659	1	0,000106	0,1887	63	4,4314
Storebrand Optima Norge	0,0214	0,0216	1	0,000382	0,5236	57	4,4314
Storebrand Vekst	0,0568	0,058	1	0,000915	1,3115	63	4,4314
Storebrand Verdi	0,00711	0,00727	1	0,000115	1,3913	63	4,4314
Swedbank Generator	0,0285	0,0302	1	0,000462	3,6797	63	4,4314

Proportion of Significant F	23,40%