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Master Thesis

Active Share and Performance of Norwegian Equity Funds

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Abstract

We measure the degree of active management in Norwegian equity mutual funds and investigate how it relates to fund performance in the period 2007-2018. Our measures of active management are active share and tracking error. We find that while the mutual funds do outperform their benchmark index, only 42% of the Carhart four-factor alphas are statistically significant, yet still not economically significant. Sorting funds into equal-weighted portfolios based on active share and tracking error, we find a positive correlation between active share and fund performance, whereas tracking error has a zero to negative relationship. Sorting funds into portfolios based on fund size and active share, we find that the level of active share has the largest positive effect on the smallest firms.

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1. Introduction

Investment and asset allocation have gained an increased focus in Norway over the last 15-20 years. The common perception is that actively managed funds do not earn high enough returns to merit their fees (e.g., Sharpe, 1991, and Bogle, 2014). As a result, there has been an increase of money flowing into index funds in the recent years (Turner & Sushko, 2018). In 2016, the share of total assets in Norwegian index funds reached approximately 20%, which is the highest level up to that point (VFF, 2016).

Even though index funds are becoming increasingly popular, most mutual funds at the Oslo Stock Exchange are actively managed. However, only a few of these funds provide higher net returns compared to the benchmark index. There has been little research into what differentiates the performance of actively managed funds in Norway. For an actively managed fund to outperform a comparable index fund, it must take positions that differ from the positions of the index fund. This can be accomplished either through stock selection, factor timing, or both.

A possible explanation for the lower net returns of actively managed funds is that they don't differ enough from their comparable index funds. In other words, their degree of actual active management is low, and in the case of lower net returns - too low to merit their higher fees. In a 2009 study of active management and performance of U.S. equity mutual funds, Cremers and Petajisto introduce a new measure of active management called active share, which they define as "the share of portfolio holdings that differ from the benchmark index holdings" (p. 3329).

We are interested in how active share applies to Norwegian all-equity mutual funds and address the following questions in our thesis:

1. *Do actively managed Norwegian equity funds outperform their benchmark index?*

2. *Is there a correlation between the degree of active share and returns in Norwegian equity funds?*

2. Literature Review

There have been several studies on mutual fund performance in Norway. Among the ones related to our thesis is *Mutual Fund Performance at the Oslo Stock Exchange* by Sørensen (2009), who examines the risk-adjusted performance of all Norwegian equity funds listed on the Oslo Stock Exchange (OSE) between 1982–2008. The research by Sørensen (2009) shows no evidence of active managers creating economic value compared to passive benchmarks. Sørensen states that "if the average mutual fund manager does possess superior skills compared to other investor groups on the OSE, it is charged as fees and not reflected in net returns" (Sørensen, 2009, p. 23).

A study called *Distinguishing Between Skill and Luck in the Returns of Norwegian Mutual Funds* (Krafft & Bringedal, 2016) builds on Sørensen's research by expanding the time period of the data set and excluding all passively managed funds. Whereas Sørensen (2009) concludes that there are only weak signs of skill, Krafft and Bringedal (2016) conclude that the top 5% of funds exhibit skills to earn 3.3% or more in annual alpha above the fees they charge, whereas the bottom 5% destroy at least 3.7% per year.

There is one study that is closely related to ours: an application of the study by Cremers and Petajisto (2009) on Norwegian mutual funds; *Active Share i Norsk Fondsforvaltning* by Sørgrav and Næss (2011). This study examines 55 Norwegian mutual funds in the period 2003–2010 to see if active share in combination with other factors can explain differences in results, size, cost and turnover. They find a strong connection between active share and tracking error, and that the funds with the highest active share outperform their benchmark. Furthermore, Sørgrav and Næss find that the difference in the excess return on funds with a high/low active share is not consistent over time. The most active managers beat the less active in times of recovery but lose during recessions. This is in contrast with the research done on the U.S. market by Petajisto (2013) which concludes that the most active managers outperform their benchmark indexes after fees, even during the financial crises of 2008–2009.

All the research mentioned above agrees that closet indexers produce the lowest net returns. Despite this, Petajisto (2013) finds that closet indexing has been increasing in popularity since 2007, and especially during volatile and bear markets. The term 'closet indexers' describes funds that proclaim to be actively managed and charge fees accordingly, while more or less replicating an index. In December 2015, Forbrukerrådet in Norway decided to bring closet indexers to court, and in November 2017, Norway's largest class action lawsuit began between Forbrukerrådet, on behalf of 180,000 fund customers, against DNB. In the Court of Appeal ('Lagmannsretten') Forbrukerrådet employed experts who by the support of active share and tracking error explained how DNB's mutual funds (DNB Norge Avanse II, DNB Norge I and DNB Norge III) were closet indexers and their customers had not received the active management they paid for. In March 2019, Forbrukerrådet won the lawsuit against DNB on behalf of its clients (LB-2018-43087), which for the first time in Norway brought legal consequences to closet indexers.

In conjunction with this trial, Geir Ormseth on behalf of Forbrukerrådet conducted a study called *Velge aktive aksjefond eller indeksfond? – 20 års analyze* (2018). Ormseth's research includes 157 mutual funds in the categories Global, European, Nordic European Countries, and Norway, in the time period 1998–2018. Ormseth (2018) concludes that actively managed funds that invest on the Oslo Stock Exchange have on average outperformed Norwegian index funds by 0.86%, including fees, while the global funds underperformed compared to the index by an average of 0.89% yearly, including fees, in the time period 1998–2018 (Ormseth, 2018).

In April 2019, Forbrukerrådet sent an official complaint of Nordea to the Consumer Authority ('Forbrukertilsynet') for violating the Marketing Act of Norway ('Markedsføringsloven'). Their claim was that the bank is misleading its clients with statements such as "Active fund management provides the highest return over time" which can be found on their webpage (Struksnæs, 2019). The CEO of Forbrukerrådet, Inger Blyverket states that the claim is undocumented for most fund categories, including global funds where the consumers have the most money outstanding. All previously mentioned studies will at best moderately support

Nordea's claims for their funds that invest only at Oslo Stock Exchange. The claim is overoptimistic at best, and fraudulent at worst. With the new focused interest driven by Forbrukerrådet on actively managed funds in Norway, we believe our research questions are of timely significance and thus we extend the sample period of previous research to 2018 to provide updated results.

3. Theory and Background Information

3.1. Mutual Funds

A mutual fund is a financial vehicle open for small or individual investors. Investors allocate their money to the fund, while a professional manager allocates the fund's assets to securities such as stocks, bonds, money market instruments, and other assets. Mutual funds can be divided into different categories dependent on what kind of securities they invest in, such as equity funds, fixed-income funds, and index funds. The manager of the fund attempts to produce capital gains for the fund's investors, and each shareholder participates proportionally in the gains or losses of the fund (Segal, 2019). In Norway, responsible management of mutual funds is ensured by the Law of Mutual Funds ('Lov om verdipapirfond') and funds' activities are subject to supervision by 'Kredittilsynet'.

3.1.1 Actively Managed Funds

An actively managed fund is a fund that strives to yield a higher return than its benchmark index. The management team in such a fund must actively analyze companies and market conditions to take positions. Because of this effort, actively managed funds have fees that are on average six times higher than for index funds (Ormseth, 2018).

3.1.2 Passively Managed Funds (Index Funds)

A passively managed fund is a fund that attempts to replicate the stock exchange's return by having the equity composition as close as possible to the fund's benchmark index (Ormseth, 2018). As this strategy requires little effort, such funds have low management fees.

3.1.3 Factor Funds

A factor fund is in many ways a combination of an active fund and an index fund. Management is automated, but instead of being based on a benchmark index, it is based on established criteria. These criteria are specific attributes associated with higher returns, such as momentum, volatility, size, and price. Due to its automated nature, the fees for factor funds are typically closer to index funds than active funds.

3.1.4 Mutual Funds in Norway

In May 2019, the Oslo Stock Exchange held 87 Norwegian funds, of which 6 were index funds. As of April 2019, total assets under management for Norwegian fund management companies were 1,235 billion NOK. The Norwegian equity mutual funds at this time served 1,314,987 customers and had assets under management totaling 625,199,754 NOK (VFF, 2019).

Figure 1: Assets Under Management
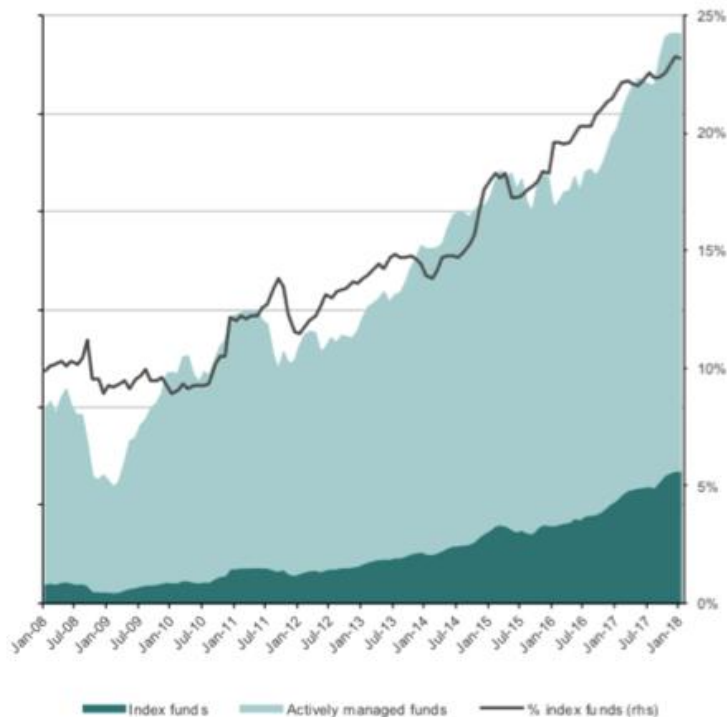
Source: Sundal, M. (2018). Nordic Fund Flows, January 2018 Update. DNB Markets.

The figure above of *Assets Under Management* reflects the large share of assets invested in actively managed funds. There has been an increase of assets into index funds over the past 10 years. However, this is not due to a transfer of funds from

actively managed funds, but rather due to increased investing. Actively managed funds make up most of the assets under management, which gives a valid reason to analyze these funds. Furthermore, analyzing funds is also important to determine relevant methods for choosing the right funds to invest in.

3.2 Bull and Bear Market

A bull market describes a market in which share prices are rising and are expected to continue to rise. A bull market is associated with optimism and investor confidence in a strong or strengthening economy. The opposite of a bull market is a bear market, where share prices are falling and expected to continue to fall. A bear market is associated with pessimism and recession.

3.2.1 Current Situation of the Norwegian Stock Market

We are currently in what many call the longest bull-market in history. Since March 9, 2009, until March 8, 2019, the OSEBX (Oslo Børs Benchmark Index) has increased by 313.5% from 208.87 to 863.6. Similar development applies for big indexes around the world.

Figure 2: OSEBX development since inception up until June 11, 2019

Source: Oslo Stock Exchange, June 11, 2019.

3.3 Survivorship Bias

Survivorship bias describes an overestimation in average returns of a fund sample, caused by excluding past returns of funds that left the sample due to underperformance (Bodie, Kane & Marcus, 2014). The reason why many studies

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neglect fund attrition is that the most commonly used databases do not include data for the unsuccessful funds (Elton, Gruber & Blake, 1996) because better-performing funds tend to stay in business and therefore remain in the sample (Bodie, Kane & Marcus, 2014). In most cases, the funds that underperform are not dissolved, but rather merged into another fund within the same company. That way, the company that owns the fund can keep earning fees on the investor's capital, while being able to erase the bad track record of the underperforming fund (Elton, Gruber & Blake, 1996). Funds that merge will typically keep the track record of the previous successful fund, while erasing the track record of the unsuccessful fund that is absorbed into the successful one. This will lead to an overestimation of performance of the remaining fund. As a result, samples that do not correct for attrition (either through dissolving or merging) are subject to survivorship bias and will overestimate the returns the funds earn for their investors.

3.4 The Efficient Market Hypothesis

The efficient market hypothesis (EMH) states that financial markets process information about securities efficiently and thus security prices fully reflect all available information (Fama, 1970). This implies that securities trade at their fair value, making it impossible for an investor to earn abnormal returns by buying undervalued securities or selling overvalued securities. There are three versions of the EMH: the weak, semi-strong, and strong form, which differ in the amount of information incorporated into security prices (Fama, 1970).

According to the weak-form hypothesis, prices reflect all past publicly available information, such as the history of past prices and trading volume, and hence investors cannot outperform the market by searching for patterns to predict future prices. The semi-strong-form hypothesis states that prices not only reflect past information but also adjust immediately to new public information, such as earnings forecasts and patents filed. In addition to all public information, the strong-form hypothesis states that prices also incorporate information available only to company insiders, i.e., prices contain all relevant information. This version is the most extreme and, if true, would mean investors could never outperform the market.

An implication of efficient markets concerns the choice between active and passive investment strategies. Proponents of the efficient market hypothesis advocate investing in low-cost passive funds that only aim to match the market because they believe no amount of analysis can give an investor a competitive edge. However, Grossman and Stiglitz (1980) argue that the market cannot be perfectly efficient because investors would have no incentives to spend time and resources to uncover information if their effort is unlikely to generate higher returns. Furthermore, the degree of efficiency could vary across markets as some markets may be less intensively analyzed than others (Bodie, Kane & Marcus, 2014, p. 352). Therefore, belief in market inefficiencies calls for investing in actively managed funds.

3.5 Measures of Active Management

The degree of active management is measured as the amount by which a portfolio deviates from its passive benchmark. There are two general ways a portfolio can deviate: through stock selection or factor timing (Fama, 1972). Stock selection involves overweighting and underweighting individual stocks relative to a benchmark portfolio, depending on the fund manager's expectation of how a stock will perform. In contrast, factor timing involves predicting general market price movements and varying a fund's exposures to systematic risk factors.

Tracking error is the most common measure of active management. However, Cremers and Petajisto (2009) argue that tracking error is inadequate on its own because the different styles of active management contribute to the measure differently. They introduce active share as a means to measure active management and predict fund performance. There exists much literature on how to measure the performance of equity mutual funds, and academia has introduced a large variety of possible measures, models and procedures. However, the use of active share to predict fund performance is relatively new.

Cremers and Petajisto (2009) suggest using active share and tracking error together to differentiate between stock selection and factor timing. While tracking error measures the volatility of portfolio return around the benchmark index, and thus can been seen as a reasonable proxy for factor bets, it lacks the ability to capture two different dimensions of active management: stock selection and factor timing.

As illustrated in Figure 3, active share adds the dimension of stock selection by measuring the deviation of portfolio holdings from holdings of the benchmark index, placing equal weight on all active bets regardless of diversification (Cremers & Petajisto, 2009).

Figure 3: Different types of active and passive management
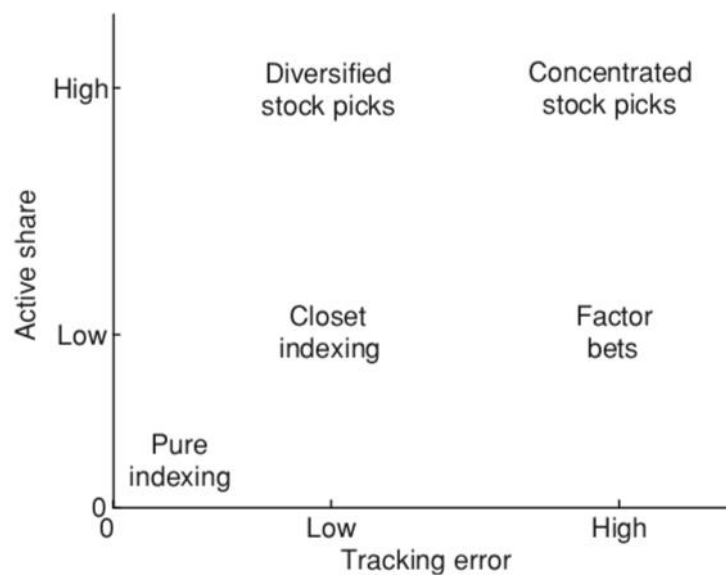
"Active Share represents the fraction of portfolio holdings that differ from the benchmark index, thus emphasizing stock selection. Tracking error is the volatility of fund return in excess of the benchmark, so it emphasizes bets on systematic risk." (Cremers & Petajisto, 2009, p. 3331)

In *How Active Is Your Fund Manager?* Cremers and Petajisto (2009) compute active share for U.S. equity mutual funds from 1980 to 2003. They find that active share does indeed predict fund performance; funds with the highest active share significantly outperform their benchmarks and exhibit strong performance persistence, while non-index funds with the lowest active share underperform their benchmarks.

Petajisto (2013) extends his and Cremers' original research from 2009 in a new study called *Active Share and Mutual Fund Performance*, where he uses a sample of 2740 funds between 1980–2009. This study adds six more years to the sample, extending it from 2003 to 2009. Petajisto makes some minor changes from the

original research in addition to the time extension. Among them, he uses the benchmark index self-reported by a manager in the fund prospectus whenever possible. If the prospectus benchmark is unavailable, he picks the index that produces the lowest average active share over the previous three years. Second, he uses each index only after its inception date. Third, he computes tracking error as the standard deviation of the benchmark-adjusted return rather than as the residual volatility from a regression of the fund return on its benchmark index. Despite the changes, Petajisto's conclusion is the same as in the original research: the most active stock pickers outperform their benchmark indexes even after fees, whereas closet indexers underperform. These patterns also hold during the 2008–2009 financial crisis.

We apply Cremers' and Petajisto's methodology, including the revisions done by Petajisto in 2013, in measuring the active management of Norwegian equity funds. In the following two sections we define the two measures of active management that we use.

3.5.1 Tracking Error

Tracking error (also called tracking error volatility) is the volatility (*stdev*) of the difference between a fund return (R_{fund}) and its benchmark index return (R_{index}) (Grinold & Kahn, 1999):

$$Tracking\ Error = stdev[R_{fund} - R_{index}]$$

A passive fund manager aims to minimize tracking error. Thus, a high tracking error volatility indicates an actively managed fund.

3.5.2 Active Share

Active share is the percentage of fund holdings that differ from the holdings of the fund's benchmark index (Cremers & Petajisto, 2009). It is calculated by computing the absolute difference in the weights of a stock in the fund and in the benchmark index, taking the sum of the weight differences across all stocks, and dividing the sum by two. The formula is as follows:

$$Active\ Share = \frac{1}{2} \sum_{i=1}^{N} \left| w_{fund,i} - w_{index,i} \right|$$

where $w_{fund,i}$ is the weight of stock i in the fund and $w_{index,i}$ is the weight of stock i in the fund's benchmark index, and N is the total number of stocks in either the fund or the benchmark index.

A fund with an active share of 100% has no holdings in common with its benchmark. On the other hand, a fund with an active share of 0% is identical to its benchmark. If a fund has an active share of 70%, 30% of its holdings are identical to the benchmark holdings (i.e., it has a 30% overlap with the benchmark) and 70% of the holdings are different. Thus, active share can also be calculated as "100% minus the sum of the overlapping weights between the portfolio and its benchmark" (Cremers, 2017, p. 2). We calculate active share using both methods and find no significant difference between the two in terms of computational time.

3.6 Factor Models

A factor is a "variable or a characteristic with which individual asset returns are correlated" (CFA, 2019), and can be for example size, volatility, or market risk. Factor models can be used to construct portfolios that focus on specific factors. In 1992, Fama and French developed a Three-Factor Model, consisting of the factors: size, value, and market risk. In 1997, Carhart expanded this to a Four-Factor Model by including momentum. 13 years after the original model, in 2015, Fama and French added an additional factor, volatility, creating the Fama-French Five-Factor Model. We base our regression on the Carhart four-factor model, as Petajisto does in *Active Share and Mutual Fund Performance* (2013).

3.6.1 Fama-French Three-Factor Model

The Fama-French Three-Factor Model is a tool used for evaluating manager performance and better measure market returns. Through their research, Fama and French find that value stocks tend to outperform growth stocks and small-cap stocks tend to outperform large-cap stocks. As a result, their three-factor model consists of the factors: size, value, and market risk. Market risk is measured as the portfolio's

excess return over the risk-free rate of return. The size factor (SMB) is measured going long in small-cap stocks and short large-cap stocks. A positive SMB indicates that the small-cap stocks have done better than the large-cap stocks. The value factor (HML) goes long high book-to-market ratio stocks and short low book-to-market ratio stocks. A positive HML indicates that the stocks with high book-to-market ratio has done better in the period than the stocks with low book-to-market ratio.

The Fama-French Three-Factor Model:

$$R_{i,t} = \alpha_{i,t} + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t$$

The regression model adjusts for the outperforming tendency of small-cap and value stocks. According to the research of Fama and French (1995), the three-factor model has the ability to explain most of the return in a diversified portfolio.

3.6.2 Carhart Four-Factor Model

During his research on mutual funds, Carhart (1997) finds that adding momentum as a fourth factor (PR1YR) gives a more accurate measurement of portfolio returns. The momentum factor is based on 'winners' remaining 'winners' and 'losers' remaining 'losers', where who are winners and losers are based on 1-12 months past returns (Bodie, Kane & Marcus, 2014). The approach is to go long on the best performers and short on the underperformers. A positive momentum factor confirms that in the specific time period, the firms who perform well will continue to perform well, while underperformers will continue to underperform.

The Carhart Four-Factor Model:

$$R_{i,t} = \alpha_{i,t} + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \varepsilon_t$$

4. Research Methodology

The basis of our research is to measure the active management of Norwegian equity mutual funds and determine whether higher degree of active management lead to better performance. To do so, we implement the methodology of Cremers and Petajisto (2009). We compute active share and tracking error to measure the two

styles of active management, where active share serves as a proxy for stock selection and tracking error serves as a proxy for factor timing. We then test how this relates to fund size and fees. Finally, we use regression analysis to examine how active management relates to fund performance.

4.1 Data

To compute active share, we need data on the holdings of mutual funds and their benchmark indexes. We collect quarterly fund holdings from Bloomberg, where the report date is the last calendar day of the month. Index holdings (constituents) are also from Bloomberg, where the report date is the last business day of the month. This means the report date of fund holdings doesn't always match the date of the index holdings. When this is the case, we use the data from the latest matching date in a quarter. Fund and index holdings that have no matching date in a quarter are dropped from our sample.

To compute tracking error and to examine the performance of active funds, we need the returns of mutual funds and their benchmark indexes. Our data on monthly and daily returns is from Oslo Børs Informasjon (OBI), which is a proprietary database to which BI students have access. The returns reported by OBI are calculated using the net asset value (NAV) of each fund, which is net of trading costs and management fees. Following the methodology of Cremers and Petajisto (2009), we compute tracking error using daily returns from the six months preceding the report date of a fund's holdings. Our analysis of fund performance is conducted using monthly returns.

To test how active management relates to fund characteristics, we use data on fund size and fees from Bloomberg. Our data on fund size consists of the quarterly-reported total market value of each fund. Fund fees are the last reported expense ratios in 2018.

4.1.1 Selection of Mutual Funds

Our data sample consists of active and passive Norwegian mutual funds that invest primarily in Norwegian equities. We obtain a list of 117 funds from Bloomberg by applying the following criteria:

- Country of domicile: Norway
- Fund geographical focus: Norway
- Fund type: Open-end fund
- Fund asset class focus: Equity

This list contains active, inactive, liquidated, delisted, and acquired funds. However, almost all of the defunct funds do not have their holdings reported in Bloomberg nor in Thomson Reuters Eikon. Furthermore, the OBI database is missing returns data for some funds. We exclude funds that are missing data on holdings or returns. Furthermore, in our performance analysis we exclude funds that have 'index' in their name as pure index funds are conceptually different; in contrast to actively managed funds, pure index funds aim to keep their tracking error and active share to a minimum. These restrictions reduce our sample in the performance analysis to 38 funds. To our knowledge, there exists no up-to-date survivorship bias-free database of Norwegian all-equity mutual funds. Therefore, given that our data sample excludes most defunct funds, we cannot rule out survivorship bias.

4.1.2 Selection of Benchmark Indexes

We use the official benchmark index reported by the fund in Bloomberg. Most of the actively managed funds in our sample have the Oslo Børs Mutual Fund Index (OSEFX) as their benchmark, and a few have the Oslo Børs Benchmark Index (OSEBX) or the Oslo Børs Small Cap Index (OSESX). OSEBX comprises the most traded stocks listed on the Oslo Stock Exchange. OSEFX is the capped version of OSEBX and restricts the weight of a security to a maximum of 10% of the total market value of the index. OSESX consists of the 10% lowest capitalized shares on the Oslo Stock Exchange. All indexes are investible and adjusted for dividend payments.

4.1.3 Sample Period

Our sample period is dependent on the history of reported holdings, which means the mutual funds in our sample have different time spans. For our performance analysis, our sample period is 2007–2018.

The funds with the longest history of holdings in our sample are Danske Invest Norge I, Danske Invest Norge II, and Danske Invest Norge Vekst, which have reported holdings from June 2005 to December 2018. However, the funds with the longest history of uninterrupted reported holdings are the funds from Storebrand, which have 49 quarterly reports going back to 2006.

The fund with the lowest number of holdings observations in our sample is Pluss Aksje with 17 quarterly reports. The fund with holdings reported over the shortest time span is Alfred Berg Humanfond, which has reported holdings from June 2010 to December 2014.

The median number of quarterly holdings, 36, is very close to our average number of quarterly holdings, 35.5. The fact that the funds have around the same number of reported holdings makes them more fitting to compare. We also require that a fund has a minimum of 15 observations, as few observations will make the regression model imprecisely estimated.

4.2 Regression model

We assess the relative performance of active Norwegian mutual funds by their estimated monthly alpha and corresponding t-statistic. We start by calculating the excess return of a fund over its benchmark index, i.e., the benchmark-adjusted return:

$$Benchmark\text{-}Adjusted\ Return = R_{fund} - R_{index}$$

We then use the monthly benchmark-adjusted returns as the dependent variable in our regression model. Petajisto (2013) argues that some indexes have statistically significant alphas in factor models, which they should not have. This can be avoided by setting the dependent variable as the excess returns over the benchmark. Another argument for using the benchmark-adjusted return is that it is natural for an investor to compare fund returns to the benchmark index as the benchmark index is stated as a means for comparison by the fund manager (Petajisto, 2013).

By regressing the monthly benchmark-adjusted returns on the four factors of Carhart (1997), we control for exposure to the market ($R_M - R_f$), size (*SMB*), value

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(*HML*), and momentum (*PR1YR*) factors and obtain an estimate of the fund's risk-adjusted performance, i.e., the fund alpha (α):

$$R_{fund,t} - R_{index,t} = \alpha_{fund} + \beta_M\left(R_{M,t} - R_{f,t}\right) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{PR1YR}PR1YR_t + \varepsilon_t$$

The monthly time series on the risk-free rate (R_f) and the SMB, HML, and PR1YR factor returns are constructed by Bernt Arne Ødegaard using Norwegian data, where the risk-free rate is estimated from government securities and NIBOR. In our measurement of the market risk premium, we use OSEFX (Oslo Børs Mutual Fund Index) as a proxy for the market (R_M). Alternatively, we could use OSEAX (Oslo Børs All-Share Index) or OSEBX (Oslo Børs Benchmark Index). OSEAX contains all listed shares on the Oslo Stock Exchange. However, it is improbable that a fund will want to replicate OSEAX, as it consists of small illiquid stocks that would make the index difficult and expensive to replicate (Sørensen, 2009). OSEFX is a capped version of OSEBX, designed to be in accordance with the mutual funds law, where the total allowable weight for a security is 10% of the total market value in index, and securities exceeding 5% must not exceed 40% overall (Oslo Stock Exchange, 2019). We therefore find this to be a more probable proxy for the market in which the mutual funds operate.

We perform diagnostic tests on our regression model to check for violations of OLS assumptions that could lead to wrong inferences. To test the hypothesis that the variance of the error term (ε) is constant, we use White's test for heteroscedasticity. The results from the test indicate that the assumption of homoscedastic error terms is violated. The consequence of having heteroscedastic error terms is that our standard errors could be inappropriate and lead to misleading inferences. We also test the regression residuals for autocorrelation using the Breusch-Godfrey test and find some evidence of autocorrelation in our data. Therefore, to correct for heteroscedasticity and autocorrelation, we use Newey-West's heteroscedasticity and autocorrelation consistent standard errors in all regressions.

To test the hypothesis that there is no relation between the error term and the independent variables, we calculate the correlation between the residuals of the regressions and each of the Carhart four-factors. We find that the correlations are zero and conclude that the OLS estimators are consistent and unbiased.

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We run the Jarque-Bera and Anderson-Darling normality tests on the regression residuals to test the hypothesis that the error terms are normally distributed. The results of both tests indicate that the residuals of almost all of our regressions are not normally distributed. A violation of the normality assumption affects the standard error of OLS estimators and the confidence interval, however, the OLS estimators are still BLUE (best linear unbiased estimators).

5. Results

In this section we analyze our results to see if actively managed Norwegian equity funds outperform their benchmark index, and if there is a correlation between the degree of active share and net benchmark-adjusted returns, which are returns after fees in excess of the returns of the benchmark index. First, we evaluate the active management of Norwegian equity mutual funds in 2018 by looking at the correlation between active share and tracking error, active share and fund size, and active share and fees. We then analyze the relationship between fund performance and active management for individual funds and portfolios of funds during 2007–2018.

5.1 Active Management in 2018

We select our results for active share and tracking error within 2018 and compile the distribution of Norwegian equity mutual funds along the two dimensions of active management. The number of funds in each category are reported in Table 1. Unsurprisingly, we find a positive correlation between active share and tracking error. Comparing our findings to that of Cremers and Petajisto (2009), we see that active share and tracking error for Norwegian mutual funds in 2018 are even more closely correlated than for U.S. mutual funds in 2009. However, the distribution is still quite wide. For example, a fund with an active share of 80-90% can have a tracking error ranging from 6-12%, and a fund with a tracking error of 4-6% can have an active share ranging from 30-80%. Due to the wide distribution, we find it meaningful, as do Cremers and Petajisto (2009), to distinguish between different styles of active management based on active share and tracking error.

Table 1: Distribution of Norwegian equity mutual funds in 2018 along the two dimensions of active management

Active Share (%)	Tracking Error (% per year)						
	0-2	2-4	4-6	6-8	8-10	10-12	All
	Number of mutual funds						
0-10	13						13
10-20	4	1					5
20-30	3	1					4
30-40		39	8				47
40-50		10	12	1			23
50-60			10	7			17
60-70			6	8			14
70-80			2	4	2		8
80-90				4	3	1	8
90-100							
All	20	51	38	24	5	1	139

The sample consists of 39 equity mutual funds. Active share is the percentage of fund holdings that differ from the holdings of the fund's benchmark index. It is computed from quarterly data on fund holdings and index composition. Tracking error is the annualized standard deviation of the difference between a fund return and its benchmark index return. It is computed from daily returns in the six months preceding a fund's holdings report date.

As shown in Table 1, the majority of the funds in our sample have an active share of 30-40% and a tracking error of 2-4%. Similarly, in Figure 4, which shows examples of funds plotted along active share and tracking error on the date of their last reported fund holdings in 2018, many of the funds are clustered between an active share of 30-50% and a tracking error of 2-5%.

As expected, the funds plotted near the origin in Figure 4 are pure index funds, with almost zero active share and tracking error. Above pure index funds, we have enhanced index funds, which aim to enhance the returns of an index without deviating significantly from the index. An example is Storebrand Aksje Innland with an active share of 15% and a tracking error of 1.7%. As we move up in the lower left corner, we reach the territory of funds that Cremers and Petajisto (2009) classify as closet indexers – funds that claim to be actively managed but stay close to the benchmark index and thus score low on both active share and tracking error. There are no explicit cut-off points in active share or tracking error to identify closet indexers. However, Cremers and Petajisto (2009) suggest a cut-off at an active share of 60% because "a fund with an Active Share less than 50% is always a hybrid

between a purely active and purely passive portfolio" (Cremers & Petajisto, 2009, p. 3342). The cluster of funds in Figure 4 suggests that many of the funds in our sample are closet indexers and thus do not justify their fees. For example, Alfred Berg Aktiv has an active share of 43% and a tracking error of 4.1%. It charges a fee of 1.5%, which amounts to 3.5% as a fraction of the fund's active positions. As Petajisto (2013) points out, this is rather expensive relative to what the fund offers because in the long run a closet indexer is unlikely to produce returns in excess of its benchmark net of all expenses.

In contrast, based on the Cremers and Petajisto (2009) classifications in Figure 3, the funds in the upper right corner are concentrated stock pickers, which generate high active share and tracking error by combining stock selection and factor bets. Examples of such funds in our sample are Pareto Investment Fund A and Storebrand Vekst, which have an active share of 82% and 81%, and a tracking error of 7.9% and 8.6%, respectively.

Funds in the upper left corner are classified as diversified stock pickers because they generate a high active share while maintaining a relatively low tracking error by taking positions in individual stocks that are diversified across industries. As Figure 4 shows, there are no diversified stock pickers in our sample of funds. Similarly, we do not have funds in the lower right corner, which Cremers and Petajisto (2009) classify as factor bets – funds betting on systematic factors and thus generating a relatively high tracking error and a moderately low active share.

Figure 4: Examples of Norwegian equity mutual funds plotted along the two dimensions of active management on the last date of reported fund holdings in 2018
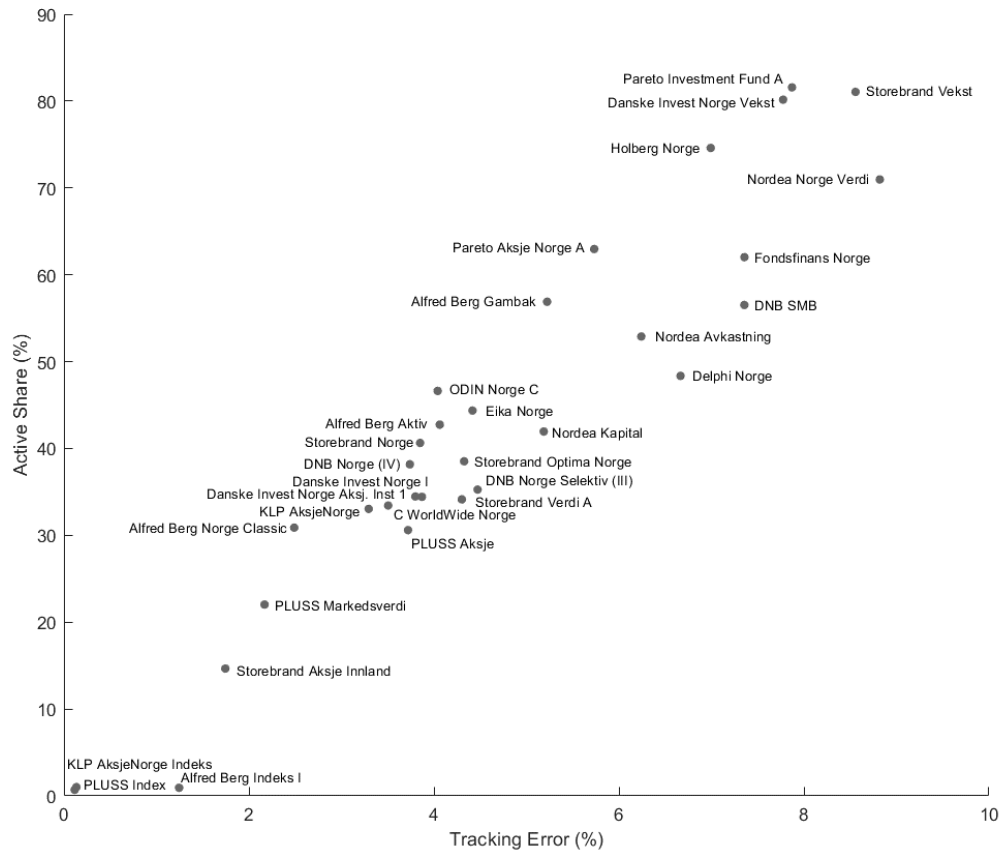
5.1.1 Fund Size and Active Management

Cremers and Petajisto (2009) find that fund size is negatively correlated with active management. We investigate whether there is a similar relationship for Norwegian mutual funds. Table 2 shows the median market value of Norwegian mutual funds in 2018, sorted by the two dimensions of active management. For funds with an active share of less than 50%, the median market value ranges from 1,366 million to 8,180 million NOK. For funds with an active share of 50% and above, the median market value ranges from 890 million to 4,498 million NOK. This suggests that funds with a higher active share are smaller, however, we do not find a monotonic relationship when going from a low to high active share. If we exclude funds with less than 20% active share, as these are likely to be pure index funds, the relationship between fund size and active share is almost monotonic, where fund size decreases from 8,180 million to 890 million NOK as active share increases. In

terms of tracking error, the relationship seems less clear, although the smallest funds are indeed in the highest tracking error group.

Table 2: Median market value of Norwegian equity mutual funds in 2018, sorted by the two dimensions of active management

Active Share (%)	Tracking Error (% per year)						
	0-2	2-4	4-6	6-8	8-10	10-12	All
	Median market value (million NOK)						
0-10	1,337						1,337
10-20	1,334	7,900					1,366
20-30	8,402	138					8,180
30-40		2,867	4,055				3,563
40-50		1,014	3,109	1,007			1,895
50-60			3,988	1,402			1,768
60-70			4,650	4,398			4,498
70-80			1,715	3,903	3,985		2,385
80-90				2,338	524	459	890
90-100							
All	1,405	2,046	4,055	1,799	615	459	2,083

The sample consists of 35 equity mutual funds. Active share and tracking error are computed as before.

Figure 5 shows a scatter plot of active share versus fund size for Norwegian equity mutual funds in 2018. There appears to be a weak negative correlation between active share and fund size. However, the dispersion in active share within each size group is too wide to reach a conclusion on the relationship between the two variables.

Figure 5: Active share and fund size of active Norwegian equity mutual funds in 2018
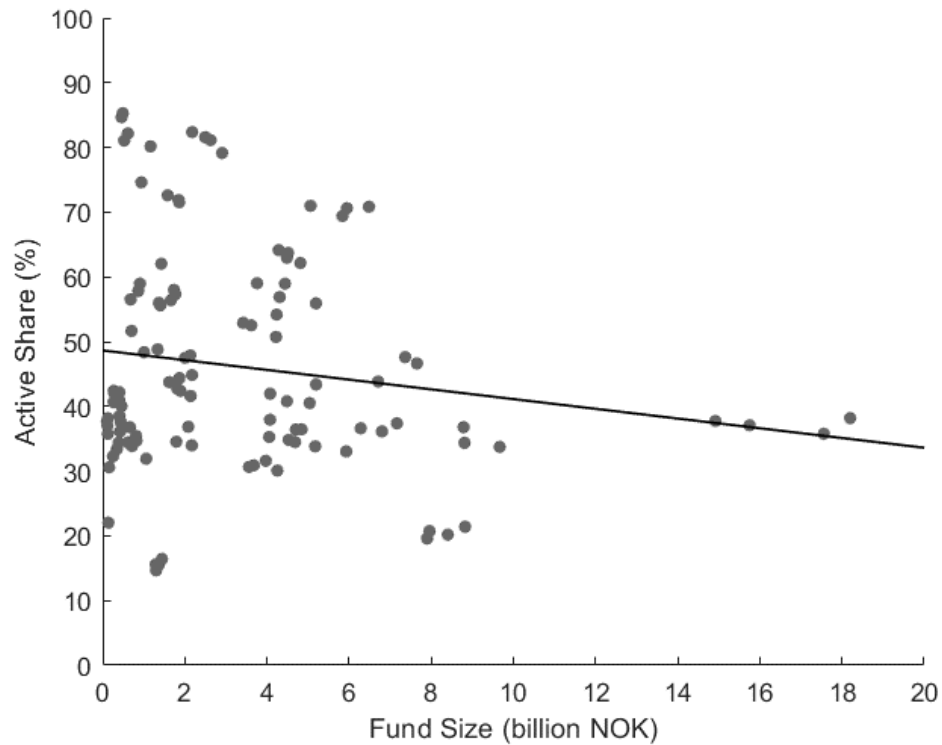
The sample consist of 32 equity mutual funds. Index funds are excluded. Fund size is total market value in billions of NOK.

5.1.2 Fees and Active Management

The funds that are most active will likely incur more expenses and therefore have the highest fees, as increasing active management requires increasing amount of work. It therefore seems fair that fees should rise in line with active management. This does indeed seem to be the case for Norwegian all-equity mutual funds. Table 3 presents the equal-weighted expense ratio of Norwegian mutual funds sorted by active share and tracking error in 2018. The equal-weighted expense ratio across all funds in the sample is 1.24% and ranges from 0.27% for the least active fund to 2.00% for the most active fund. The expense ratio is clearly increasing with both active share and tracking error.

For funds sorted by active share alone, the expense ratio increases the most for funds with an active share below 60%, ranging from 0.27% to 1.65%. In contrast, there is a low additional cost to moving between funds that have an active share of 60-90%, where the expense ratio ranges from 1.60% to 1.85%.

Table 3: Expense ratios of Norwegian equity mutual funds in 2018, sorted by the two dimensions of active management

Active Share (%)	Tracking Error (% per year)						
	0-2	2-4	4-6	6-8	8-10	10-12	All
	Equal-weighted expense ratio (%)						
0-10	0.27						0.27
10-20	0.60	0.28					0.44
20-30	0.28	0.90					0.59
30-40		1.19	1.16				1.17
40-50		1.40	1.42	2.00			1.43
50-60			1.65	1.56			1.65
60-70			1.83	1.60			1.60
70-80			1.50	1.50	1.65		1.60
80-90				1.78	2.00	2.00	1.85
90-100							
All	0.33	1.16	1.46	1.66	1.77	2.00	1.24

The sample consists of 39 equity mutual funds. Active share and tracking error are computed as before.

5.2 Fund Performance

5.2.1 Individual Fund Regression Results

We start our performance analysis by looking at the net benchmark-adjusted returns and the net four-factor alphas of individual funds. The average active fund in our sample outperforms its benchmark index by 0.35%. Under the Carhart four-factor model, this increases to 0.41%. As shown in Table 4, the worst performing fund is ODIN Norge C, which underperforms its benchmark by 0.03% and is the only underperforming fund in our sample. However, under the four-factor model, it is Holberg Norge that is the worst performer, with a net alpha of 0.01%. DNB SMB is the best performer in terms of benchmark-adjusted return and outperforms its benchmark by 0.59%. This is also the fund with the highest alpha of 0.77%.

Active share in our sample ranges from 10.7% to 83.23%, with an average of 42.1%. According to Cremers and Petajisto (2009), funds with an active share of less than 20% are pure index funds and funds with an active share of 20-60% are closet indexers. In our sample we find two funds with an active share below 20%: DNB Norge Avanse (10.70%) and Storebrand Aksje Innland (14.80%). Thus, our

findings support Forbrukerrådets notion that DNB Norge Avanse is not actively managed. Among our sample, 20 funds have an active share of 20-40%, 8 funds have an active share between 40-60%, and 8 funds have an active share above 60%.

We expect the fund with the lowest active share to have the lowest expense ratio, however, this is not the case. DNB Norge Avanse has an expense ratio (1.2%) that is about four times as high as the lowest expense ratio in our sample, which is 0.28% for Storebrand Norge I. For comparison, Storebrand Norge I has an active share of 26.24%.

Table 4: Individual fund performance and active management

Fund	Benchmark	Expense Ratio	Time Span		Benchmark-Adjusted Return	Volatility	Alpha	Active Share	Tracking Error
ODIN Norge C	OSEFX	1.50	09-2009	08-2018	-0.03 (-0.14)	2.38	0.13 (0.43)	57.23	8.30
Holberg Norge	OSEFX	1.50	12-2009	12-2018	0.01 (0.06)	2.31	0.01 (0.03)	65.77	7.45
Pareto Aksje Norge A	OSEFX	3.00	06-2009	12-2018	0.15 (0.61)	2.70	0.38 (1.33)	64.31	8.42
Pareto Aksje Norge B	OSEFX	2.00	06-2009	12-2018	0.16 (0.64)	2.73	0.40 (1.35)	64.31	8.23
DNB Norge	OSEFX	1.40	03-2009	11-2018	0.17 (1.06)	1.74	0.36 (1.80)	27.04	3.20
DNB Norge (III)	OSEFX	1.00	03-2009	11-2018	0.23 (1.40)	1.75	0.42 (2.06)	27.04	3.21
Eika Norge	OSEFX	1.50	02-2008	12-2018	0.24 (1.11)	2.51	0.35 (1.26)	47.68	5.65
DNB Norge (IV)	OSEFX	0.75	03-2009	11-2018	0.25 (1.55)	1.75	0.44 (2.17)	27.18	3.22
Storebrand Verdi A	OSEBX	2.00	11-2006	12-2018	0.25 (1.51)	2.03	0.32 (1.56)	36.17	4.17
Pareto Aksje Norge I	OSEFX	0.50	06-2009	12-2018	0.28 (1.12)	2.73	0.53 (1.76)	64.31	8.23
KLP AksjeNorge	OSEFX	0.75	12-2009	12-2018	0.28 (1.73)	1.72	0.33 (1.49)	32.76	3.27
PLUSS Aksje	OSEFX	1.20	09-2009	12-2018	0.30 (2.01)	1.58	0.31 (1.89)	32.48	3.93
DNB Norge (I)	OSEFX	1.80	03-2009	03-2014	0.30 (1.14)	2.07	0.49 (1.63)	20.73	3.24
Alfred Berg Humanfond	OSEFX	1.20	06-2010	12-2014	0.31 (1.12)	2.06	0.31 (0.85)	29.96	3.28
PLUSS Markedsverdi	OSEFX	0.90	09-2009	12-2018	0.32 (2.30)	1.46	0.35 (2.11)	23.93	2.86
C WorldWide Norge	OSEFX	1.20	12-2009	12-2018	0.34 (2.27)	1.55	0.27 (1.33)	29.13	3.07
Storebrand Aksje Innland	OSEBX	0.60	11-2006	12-2018	0.34 (2.33)	1.77	0.40 (2.12)	14.80	1.68
Storebrand Optima Norge	OSEBX	1.00	11-2006	12-2018	0.35 (1.90)	2.26	0.43 (2.01)	40.27	5.13
DNB Norge Selektiv (III)	OSEBX	0.80	03-2009	11-2018	0.36 (1.98)	1.95	0.46 (2.14)	31.89	3.59
Delphi Norge	OSEFX	2.00	05-2006	12-2018	0.36 (1.65)	2.70	0.30 (1.13)	55.04	7.15
Storebrand Norge	OSEFX	1.50	11-2006	12-2018	0.37 (2.23)	1.99	0.38 (1.79)	25.94	3.23
Storebrand Norge I	OSEBX	0.28	11-2006	12-2018	0.38 (2.33)	1.95	0.45 (2.19)	26.24	3.05
Nordea Avkastning	OSEFX	1.50	12-2009	12-2018	0.38 (2.40)	1.64	0.38 (1.84)	38.01	3.86
Alfred Berg Aktiv	OSEFX	1.50	06-2010	11-2018	0.38 (2.05)	1.89	0.30 (1.15)	42.25	4.48
Fondsfinans Norge	OSEFX	1.00	12-2009	12-2018	0.40 (1.76)	2.36	0.46 (2.05)	57.75	6.75
Danske Invest Norge I	OSEFX	1.75	06-2005	12-2018	0.40 (2.80)	1.82	0.44 (2.47)	35.66	3.84
Nordea Kapital	OSEFX	1.00	12-2009	12-2018	0.40 (2.59)	1.60	0.42 (2.04)	34.74	4.01
Alfred Berg Norge Classic	OSEFX	1.20	08-2010	11-2018	0.40 (2.70)	1.49	0.39 (1.56)	29.00	3.20
Nordea Norge Verdi	OSEFX	1.50	12-2009	12-2018	0.45 (1.98)	2.36	0.57 (2.08)	66.96	8.57
Danske Invest Norge II	OSEFX	1.25	06-2005	12-2018	0.46 (3.21)	1.83	0.51 (2.77)	35.90	3.77
Alfred Berg Gambak	OSEFX	2.00	06-2010	11-2018	0.46 (2.09)	2.23	0.29 (1.27)	57.49	6.32

Fund	Benchmark	Expense Ratio	Time Span		Benchmark-Adjusted Return	Volatility	Alpha	Active Share	Tracking Error
Danske Invest Norge Aksj. Inst 1	OSEFX	0.90	07-2006	12-2018	0.47 (3.15)	1.83	0.51 (2.70)	34.82	3.64
Danske Invest Norge Aksj. Inst 2	OSEFX	0.90	06-2009	12-2018	0.48 (3.06)	1.69	0.52 (2.44)	33.67	3.78
Pareto Investment Fund A	OSEFX	1.80	12-2009	12-2018	0.51 (2.37)	2.23	0.30 (1.38)	61.26	6.58
DNB Norge Avanse (II)	OSEFX	1.20	03-2009	02-2013	0.52 (1.63)	2.23	0.61 (1.39)	10.70	1.81
Storebrand Vekst	OSEBX	2.00	11-2006	12-2018	0.54 (1.72)	3.78	0.70 (1.76)	80.56	12.90
Danske Invest Norge Vekst	OSESX	1.75	06-2005	12-2018	0.55 (2.49)	2.84	0.70 (2.66)	83.23	9.53
DNB SMB	OSESX	1.75	03-2009	11-2018	0.59 (2.57)	2.49	0.77 (2.45)	53.18	6.88
Min		0.28			-0.03	1.46	0.01	10.70	1.68
Max		3.00			0.59	3.78	0.77	83.23	12.90
Average		1.35			0.35	2.11	0.41	42.09	5.09
Median		1.33			0.36	2.01	0.40	35.78	3.90

Funds are sorted in ascending order of benchmark-adjusted return. Benchmark-adjusted return is the time-series average of the monthly excess return of a fund over its benchmark index, after fees. Volatility is the standard deviation of benchmark-adjusted returns. Alpha is estimated by regressing benchmark-adjusted returns on the Carhart four-factor model. Active share is the average of quarterly-calculated active share over the sample period. Tracking error is the average of annualized tracking error. All numbers are in percent. The numbers in parentheses are t-statistics. Pure index funds are excluded.

5.2.2 Equal-Weighted Portfolio Regression Results

For each month in our sample period of 2007–2018, we sort funds into three groups of active share and then further into three groups of tracking error, creating nine fund portfolios. We calculate the equal-weighted monthly benchmark-adjusted return in each portfolio and then take the average of these returns over the sample period. These results are reported in panel A of Table 5. We then regress the benchmark-adjusted return of each portfolio on the Carhart four-factor model. The intercept of the time series regressions, i.e., the portfolio alphas, are reported in panel B.

The average net benchmark-adjusted return for a portfolio of all the funds in our sample is 0.32% (t = 1.94), which increases to 0.37% (t = 1.83) under the four-factor model. Although this indicates that the average fund does outperform its benchmark index, these numbers are neither economically significant nor statistically significant at the 5% level.

Looking at active share alone, we find that it is positively related to fund performance. The difference in net benchmark-adjusted returns between the high and low groups of active share is 0.10% (t = 1.76), which increases to 0.25% (t = 4.80) and becomes statistically significant under the four-factor model. Even within the tracking error groups, going from a low to high active share improves fund performance: the returns in the High-Low rows in Table 5 are all positive, though not all are statistically significant.

In contrast to active share, the difference in net benchmark-adjusted returns between the high and low groups of tracking error is 0.07% (t = 3.68), which decreases to 0.03% (t = 1.83) under the four-factor model. Within the active share groups, tracking error shows a zero to negative relationship with fund performance: going from a low to high tracking error results in a net alpha of -0.22% (t = -4.91) within the high active share group, and a net alpha of -0.08% (t = -3.57) within the low active share group.

The results in both panels suggest that an investor should pick funds based on their active share. Funds in the high active share group outperform their benchmarks by

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0.42% (t = 1.95), which increases to 0.60% (t = 1.88) under the four-factor model. On the other hand, funds in the high tracking error group outperform their benchmarks by 0.35% (t = 1.87), or 0.37% (t = 1.83) under the four-factor model.

The estimated betas across all funds in our sample are small, as shown in Table 6. Moreover, there are no patterns in the betas across the active share groups. However, the tracking error groups do exhibit a higher exposure to the RMRF (market excess return) and HML factors.

Table 5: Net equal-weighted alphas for EW portfolios of Norwegian equity mutual funds in 2007–2018

Active Share	Tracking Error				
	Low	Medium	High	All	High-Low
Panel A: Benchmark-adjusted return (%)					
Low	0.29	0.32	0.28	0.32	-0.01
	(1.85)	(1.83)	(1.60)	(2.00)	(-0.37)
Medium	0.43	0.27	0.47	0.35	0.04
	(2.55)	(1.52)	(2.24)	(1.92)	(0.97)
High	0.41	0.47	0.43	0.42	0.01
	(1.69)	(1.43)	(1.46)	(1.95)	(0.27)
All	0.28	0.31	0.35	0.32	0.07
	(1.67)	(1.84)	(1.87)	(1.94)	(3.68)
High-Low	0.12	0.15	0.14	0.10	
	(1.40)	(2.64)	(1.24)	(1.76)	
Panel B: Four-factor alpha of benchmark-adjusted return (%)					
Low	0.36	0.34	0.28	0.35	-0.08
	(1.82)	(1.53)	(1.26)	(1.76)	(-3.57)
Medium	0.57	0.22	0.63	0.42	0.07
	(2.54)	(1.16)	(2.26)	(1.91)	(2.01)
High	0.61	0.60	0.38	0.60	-0.22
	(1.66)	(2.16)	(1.68)	(1.88)	(-4.91)
All	0.36	0.34	0.39	0.37	0.03
	(1.74)	(1.60)	(1.77)	(1.83)	(1.83)
High-Low	0.25	0.26	0.10	0.25	
	(2.61)	(1.59)	(0.85)	(4.80)	

Funds are sorted by active share and then tracking error. Active share and tracking error are computed as before. The table shows monthly net returns, followed by t-statistics in parentheses. Net returns are returns after transaction costs and management fees. Pure index funds are excluded.

Table 6: Regression coefficients for EW portfolios of Norwegian equity mutual funds for the period 2007–2018

Portfolios of Funds	α	β_{RMRF}	β_{SMB}	β_{HML}	β_{PR1YR}
All	0.37%	-0.09	0.02	-0.08	-0.06
	(-2.25)	(-2.40)	(0.35)	(-1.78)	(-1.44)
Low Active Share	0.35%	-0.09	-0.04	-0.10	-0.04
	(2.16)	(-2.48)	(-0.73)	(-2.21)	(-1.01)
Medium Active Share	0.42%	-0.11	0.05	-0.04	-0.07
	(2.31)	(-2.68)	(0.78)	(-0.70)	(-1.54)
High Active Share	0.60%	-0.09	0.08	-0.08	-0.18
	(2.80)	(-1.90)	(1.12)	(-1.37)	(-3.39)
Low Tracking Error	0.36%	-0.08	0.02	-0.06	-0.08
	(2.12)	(-2.14)	(0.26)	(-1.21)	(-1.87)
Medium Tracking Error	0.34%	-0.09	0.02	-0.07	-0.03
	(1.97)	(-2.33)	(0.43)	(-1.50)	(-0.66)
High Tracking Error	0.39%	-0.11	0.05	-0.11	-0.06
	(2.10)	(-2.47)	(0.73)	(-2.20)	(-1.20)

Funds are sorted by active share and tracking error. Active share and tracking error are computed as before. The table shows Carhart four-factor alphas net of transaction costs and management fees and factor betas. The numbers in parentheses are t-statistics.

5.2.2.1 Fund Size and Active Share

Following the methodology described in the previous section, we examine how fund size relates to active share and fund performance. We sort funds into three groups of size and then further into three groups of active share. We then regress the benchmark-adjusted return in each portfolio on the four-factor model to obtain the alphas reported in Table 7. The median fund sizes in the size groups across our sample period are 582 million NOK, 3,422 million NOK, and 5,387 million NOK.

Cremers and Petajisto (2009) find that when controlling for size, active share again predicts fund performance, and that it is especially in the smaller funds that the highest active share exhibits economically significant stock-picking ability. Our results also indicate that the level of active share has the largest positive effect on the smallest firms. The difference in net alphas between the high and low groups of active share within the smallest fund size group is 0.43% (t = 5.84), whereas in the largest fund size group, a difference in net alphas of 0.06% (t = 0.18) is economically and statistically insignificant. For medium-sized firms, the degree of active share exhibits a negative relation with fund performance.

Furthermore, our results are consistent with the findings of Cremers and Petajisto (2009) in that fund size is negatively related to fund performance: the net alphas in the High-Low column of Table 6 are all negative. Therefore, an investor would achieve the highest alpha (0.79%, t = 2.07) by picking the portfolio with high active share and low fund size.

Table 7: Net equal-weighted alphas for EW portfolios of Norwegian equity mutual funds in 2007-2018

| | Fund Size | | | | |
Active Share	Low	Medium	High	All	High-Low
	Four-factor alpha of benchmark-adjusted return (%)				
Low	0.36	0.35	0.25	0.36	-0.11
	(1.55)	(1.87)	(0.77)	(1.80)	(-1.39)
Medium	0.52	0.30	0.01	0.43	-0.50
	(2.37)	(1.49)	(0.05)	(1.94)	(-13.09)
High	0.79	-0.13	0.31	0.61	-0.48
	(2.07)	(-0.49)	(0.38)	(1.84)	(-1.40)
All	0.41	0.36	0.20	0.39	-0.20
	(1.93)	(1.73)	(0.94)	(1.90)	(-15.61)
High-Low	0.43	-0.48	0.06	0.24	
	(5.84)	(-2.60)	(0.18)	(4.69)	

Funds are sorted by fund size and then active share. Active share is computed as before. The table shows monthly net returns, followed by t-statistics in parentheses. Net returns are returns after transaction costs and management fees. Pure index funds are excluded.

6. Conclusion

Through our research on Norwegian all-equity mutual funds, we wished to answer 1) if actively managed Norwegian equity funds outperformed their benchmark index and 2) if there was any correlation between their degree of active share and returns.

In our performance analysis of individual funds, we find that all but one (ODIN Norge C) of the funds in our sample earned positive net benchmark-adjusted returns, and under the four-factor model, all the alphas were positive. While this does mean our sample of actively managed funds outperformed their benchmark index, only 53% of the benchmark-adjusted returns and 42% of the alphas are statistically significant. Even when the returns and alphas are statistically

significant, they cannot be said to be economically significant, as the highest alpha translates to an added value of 0.77% above the benchmark index.

When we sort funds into equal-weighted portfolios based on their active share and tracking error, we find there is a positive correlation between active share and fund performance, whereas tracking error has a zero to negative relationship. This suggests that an investor should pick funds with the highest active share. Furthermore, when we sort funds into portfolios based on their size and active share, our results indicate that the level of active share has the largest positive effect on the smallest firms and that an investor would achieve the highest alpha by picking the portfolio with high active share and low fund size.

The hardest task in our research was collecting complete data that was free of survivorship bias. Had we been able to produce a sample without survivorship bias, our findings on the added value of active management would have likely been lower. However, we could not obtain information about liquidated and acquired funds as they did not have their holdings reported in Bloomberg nor in Thomson Reuters Eikon, and fund managers were unable to accommodate our requests for data. For us to be able to make meaningful inferences and draw conclusions, we need more observations from a larger sample of funds. Therefore, we recommend for the Norwegian Fund and Asset Management Association (VFF) to require Norwegian mutual funds to report their holdings consistently, similarly to how the SEC requires U.S. mutual funds to report their holdings on a quarterly basis.

7. References

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