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# Norwegian Equity Funds

*An Empirical Study of Active Management & Performance*

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# Abstract

This thesis is a comprehensive study of fund management in Norway, with particular emphasis on active management and performance. The utilized sample include 59 Norwegian equity mutual funds from 1996-2014. In general, we apply well-known methodologies with different modifications, investigating the degree of active fund management and fund performance. Our analyses can be divided into three separate examinations to keep contextual tidiness. The yielded results should, however, be contemplated in coherence.

First, we look at the degree of active management using the statistical measure $R^2$. This is obtained from a regression of fund returns on a multifactor benchmark model. Lower $R^2$ indicates greater deviation from the benchmark, and our results indicate that half of the Norwegian equity funds are close to being index funds. We see that loading on the small-minus-big risk factor is particularly prevalent, and captures most of the deviation from the market.

Second, we examine the hypothesis that fund performance can be predicted by its degree of active management. Equity funds sorted into highest quartile lagged $R^2$ generally outperforms the lowest quartile lagged $R^2$. However, we do not find enough consistency in our results to prove that $R^2$ is a credible predictor of performance. Moreover, we observe that the importance of preceding performance increases as $R^2$ decreases.

Third, we examine the effects of fund characteristics on its degree of active management. Across funds, more active management is positively associated with expenses and fund age. In addition, the investment style coefficients show that more active funds invest in small size stocks.

# Preface

This Master thesis was written in the fall of 2015 to conclude our Master of Science degree in Economics & Business Administration at the Norwegian School of Economics (NHH). This fall we have spent all our time delving into one of the most interesting topics within our specialization Financial Economics, namely active fund management. Anchored in portfolio management the topic is important for academics and researchers, but not least of interest to the average investor. The subject is often in the media's spotlight and the debate on active fund management is going strong. Different researchers and experts make statements on both sides of the debate and never seem to agree. In addition, Norwegian funds have been receiving criticism because of their lack of activeness, which further caught our attention of the subject.

The thesis is written and prepared in the Microsoft Office 2013 suite. Calculations and analysis have mainly been executed in Microsoft Excel and STATA. The thesis data is mainly obtained from Morningstar Direct and Børsprosjektet (NHH).

We would like to take the time to thank our supervisor, Professor Svein-Arne Persson for counselling, help and support during the process. Furthermore, we would like to thank Professor Trond Døskeland for useful input as well as illuminating the subject of active management during his class Asset Management. Last, but not least we would like to thank our families for love and support throughout our academic career.

The results and conclusions in this thesis is entirely those of the authors.

Bergen, 18 December 2015.

Kristian Wiik Johnsen

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# 1. Introduction

## 1.1 Motivation

*"Think picking stocks is hard? Try picking a good mutual-fund manager."*

Joe Light (Light, 2013), journalist Wall Street Journal

Mutual funds have existed in Norway since the late 70's. The market has developed and matured substantially during the 90's. However, it is only in the recent years that the debate on actively managed funds versus passive funds has blossomed. Several studies aim to provide insight on whether active or passive funds obtain the best returns, and if there is persistence in returns or not. For example, Sørensen (2010) finds no evidence that Norwegian funds have created economic value compared to passive benchmarks. The growing debate on whether active funds are able to create returns that are superior to index fund are interesting as it is. However, we want to take the discussion one step further. Martijn Cremers, a leading researcher on mutual fund performance, said the following to the Wall Street Journal (2013), "The debate can't just be active versus passive, not all active funds are alike". Therefore, we want to conduct an analysis where we compare only active funds, and not indexes, to see if it is possible to pick winners based on their degree of active management.

In an interview with the Wall Street Journal, Professor Amihud claimed, based on his insight in the US mutual fund market, that the great majority of funds are "closet-indexers" that nearly mimic common benchmarks (Light, 2013). Hence, investors should look for funds that are actually trying to beat their benchmark. Furthermore, Finanstilsynet (2015) (the financial supervisory authority of Norway) released a report regarding actively managed funds in early 2015. The report revealed that DNB and Nordea sold funds as active, but when they, in fact, behaved as index funds.[1] We find these revelations interesting as this has implications for the average investor and his choice of investments. As a result, we want to see how active Norwegian equity funds really are. When charging larger fees, fund managers indirectly promise that they will try to manage the fund in a manner that provides returns that are greater

[1] Finanstilsynet - http://tinyurl.com/zu67bef

than that of an index. This is only obtainable by deviating its asset allocation from the benchmark, known as active management.

## 1.2 Research Objective

This thesis aims to shed light on Norwegian equity mutual funds to see how actively managed they are, and if it is possible to pick winners based on their degree of activeness. In addition, we want to identify the characteristics of active funds. More specifically our goal for the thesis is to answer the following research questions.

- *How active are Norwegian equity mutual funds?*
  Based on a simple and intuitive measure, $R^2$, we will analyse how active Norwegian funds are compared to a benchmark model.

- *Is it possible to pick superior performing funds based on their degree of active management?*
  We examine a strategy where we use lagged $R^2$ as a performance indicator to see whether the degree of activeness is related to risk-adjusted returns.

- *What effect does fund characteristics have on active management?*
  We examine if fund characteristics can explain the differences in $R^2$.

## 1.3 Thesis Purpose

This thesis aims to highlight how actively managed Norwegian funds have been in the period 1996 to 2014. We then try to unveil and explain if there is possible to pick winners among actively managed fund based on a measure that is easy to calculate and understand. We hope to contribute on the subject and provide new insight on the topic that could possibly lead to a shift in the debate from not only active versus passive, but to which active fund to choose. Lastly, we hope that our results will be of importance for academics and investors trying to maximize their utility when investing their savings.

## 1.4 Structure of the Paper

We begin with building a framework on mutual funds and the industry. We discuss the different types of funds and especially equity mutual funds. Further, we provide a definition of active and passive management before we enlighten fund fee structure.

Next, chapter 3 describes the relevant theory needed to understand the work conducted in this thesis. We touch on the basics of linear regression and our preferred method, ordinary least squares. In particular, we present and elaborate our measure of activeness, $R^2$. We take a walk through the field of financial theory discussing active management, to develop an understanding of why active management exists. Additionally, we introduce several measures of active management and culminate with defining what is considered an active fund and not.

Chapter 4 provides a review of existing literature on the subject. To understand common approaches, consistencies and inconsistencies we spent a great amount of time delving into empirical results. We present previous work on the degree of active management, the link between active management and performance, and fund performance in general.

In chapter 5, we outline the methods and applications used in our analysis. We also check whether our sample meets the requirements of the methods, and potential adjustments made to comply with the prerequisites.

A description of our dataset is found in chapter 6. We discuss the criteria set for including a fund, and present the sample. Furthermore, we address survivorship bias and adjustments applied to our sample. Lastly, we provide summary statistics for our utilized sample.

Chapter 7 contain our analysis and answer to the research questions. We comment and interpret our result, and try to assess them in context with previous work.

Concluding remarks are made in chapter 8.

# 2. An Introduction to Equity Mutual Funds

To make sure our reader fully understand our work we provide a thorough framework for the thesis. We start by introducing the mutual fund market in Norway, where we will define what a mutual fund is and enlighten some historic facts and the development of the market. We then move on to define different types of funds and especially the type used in our sample. Lastly, the differences between active and passive management are explained.

## 2.1 Mutual Funds – What Are They?

The common name for an open-end investment company is mutual fund. By open-end, we mean that issuance and redemption of shares happen at their net asset value, such that investors can "cash out" whenever they want to. Mutual funds are together with bank deposit and stocks the dominant form of financial saving in Norway (Statistics Norway, 2015). The financial intermediaries, or mutual funds, collect capital from individual investors and invest in a potentially wide range of securities or other assets. The key idea behind mutual funds is pooling of assets. Each investor has a claim to the mutual fund in proportion to the amount invested. A mutual fund provides a mechanism for small investors to join forces and obtain the benefits of large-scale investing. First, they offer diversification and divisibility such that small investors can act as large investors. Secondly, investors get the opportunity to achieve superior investment results due to professional management and a full-time staff of analysts. Thirdly, the possibility of large trading volumes gives mutual funds substantial savings on commissions and brokerage fees. Lastly, there are other benefits such as record keeping and administration and tax benefits (Bodie, 2014). In Norway, mutual funds are managed after the "Mutual fund law" (Verdipapirfondloven), which assures responsible management of the investor's assets. In addition, mutual funds must invest according to its stated investment strategy in the mandatory prospectus.

## 2.2 The Norwegian Fund Market

In Norway, there are currently (31.10.2015) 21 companies offering mutual funds to investors. The largest mutual fund providers in Norway and their market share based on total asset under management (AUM) are presented below.

**Table 1: Top five fund providers in Norway**

| Fund name | Market share (*#funds*) |
|---|---|
| DNB | 25% (87) |
| KLP | 16% (33) |
| Nordea | 11% (100) |
| Skagen | 11% (32) |
| Storebrand | 11% (38) |

*In parenthesis are the number of funds provided. The count includes all types of funds offered.*

These five account for a substantial part of the Norwegian market and offers 290 different mutual funds of a total 618. In total, their AUM is 691 billion NOK of a total AUM in Norway of 918 billion NOK. The figure below shows the development of AUM from 1996 to 2014 divided into different types of funds (Statistics Norway, 2015).

***Figure 1: Development in the Norwegian Fund Market in Sample Period.***

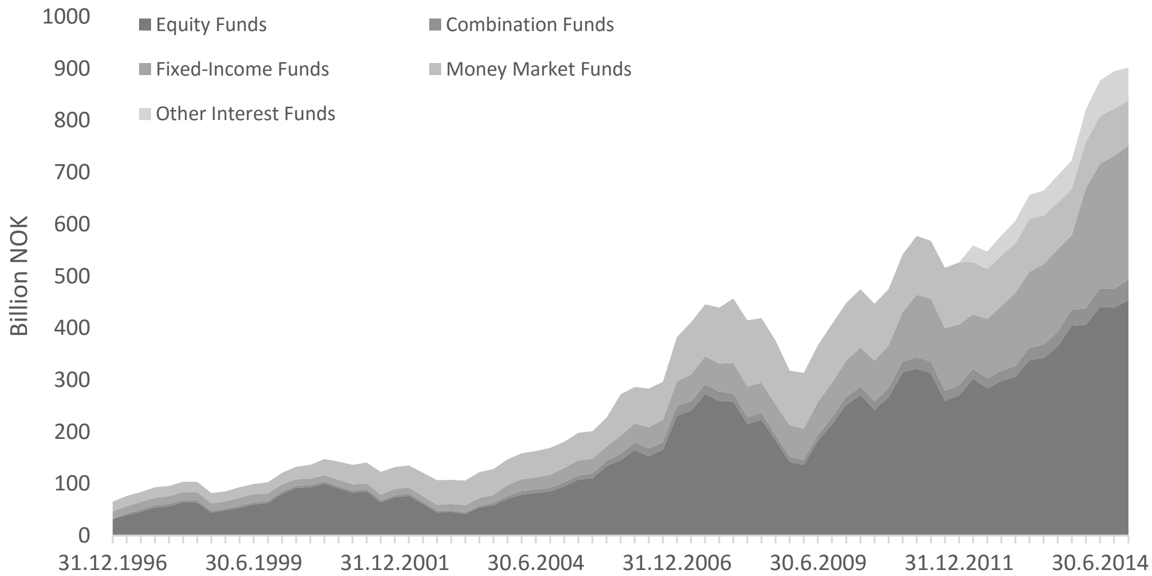
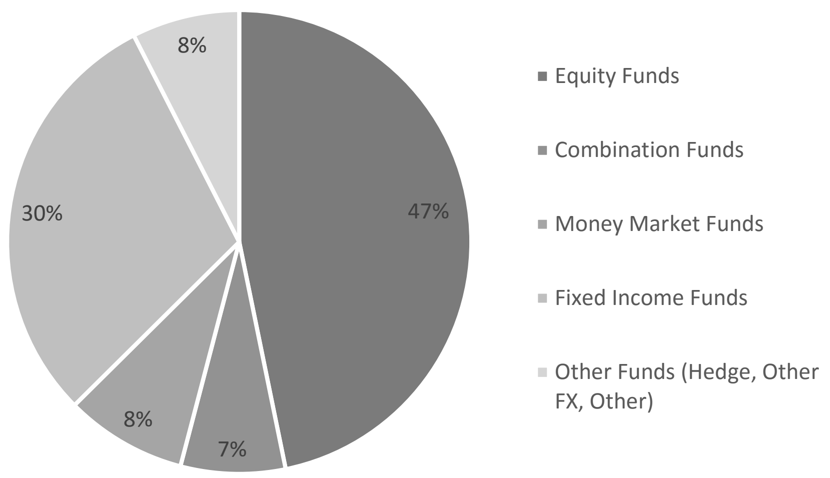



Figure 1 shows a strong development in AUM during the whole period, with the exception of the turbulence in 2008 caused by the financial crisis. From 2011 funds in Norway were defined somewhat differently, hence, the other interest funds showing in the figure. Since 2008, AUM has grown with 314%. This is caused by two factors, namely the underlying value creation of securities and the increased inflow to funds.

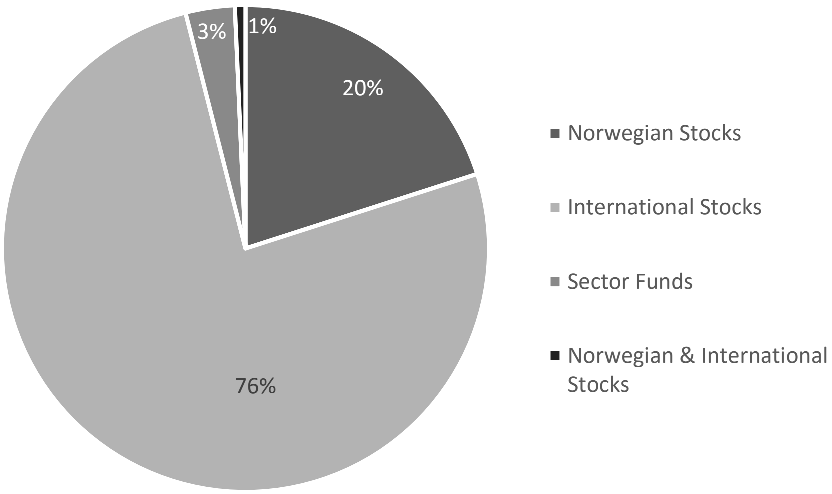
Figure 2 shows the allocation of total AUM into the different fund types (Statistics Norway, 2015).

**Figure 2: Allocation of the total fund market based on AUM**




As this thesis will evolve around equity funds, we show in figure 3 the asset placement in different types of equity funds (Statistics Norway, 2015).

***Figure 3: Allocation amongst equity funds provided in Norway.***




A substantial amount of AUM is placed in funds that invest in international stocks. Investing worldwide is more common now as this enables better diversification considering the small market in Norway. Equity funds account for 429 billion NOK of the total AUM, whereas equity funds investing in Norwegian stocks accounts for 86 billion. This is roughly 10% of the total fund market in Norway.

## 2.3 The Different Types of Mutual Funds

*Equity funds*

Equity funds are, as the name imply, funds that invest primarily in equity. The Norwegian Fund and Asset Management Association state that the following requirement must be fulfilled to be classified as an equity fund. The fund has to invest at least 80% of its assets under management in equity. The requirement does not say which equity market to invest in, only equity as an asset class. Equity funds will commonly hold 5% of total assets in money market securities to provide the necessary liquidity to meet potential redemption of shares. Further, equity funds are commonly classified by their emphasis on income versus growth. This implies a trade-off between current income (dividends) and growth (capital gains), which also is a distinction concerning the level of risk these funds assume (Bodie, 2014). Each fund has a specified investment policy, described in the fund's prospectus. The investment policy narrows down the investment universe. This should reflect the manager's skill and specialization towards a given market. Geography, style and sector, or a combination of these, delimits a fund's investment universe. In this thesis, we will look at funds delimited by region, namely Norwegian equity funds. To be classified as a Norwegian fund it has to invest more than 80% of its assets in the Norwegian stock market and have Norway as its domicile.[2]

*Money Market Funds*

Money market funds invest solely in short-term securities. The standard is fixed-income securities with maturity of less than a year, mostly treasury bills. This type of saving have low risk, and will thus yield low returns. Money market funds are measured against a benchmark and split into groups based on the interest rate sensitivity to the benchmark. In addition, funds are ranked by credit risk (Bodie, 2014). A typical benchmark in Norway is the Norway Government Bond 0.25Y (ST1X).

*Fixed-Income Funds*

Fixed-income or bond funds are similar to money market funds in the way that capital is invested in fixed-income securities. However, the maturity of the investments varies. The most important difference is the risk involved due to interest rate sensitivity. Therefore, their expected return is also higher over time. There are several types of bonds to invest in such as government and corporate debt with different credit rating. If the interest rate goes up, the value of the funds go down and vice versa (Bodie, 2014).Norway Government Bond 3Y (ST4X) is a common benchmark for fixed-income funds in Norway.

*Other Funds*

Balanced funds have an objective to provide a mixture of safety and expected return. The strategy is to invest in a combination of equity and fixed income. The weighting will vary from fund to fund according to the fund's risk profile. A benchmark for balanced funds is usually composed of several indexes weighted according to the investment philosophy. Specialized sector funds concentrate on investments in a particular industry such as technology, utilities or telecommunications. International and regional funds are classified based on their investment universe. Regional funds concentrate on a particular part of the world, emerging

[2] Verdipapirfondenes Forening - http://tinyurl.com/zzfncjs

market funds invest in companies in developing countries and global funds invest worldwide (Bodie, 2014).

*Index Funds*

These funds try to match the performance of a broad market index (benchmark). The fund tries to hold a portfolio of securities in proportion to the security representation in that index. By doing so, the expected return should be close to the index. Index funds represent the market and should harvest the market risk premium. In Norway, a typical equity index fund provided by an investment company tries to mimic the main index known as OSEBX, which consists of a representative selection of all stocks listed on the Oslo Stock Exchange.

## 2.4 Mutual Fund Management

Mutual funds are managed in line with their prospectus. There are two main categories of mutual fund management: active management and passive management. The latter should be the cheaper alternative while actively managed funds often charge higher fees due to costs of more thorough market analysis.

*Passive Management*

The goal of passive management is to achieve the same return and risk as a benchmark. Thus, the fund's portfolio must consist of the same securities, and with the same proportion, as the benchmark. The most used benchmarks for Norwegian equity funds are the Oslo Stock Exchange Benchmark Index (OSEBX) and the Oslo Stock Exchange Mutual Fund Index (OSEFX). Passive funds are often referred to as index funds.

An example of a passive fund is DNB Norge Index. Its prospectus states:

*"DNB Norge Index is an index fund with a passive investment strategy where the goal is to mimic the Oslo Stock Exchange Benchmark Index' portfolio and return as closely as possible. There will not be attempted to achieve a higher return for the fund than the OSEBX-index." (Morningstar, (2015))*

The advantage of passive management compared to active management is the fee level. Fees should be lower due to the limited resources needed to analyse the market. The main counterargument is the possibility of missing excess returns due to mispricing. However, mispricing is a question of whether markets are efficient or not. We will comment further on this in chapter 3.

*Active management*

The goal of active management is to achieve returns in excess of a benchmark. There are two main methods of active management. Active fund managers look for mispricing in the market, and trade based on their analysis of which sectors or companies are over (undervalued). This is known as alpha-bets or stock picking. The second way to beat the market is to change the exposure to the market by holding a low (high) beta portfolio when you believe the market will fall (rise). This is known as tactical allocation, beta-bets or timing (Døskeland, 2015) Active management requires that you have superior information about certain companies, sectors or the market in general compared to competitors. This is time-consuming and costly, but the best fund managers should be able to achieve positive alpha. If not, no investor would incur the costs of active management.

An example of an actively managed fund is DNB Norge Selektiv (I). The fund's investment philosophy is:

*DNB Norge Selektiv have an active investment strategy where the target is to achieve excess returns over the OSEBX. The fund managers has great freedom to make active shifts against the companies they believe has the greatest potential for value creation (Morningstar, (2015)).*

The benefit of active management is the potential excess return while the drawback is the higher fees and the incremental risk.

*Fee Structure*

When choosing a mutual fund, an investor should not only consider the investment policy and past performance, but also the management fees and other expenses. The fees each funds charge is stated in the prospectus. There are in general four classes of fees to be aware of.

The first type of cost is operating expenses, which is the cost incurred from operating the portfolio, including an advisory fee to the manager, and administrative expenses. These expenses are usually a percentage of total asset under management, and may range from typically 0.2% to 2%. The expenses are deducted from the assets of the fund. The second type of cost is the front-end load, which is charged when purchasing the shares. It might be as high as 6%, but has in recent years decreased or vanished due to increased competition in the Norwegian fund market. The third type of cost is back-end load or deferred sales charge. This fee incurs when you sell your shares. This might be up to 6% and is often reduced by 1 percentage point for every year the funds are left invested.  Many Norwegian funds have no back-end load due to competition. In addition, funds may claim a performance fee triggered when reaching a certain point of positive return (Bodie, 2014).

This section has introduced the mutual funds and the mutual fund market in Norway. Further, we will present finance theory that will add on the foundation needed to comprehend our study.

# 3. Theory

In this chapter, we introduce the fundamental theory necessary to understand the work we do. First, we look at different perspectives of return, before we introduce the basis of linear regression. In particular, we elaborate on the coefficient of determination ($R^2$) as this is the measure of active management in our thesis. Having the linear regression as a foundation, we visit the essential theory on the capital asset pricing model, the single-factor model and the multifactor model. Then we explain different measures of active management and introduce the efficient market hypothesis. A theory needed to understand the potential value of active management. Lastly, we define when a fund is active.

## 3.1 Returns

When calculating the average rate of return, there are two main methods; arithmetic returns and geometric returns. Which one to use depends on the calculations one wishes to conduct.

*Arithmetic average:*

$$\bar{r} = \frac{1}{n}\sum_{i=1}^{n} r(i)$$

Here the arithmetic average is represented by $\bar{r}$. Each period return is represented by r(i), and each observation is equally weighted. The formula tells us that the arithmetic average is the sum of all returns divided on the number of observations (n). This method is used when dealing with independent events and when calculating expected returns. The arithmetic average provides an unbiased estimate of the expected future return.

*Geometric average:*

$$Geometric\ return = \left(\prod_{i=1}^{n}(1 + r_i)\right)^{\frac{1}{n}} - 1$$

Geometric average return or time-weighted average return considers compounding and is often used as a metric when conveying return performance of investments. It also considers that negative returns should be weighted more than positive. I.e. a 50% loss on a 100 NOK investment require a 100% gain in next period to compensate. Because of this, the geometric return will usually be lower than the arithmetic.

*Excess return*

Excess return is often referred to as the rate of return above that of a risk-free investment. Nevertheless, it can also be used as the rate of return over a comparable investment or benchmark. Unless otherwise stated excess return refers to returns above benchmark in this thesis.

$$Excess\ return = r_i - r_b$$

where $r_i$ is the return of an investment or fund and $r_b$ is the return of a benchmark. Excess return is an important metric within the field of performance evaluation. However, excess return is not a good standalone measure of performance, as it does not reveal the additional risk taken to obtain this superior rate of return.

*Risk-adjusted return*

When considering returns one should always consider the amount of risk taken. Measuring performance based on excess return alone is not useful. Different investment styles induce varying levels of risk. This implies that managers should not be awarded for high returns if this is a result of excessive risk taking. Several measures of risk-adjusted returns exist, such as Sharpe ratio, Treynor's measure and Jensen's alpha (Bodie, 2014). The measure of risk-adjusted return in this thesis will be the intercept of the regression model, which we will denote as alpha (α). Alpha is the average return of the fund not predicted by a benchmark model, given the funds exposure to well-known risk factors included in the benchmark model. By using alpha, we are able to consider risk and we can fairly compare funds' performance with each other. We will further explain alpha and its relation to the regression model in the following section.

## 3.2 Linear Regression

Linear regression analysis is a technique with linear parameters, where the dependent variable (explained variable) is a function of independent variables (explanatory variables), plus an error term. Multiple regression is a regression model with more than one explanatory variable that may affect the dependent variable. The general linear regression model can be written as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_i X_i + \ldots + \varepsilon_t$$

*where,*

*Y = the dependent (explained) variable*

*$X_i$ = the independent (explanatory) variables*

*$B_0$ = the intercept. It represents the average value of Y when X2 and X3 are set equal to zero, also known as alpha (α)*

*$B_1$ = partial slope coefficient. Measures the change in the mean value of Y, E(Y), per unit change in X1, holding X2 constant*

*$B_2$ = partial slope coefficient. Measures the change in the mean value of Y, E(Y), per unit change in X2, holding X1 constant*

*ε = the stochastic disturbance term which captures all factors that X misses that influences Y*

The goal of the regression model is to estimate the relationship between Y and $X_i$. To define the relationship we need a way to estimate the coefficients ($\beta_i$). One of the most used methods, which we use, is the Ordinary least squares.

### 3.2.1 Ordinary Least Squares

Ordinary least squares (OLS) is the method most frequently used to estimate a sample regression function. The goal of OLS is to fit a function with the data as closely as possible. It does so by minimizing the sum of the squared residuals from the data. The method involves taking the squared vertical distance from an observation to the estimated line and minimize the sum of these squares. If $y_t$ is the actual data point for observation t, and $\hat{y}_t$ is the estimated point on the regression line. Then the value $x_t$,$\hat{y}_t$ is the value for y the model will predict. In addition, we let $\hat{\varepsilon}_t$ be the residual, which is the distance from the actual observation y and the estimates value $\hat{y}$ on the regression line. For a detailed explanation of OLS, we refer to *Essentials of Econometrics (2010)*.

### 3.2.2 Coefficient of Determination ($R^2$)

In our thesis, the coefficient of determination ($R^2$, read as r squared) is an important measure so we will dedicate some time to explain and understand it. $R^2$ is computed by measuring the distance from the actual data point observation and the mean and predicted value of those observations. A high $R^2$ score is achieved if the squared distance between the actual observation and the mean is close to the squared distance between the predicted value and the mean. This is easily described in the equation below. We denote the actual observation $y_i$, the mean is $\bar{y}$ and the regression model's predicted value is $\hat{y}_i$.

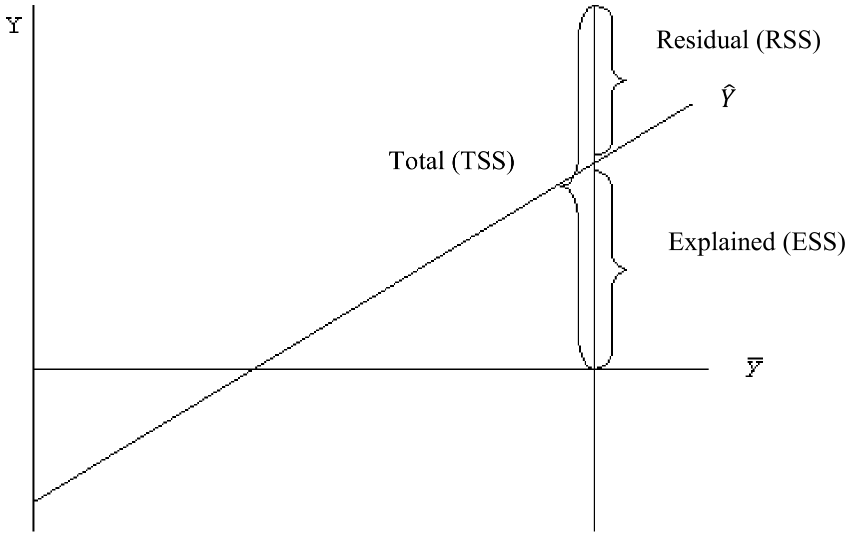
$$\underbrace{(y_i + \bar{y})}_{\text{Variation in } y_i \text{ from its mean}} = \underbrace{(\hat{y}_i + \bar{y})}_{\text{Variation in } y_i \text{ explained by } X(=\hat{y})} + \underbrace{(y_i + \hat{y}_i)}_{\text{Unexplained variation}}$$

Notice that the last part of this equation is the same as the error term of the regression model, denoted $\varepsilon_i$. In order to detect the absolute variations for all X values, each part of the above equation is summed and squared. This can also be written as:

$$TSS = ESS + RSS$$

Where TSS is the total sum of squares, ESS is the explained sum of squares and RSS is the residual sum of squares. As we can see the sum of ESS and RSS result in TSS, thus if RSS (the error term) takes on a small value then ESS explains the TSS well. This again will lead to a high $R^2$ value. To further illustrate this consider Figure 4:

**Figure 4: Sum of squares**




This relationship is described mathematically here:

$$R^2 = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}$$

Where,

$y_i$ = observed value

$\hat{y}_i$ = predicted value

$\bar{y}$ = mean of the observed data

From this equation, we can see that $R^2$ may be looked at as the percentage number of how well the regression model explains the true variations in the observed data. Hence, an $R^2$ value of 1 indicates that the model describe the actual variations perfect, or that an $R^2$ value of 0.5 indicate that the model only explains 50% of the true variation.

## 3.3 CAPM, Single-Factor and Multi-Factor Model

With the statistical foundation in place, we now move on by applying finance theory to the regression model.

Many recognize the Capital Asset Pricing Model (CAPM) as the number one asset-pricing model. This is in particular due to its simplicity and not necessarily grounded in its accuracy. Treynor, Sharpe, Lintner and, Mossin introduced the CAPM in the 60's and it is based on the work of Harry Markowitz in the field of modern portfolio management, where diversification is a key element. CAPM describe the pricing of stocks through a risk-free investment ($r_f$) and the market premium ($E(r_m) - r_f$) multiplied with that specific security's sensitivity to the market portfolio, represented by beta ($\beta$).

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f]$$

CAPM is an economic, equilibrium–based model intended to calculate the expected returns. Opposed to the single-index model, which is a statistical model of security returns. The single-factor model assumes that stocks have a tendency to move in tandem, driven by the same economic forces and thus, can be described by one factor. This factor is in most cases a broad market index (this thesis uses OSEFX as a market factor proxy). Symbolically it is similar to the CAPM as we can see below.

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

The individual stock sensitivity to market fluctuations is absorbed in the single-index beta (β). While the return not described by the model is captured by the models alpha (α). This is the metric used to describe risk-adjusted return in this thesis. Idiosyncratic risk is represented through the residual term epsilon (ε). Epsilon has an assumed normal distribution and a mean of zero and is, therefore, diversifiable. The total risk of an asset is described as:

$$\sigma_i^2 = \beta_i^2\sigma_m^2 + \sigma^2[\varepsilon_i]\,,$$

What we can see from this equation, with epsilon having a mean of zero, is that as we increase the number of assets in our portfolio the total risk ($\sigma_i^2$) is emerging towards beta times the market risk ($\sigma_m^2$). Thus, leaving us with only systematic risk ($\beta_i^2\sigma_m^2$).

In 1992, Eugene Fama and Kenneth French (1992) published a study where they observed deviation in returns in stocks with different characteristics on the New York Stock Exchange (NYSE), Amex and NASDAQ. This study, provoked by the observation of several empirical contradictions of the Treynor-Sharpe-Lintner-Mossin Capital Asset Pricing Model, identified stock characteristics that could more accurately describe a security's expected return. The 1992 study culminated in the well-known Fama-French Three-Factor Model (FF3F). The factors in the multi-factor model are based on factors that have earned premium returns over long periods, reflecting exposure to systematic risk and are grounded in the academic literature (Bender et al., 2013).

Inspired by Rolf W. Banz's (1980) earlier findings regarding the size effect, they developed a factor called Small-minus-big (SMB). Banz found that market capitalisation adds to the explanation of the cross-section of average returns provided by markets beta. Average returns on small market capitalisation stocks are too high given their beta estimates, and average returns on large market cap stock are too low.

The second factor, High-Minus-Low (HML), was inspired by Dennis Stattman (1980) and Barr Rosenberg, Kenneth Reid and Ronald Lanstein (1985). This factor uses book-to-market ratio and its relationship to abnormal returns compared to returns predicted by the CAPM. In greater detail it captures excess returns to stocks that have low market value compared to their fundamental value, often identified through their book-to-market ratio, hence the name value factor. These two factors in addition to the market factor $(R_m - r_f)$ constitute the Fama-French Three Factor Model, as shown below:

$$r_i - rf = \alpha_i + r_f + \beta_m(R_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_i$$

In a study on mutual fund performance, Carhart (1997) expanded the FF3F to a Four-Factor Model by including momentum as an additional explanatory variable. The additional factor is named UMD in our model and is based on the tendency of persistence in stock movement over time. With the new factor the model looks like this;

$$r_i - rf = \alpha_i + r_f + \beta_m(R_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_i$$

This is the main model used in this study to evaluate the funds exposure to well-known systematic risk factors and consequently their degree of active management.

## 3.4 Metrics of Active Management

This section will introduce different metrics for active management used by practitioners and academician. We look at how they differ and assess their strength and weaknesses.

### 3.4.1 $R^2$

$R^2$ is a measure of the relationship between the variance in returns of a fund and the variance in returns of a benchmark. A high $R^2$ indicate that the returns of the fund are highly correlated with the returns of the benchmark. Low $R^2$ indicates little correlation between fund returns and benchmark returns. As discussed in section 3.2.2, the measure originates as the coefficient of determination from the analysis of variance method (ANOVA). Hereunder, we will explain $R^2$ as a practical measure of active management rather than a statistical number.

To illustrate $R^2$ we use an example related to our thesis. Imagine we run a regression on the returns of fund X against the returns of the single-factor model, where we use OSEFX as the suitable market proxy. The regression gives us an $R^2$ of 1. This means that all of fund X's variation in returns can be explained by OSEFX's variation in returns. In other words, this implies that fund X and OSEFX have the same returns. Hence, fund X hold the same portfolio as OSEFX and can be characterized as an index fund. If $R^2$ is 0.5, only 50% of fund X's variation in returns are explained by the OSEFX returns. This indicates that fund X deviates from the index and is an actively managed fund.

We use the single-factor and four-factor model as models for estimation of $R^2$ in this study. The risk factors serve as explanatory variables and the $R^2$ (coefficient of determination) will indicate in what degree Norwegian mutual funds deviate from their benchmark and well-known risk factors. Moreover, a high $R^2$ indicates that the fund has low non-systematic risk (diversifiable risk), which means that the higher the value of $R^2$, the better diversification and less active it is. A fund that diverge from its reference index (and risk factors) will yield a lower coefficient of determination. Thus, the fund is more active and less diversified. $R^2$ is the preferred measure in this thesis due to its ability to absorb different types of risk (the four factors) and its simplicity.

### 3.4.2 Active Share

Active Share is simply the percentage of the fund's portfolio holdings that differs from the fund's benchmark portfolio holdings. For an all-equity mutual fund that has no leverage or short positions, the Active Share of the fund will always be between 0% and 100% (Cremers and Petajisto, 2009). Symbolically it can be formulated like this;

$$Active\ share = \frac{1}{2}\sum_{i=1}^{N} |W_{fund,i} - W_{index,i}|$$

Where $W_{fund,i}$ is the weight of stock i in the fund's portfolio, $W_{index,i}$ is the weight of the same stock in the benchmark portfolio, and the sum is computed over all the stocks in the applicable investment universe. Thus, in order to calculate active share you need data on the portfolio composition of the fund and its benchmark, which may be hard to obtain. If you get hold of this data, it is most likely going to be quarterly single point-in-time data, meaning that the day of data extraction holdings may differ substantially from the "typical" holding of the fund. In addition, few data points require longer observations to spot trends. This issue advocates the use of simpler measure for activeness like the $R^2$ measure used in this thesis.

### 3.4.3 Tracking Error

Tracking error (TE) can be described as the divergence between the return behaviour of a portfolio and the return behaviour of a benchmark. Contrary of what the name implies, high TE is not necessarily bad for an investor, as it only indicates variance of the difference in returns of a portfolio and a benchmark. Thus, a high TE could mean that your portfolio has outperformed the benchmark. Moreover, high TE indicates an active management strategy. Symbolically it can be noted as follows;

$$TE = \sqrt{}(Var(r_p - r_b)$$

Where $r_p$ is the return of the fund portfolio and $r_b$ is the return of the benchmark. TE is usually reported as standard deviation, and is often a measure used to regulate or evaluate mutual funds degree of risk taking compared to their mandate. A portfolio manager would like to have a low TE in combination with a high excess return over the benchmark. This indicate that the manager is achieving good return with a minimum of extra risk.

## 3.5 Efficient Market Hypothesis

To understand the dynamics of the formation of stock prices in the market we present the efficient market hypothesis (EMH). There is a close link between the EMH and the "random walk hypothesis" introduced by Eugene Fama (1965) in his Ph.D. thesis, "The Behaviour of Stock Market Prices" in 1965. Further on in 1970, in the paper "Efficient capital markets: A review of theory and empirical work" (Malkiel and Fama, 1970), he stated that "A market in which prices always "fully reflect" available information is called efficient". In an aforementioned market, only new information will affect the price of an asset. By definition, new information is random, and we get the link to the random walk hypothesis. Fama further introduced three different forms of efficient markets, weak form-, semi-strong form- and strong form efficient markets.

The *weak-form hypothesis* asserts that stock prices reflect all information derived by examining market trading data such as the history of past prices, trading volume, short interest, and so on.

The *semi-strong form hypothesis* states that all public available information is reflected in the prices. Public information includes relevant information about the prospects of the company. Such information would be, in addition to past prices, fundamental data on the firm's products, quality of management, balance sheet composition, earnings forecast, market position and so on.

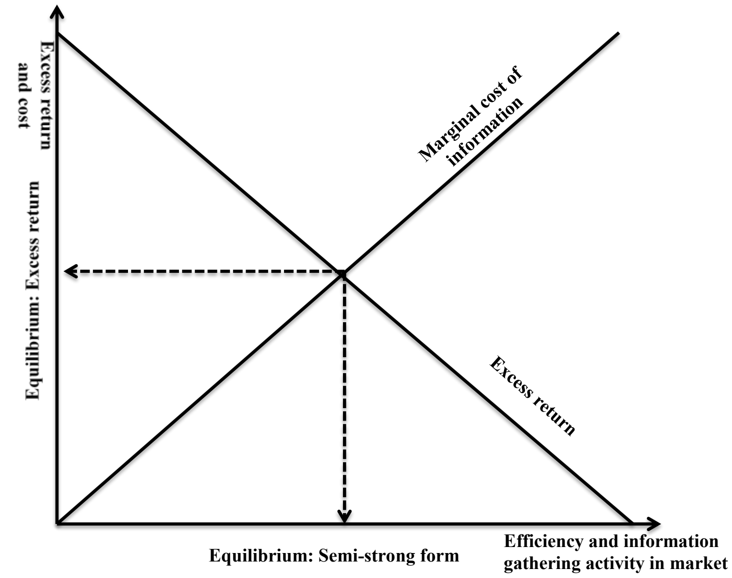
Finally, the *strong-form* version of the efficient market hypothesis states that stock prices reflect all information relevant to the firm, public or non-public. This version is quite extreme: e.g. few would argue that non-public inside information is sooner available to corporate officers at the firm than the markets participants.

So what are the implications of the EMH and the prospects of excess return based on market analysis? Technical analysis is the search for recurrent and predictable patterns in stock prices. The efficient market hypothesis claims that all information regarding past prices is reflected in stock prices and technical analysis is, therefore, useless in the quest for excess returns. Fundamental analysis uses earnings and dividends prospects of the firm, expectations on future interest rates, and risk evaluations to determine the present value of the future cash flows available to investors. If you observe that today's stock price is below the present value of the future cash flows derived from your fundamental analysis, you believe the stock is under-valued and that you should buy the stock. Again, the efficient market hypothesis predicts that most fundamental analysis would be pointless. The fundamental analysis is based on publicly available information, thus also available to rival analysts. It is unlikely that your analysis of a firm will be significantly different or more accurate than that of rival analysts. On that basis, EMH regards fundamental analysis as futile. In best case, your excess returns, as a result of a fundamental analysis, would be enough to cover your cost of information gathering, processing and implementation of the analysis conclusion.

The EMH is the main argument for the proponents of passive portfolio management, mainly because of what is mentioned above. They believe that active management is largely a waste of resources and unlikely to justify the expenses that occur because of it. Therefore, they advocate a passive investment strategy that do no attempt to pick mispriced stocks. The strategy is rather to mimic a benchmark, and not try to find over- or undervalued stocks. A passive management is often characterised by a buy-and-hold strategy. Because the EMH indicates that stock prices are at fair levels, given all available information, it makes no sense to buy and sell frequently, which generates large transaction costs without increasing expected returns.

On the other hand, we have the advocates of active portfolio management. Amongst their strong arguments, we find the "efficiency paradox", introduced by Grossman and Stiglitz (1980). If all information were reflected in market prices, market agents would have no incentive to acquire the information of which prices are based. This indicates that excess returns indeed are obtainable through an active management strategy.

**Figure 5: The Grossman-Stiglitz Paradox**




If no market participants engaged in information analysis, then stock prices would no longer reflect all information and this would open for profits to be made by conducting such activity. More and more market participants would participate in this activity until the profit of information gathering no longer surpass the cost of collecting the information, thus ending up in a market equilibrium, where the average investor generates only enough profit to cover his cost. A point where the marginal income of information gathering equals the marginal cost of that activity. This implies that the best analyst in the market would generate a significant profit through active stock picking while the poor ones would destroy value for their investors.

## 3.6 Defining an Active Fund

An active fund manager can attempt to generate excess return compared to its benchmark in two different ways: either by stock selection or by factor timing (or both). Stock selection involves picking individual stocks which the manager expects to outperform its peers. Factor timing involves time-varying bets on systematic risk factors such as entire industries, sectors of the economy, or more generally any systematic risk relative to the benchmark index. It is not clear how to quantify active management across all funds, as funds favour one approach over the other (Cremers and Petajisto, 2009). With this in mind, we need to define what an active fund is. If a fund manager loads heavily on a well-known risk factor, e.g. SMB, and most of the excess return (over benchmark) can be explained by this exposure, should this be attributed to skill?

In this thesis, we use a multi-factor model based on established risk factors as a benchmark model for evaluating funds' activeness and risk-adjusted returns. We believe that this a fair model as an investor could buy cheap exposure to well-known risk factors in indices, ETF’s etc. Hence, exposure to well-known risk factors may not be regarded as active management. In addition, multi-factor models are the preferred method when evaluating fund performance. Nevertheless, as we will comment later, these systematic factors do vary over time and exploiting them efficiently require managers to conduct analysis and evaluate when to load in these factors. Thus, some would argue that this indeed is active management.

We now need to define when a fund is active based on our measure of activeness, $R^2$. There is no recognized definition of an active fund, but many practitioners say that an active fund should not score an $R^2$ over 0.90-0.95. As the Norwegian market is quite small, we believe that a 0.90 limit would be unfair. Because of the market size, there are fewer bets to do and the deviation from benchmark is harder to achieve without doing “unheard-of bets”. We define an active fund as a fund that has an $R^2$ below 0.95. Further, in this thesis we define funds with $R^2$ above 0.95 as “closet-indexers”. These funds charge fees as an active fund but barely deviates from their benchmarks.

# 4. Literature Review

To excel our study, we spent considerable time on a thorough literature review, trying to investigate and understand the topic and previous results. There are a great number of studies on fund performance, whereas studies on $R^2$ as performance indicator are not as widespread. We have delved into the world of literature attempting to excavate studies and research that are relevant for our study. Hereunder we present the essential works covering our topic.

In 2013, Amihud and Goyenko (2013) conducted a study called, "Mutual fund's $R^2$ as predictor of performance". The authors use $R^2$ to measure how active a fund is, and predict performance based on this measure. The study is conducted on US equity mutual funds in the period 1988-2010. Arguing that not all active mutual funds are equal, they believe in shifting the attention from active versus passive to further examining active management. Introducing $R^2$ as an intuitive and easily calculable measure of active management, they differ from studies using fund holdings data. Amihud and Goyenko point out the applicability of their measure compared the measures using fund holdings data. They emphasize on $R^2$'s ability to pick up several risk factors, whilst measures using fund holding data struggles to define an accurate benchmark portfolio. The Fama-French (1993) and Carhart (1997) model is the preferred model by Amihud and Goyenko, as the risk factors included are well documented and recognized. Applying an estimation period of 24 months and a test period of 1 month, they comply with findings on stock picking abilities and persistence. The result from their study is that $R^2$ is a significant predictor of fund performance. They find that $R^2$ is, with a negative coefficient, related to a positive alpha. Hence, management that is more active creates economic value. Sorting funds in each period into quintiles by $R^2$ and alpha they find that the most active funds with the highest alpha generate a significant alpha of 3.8% in the following period. They unveil a pattern where decreasing $R^2$ leads to higher returns. In addition, funds generating high alpha perform better than funds with low alpha in the subsequent period.

Cremers et.al. (2015) do a comprehensive study on fund performance, including the method that Amihud and Goyenko use, with historical data from 2002-2007. Their sample consists of funds domiciled in 30 different countries from North America, Europe (including Norway) and Asia. The authors calculate $R^2$ with a rolling window of 36 months, without justifications. In regards of four-factor alphas, they find that lower $R^2$ do not indicate better performance. In addition, the study presents median fund $R^2$ for each country. The median $R^2$ in their sample was 0.87, in comparison, the median in Norway was 0.89. It is noteworthy that their sample includes all equity funds and ETF's. The benchmark applied for Norwegian funds is the MSCI Norway TR.

Titman and Tiu (2011) assess the same research question only with hedge funds. Looking at the period 1994-2005 in the US, they find that $R^2$ is a predictor of performance. They find that hedge funds exhibiting lower $R^2$'s generates higher Sharpe ratios. That is higher return for a given level of risk.

There are several studies using fund holdings data determining the relation between active management and returns. Brands et.al. (2005), Kacperczyk et.al. (2005), Cremers and Petajisto (2009) and Cremers et.al. (2015) are some of the leading papers on the subject. These studies claim that active management, measured by the difference in portfolio composition (the weights of the stock held in a portfolio) between a fund and a benchmark, increases fund performance.

In Norway, Smørgrav and Næss (2011) and Post and Vethe (2012) both evaluate how active Norwegian funds are. Smørgrav and Næs measures active management with active share in the period 2003-2010. They find that almost 20% of Norwegian equity funds are "closet-indexers". However, after a thorough investigation, we are not entirely convinced by these results. According to Petajisto (2013), funds with active share below 20% are pure index funds, and funds with active share between 20-40% are "closet-indexers". This implies that there are several more Norwegian funds in their study that should be categorized "closet-indexers" than Smørgrav and Næss states. They further show that the most active portfolio (high active share) generates 0.67% higher return than the least active portfolio (low active share), although insignificant. After reading their study, we observe no significant relationship between active management and performance. Post and Vethe look at the activeness of Norwegian equity funds in the period 1996-2011. They use $R^2$ as their measure of active management and concludes that many Norwegian funds are "closet-indexers". More specifically, they unveil that around 190 000 investors own a "closet-index fund", which is quite a substantial amount regarding Norway's population of 5 million.

Recently Sørensen (2010) executed one of the most comprehensive studies on fund performance in Norway. He constructs a sample of Norwegian equity funds from 1982-2010, including dead funds. Using the Fama-French and Carhart benchmark model, he finds no evidence that active managed funds creates economic value to investors. He claims that alpha is indistinguishable from zero for active funds as a whole. Hence, actively managed funds have not outperformed the market (≈index funds).

Using data from markets worldwide, Dyck et.al. (2011) evaluates the value of active management. In short, they state that active management depends on the efficiency of the underlying market and how sophisticated the investor is. Moreover, they say that active fund managers in the US underperform, but in emerging market they do create economic value.

After a thorough review of existing empirical literature on active fund management and performance, we believe we have a sound understanding on the subject. Methodological issues are identified, and they will subsequently lay the basis for the methodology and data chapter.

# 5. Methodology

In this chapter, we explain the models we use to answer our research questions. Specifically, we express the regression equations we use and explain the different premises we apply. The thesis has three research questions and we present each individually. Research question three uses panel data, thus we introduce the basics of this method. Ordinary least squares and panel data has several assumptions for generating correct and efficient estimates. Therefore, we present a section where we check our sample for the required assumptions. In addition, we show how we correct our sample for violations of these assumptions.

## 5.1 Our Usage of the Methodology

### 5.1.1 Research Question I

We regress funds monthly excess returns (over one-month NIBOR rate) on the returns of two benchmark models. The first is the single-factor model expressed as

$$r_i - r_f = \alpha_i + \beta_i(\text{OSEFX} - r_f) + \varepsilon_i.$$

Secondly, we employ a factor mimicking portfolio benchmark, which we denote FFC, developed by Fama and French (1992) and Carhart (1997). This model uses the risk factors $R_M$-$R_f$ (market excess return, OSEFX-$R_f$), SMB (small-minus-big capitalisation stocks), HML (high-minus-low book-to-market ratio stocks) and UMD (preceding winner minus preceding loser stocks). The model is presented symbolically below:

$$r_i - rf = \alpha_i + \beta_m(R_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_i$$

This regression provides an alpha (intercept of the regression) and $R^2$ for each fund, as well as the risk factor coefficients. The risk factor coefficients allow us to attribute the differences in activeness to bets on well-known risk factors. From these results, we are able to analyse the activeness of funds based on $R^2$ in comparison to our benchmark models. In addition, the alpha obtained gives an insight to the risk-adjusted returns for each fund.

### 5.1.2 Research Question II

The main method used in research question 2 (RQII) is a rolling regression, where the actual regression model is identical to what we used in RQI. The estimation window in the rolling regression is set to a period of twenty-four months, followed by a test period of one month.[3] In the estimation period, we regress monthly excess returns (over risk-free return) for each fund on the FFC model, moving the window one month at a time. Hence, the regression window will be 1-24, 2-25, 3-26 and so on.[4] This regression gives us the alpha and $R^2$ for each fund in every estimation period, which we then use to construct portfolios in the next period. As our research questions states, we explore a strategy that predicts fund performance based on funds lagged $R^2$ (activeness) and alpha. First, we sort all funds into quartiles based on $R^2_{t-1}$ in each month t. Second, within each quartile, we sort funds into four more quartiles by their $alpha_{t-1}$. The latter we do because of Brown and Goetzmann (1995) earlier research of persistence in mutual fund performance. Each fund is equally weighted in their respective portfolios, this results in 16 (4x4) different portfolios.[5] The returns of these constructed portfolios are then regressed on the FFC-model described earlier to retrieve the alpha for each portfolio. We then use the results from this regression to analyse the risk-adjusted returns of the aforementioned strategy.

### 5.1.3 Research question III

We apply panel data, known as longitudinal data in research question III. Panel data consists of time-series for each unit in the sample, such as firm, country or fund, over several periods. A key feature of panel data is that the same cross-sectional units are followed over a given period, and includes both a time series and a cross-sectional dimension. Benefits reaped from observing the same units over time is that we can control for unobserved characteristics of the units, and it often allows us to study the result of decision making. However, we cannot assume

[3] The reason for the twenty-four month test period Busse (2005) findings that stock selection ability last a short period. In addition, Berk and Green's (2004) suggest that superior performance in mutual funds cannot persist due to decreasing returns to scale caused by large inflows when performing well.

[4] A full range of observations (n=24) is required for a fund to run the regression

[5] The number of funds in each of the constructed portfolios may vary due to the number of funds in each month does not always divide by 16.

that the distribution of observations are independent across time or unit. Factors that affect one firm's return in one year might affect other firms return as well. We will further comment on how to deal with this later (5.2.4). For a detailed explanation of panel data, we refer to Microeconomics Using Stata (2010), chapter 8.

Given the negatively skewed distribution of $R^2$, with the majority of values close to 1.0, we use a logistically transformed $R^2$. The transformed $R^2$ is denoted $TR^2$ and it is derived from the following equation:

$$TR^2 = ln\left[(\sqrt{R^2} + \frac{0.5}{n})/\ (1 - \sqrt{R^2} + \frac{0.5}{n})\right]$$

Where $TR^2_{i,j}$ is the transformed $R^2$ for each fund at time t, and n = sample size (24 months). This adjustment is first suggested by Cox (1970) and applied by Amihud & Goyenko (2013). It results in a more symmetric value than the raw $R^2$ provides. We regress $TR^2$ on lagged fund characteristics to examine if there is a relationship between fund characteristics and activeness. The characteristics we look at are operational expenses (fees), fund size, fund age and manager tenure. All explanatory variables are log transformed except fees. This provides the best distribution of the variables observations. Turnover is omitted due to missing data. In RQII $R^2$ is estimated over 24 months, hence we use nine non-overlapping periods of 24 months from 1996-2014. All fund characteristics are end of year before the start of the 24-month estimation period. The regression model described is expressed symbolically below:

$$TR^2_{i,t} = \beta_0 + \beta_1 Fees_{i,t-1} + \beta_2 \ln(Size)_{i,t-1} + \beta_3 (\ln(size))^2_{i,t-1} + \beta_4 \ln(age)_{i,t-1} + \beta_5 \ln(tenure)_{i,t-1} + \sum_{n-1}^{9} y_{nt}\ StyleDummy_{i,t-1} + \varepsilon_t,$$

where i=entity and t=time, $\beta_0$ is the intercept, $\beta_{1-5}$ represents the coefficients for the independent variables (fund characteristics), y is the coefficient of the style dummies and ε is the error term. Standard errors are clustered by fund.

## 5.2 Fulfillment of Regression Assumptions

In order to obtain the best estimate from the regression model, certain assumptions must be met. That is linearity in parameters, the error term is statistically independent, the expected mean of the error term is zero, homoscedasticity, no autocorrelation and no exact collinearity. A detailed explanation of these assumptions is presented in Appendix 1. In this subsection, we are looking at our data sample concerning if it fulfil these assumptions.

### 5.2.1 Normality of the Error Term

We execute the Ryan-Joiner test on our variables to check if the error terms of the returns are normally distributed. The null hypothesis ($H_0$) of the test is that the sample is normally distributed, meaning that a p-value less than a given significance level rejects the hypothesis that the data tested is from a normally distributed population. As seen in Appendix 2, the p-values of the Ryan-Joiner test on the sample of funds are presented. Only 7% of the funds satisfy the $H_0$ of the test and thus indicate that the error terms in our dataset are not normally distributed. We do not see this as a problem, as normality of the dependent variable residuals is not a prerequisite for obtaining robust output from our model (Gujarati, 2010). It is the following issues however, that will inflict with our analysis the most.

### 5.2.2 Heteroscedasticity

We ran the Breush-Pagan (B-P) test to test for Heteroscedasticity. The reason for this is that the B-P test checks for the linear form of heteroscedasticity, which suits our data well (Gujarati, 2010). Symbolically we can describe heteroscedasticity as follows:

$$E(\varepsilon_i^2) = \sigma_i^2$$

Where the subscript $_i$ indicate that the variance of $\varepsilon_i$ is no longer constant, but varies from observation to observation.

The results from the B-P test indicate that 64 % of our sample is heteroscedastic (Appendix 2). As a remedial measure, we use Newey-West (1987) corrected standard errors.

### 5.2.3 Autocorrelation

Autocorrelation can be viewed as "correlation between members of observations ordered in time" (Kendall, 1971). The theory of mean-reversion in stock returns, leads us to expect negative autocorrelation in our dataset. However, we find that our dataset generally does not indicate autocorrelation. To identify autocorrelation we have used the well-recognized Durbin-Watson test and the result is displayed in Appendix 2.

The implications of autocorrelation in our dataset would be underestimating the true variances and SE, thereby inflating the t-values. This would give the impression of coefficients being statistically different from zero when in fact it might not be. Thus, if left uncorrected, an insignificant relationship can be mistakenly viewed as highly significant. This will affect both the assessment of risk-adjusted returns, as well as lead to an inaccurate level of $R^2$. To adjust for any autocorrelation, we have as aforementioned used Newey-West (1987) corrected standard errors as done in Sørensen (2010). This method compensates for both heteroscedasticity and autocorrelation. Having checked and corrected for potential flaws in our method we are confident that the results from our study will be reliable and valid.

### 5.2.4 Panel Data Assumptions

When analysing panel data there are several different methods one could use, dependent on the sample. Since we have used OLS thus far, we thought of using pooled OLS on our panel data. We examined our dataset with the Lagrange multiplier test resulting in an exclusion of pooled OLS (see Appendix 3 for test results). We then ran the Hausman (1978) test to check whether to use fixed effects estimator or random effects estimator (Appendix 4). A shortcoming of the Hausman test is that it requires the random effects estimator to be efficient. That is, cluster robust standard errors should not differ substantially from default standard errors (Cameron and Trivedi, 2010). Since this is the case in our sample, we ran a robust Hausman test described by Wooldridge (2011). After conducting this test, we ended up using the fixed effects estimator (see Appendix 5 for test results). Standard errors are clustered by fund.

# 6. Data

To make sure our study is as comprehensive as possible we have spent considerable time and effort collecting and structuring our data sample. Whether the data is obtained accordingly is highly important for the soundness of our results. We use the highly trusted Morningstar Direct as our main source of data. In addition, we have used Børsprosjektet (NHH) as a supplementary source.

## 6.1 Norwegian Equity Mutual Funds

We obtain our data from Morningstar Direct, which has one of the most comprehensive databases on mutual funds in the world. Morningstar provides monthly net asset values (NAV), as well as fees, fund age, tenure, etc. The NAV assumes that all income and dividends are reinvested and are net of fees, but neglect front-end loads, deferred and redemption fees. In total, we obtain data for 59 actively managed open-end Norwegian equity mutual funds from January 1996 to December 2014. In addition, we collect data for six index funds for additional analysis. Asset management typically offers more than one fund, but we treat each fund as a separate unit. We include funds that have been terminated and incepted within our sample period, thus avoiding survivorship bias in our dataset. From the NAV we calculate monthly returns as follows:

$$r_{i,t} = \frac{NAV_{i,t}}{NAV_{i,t-1}} - 1$$

where, $NAV_{i,t}$ is the net asset value of fund *i* at month *t*, and $r_{i,t}$ is the return of fund *i* at month $t$.

Furthermore, we have calculated the gross returns by backing out the most recent net expense ratio. We do this as a simulation of the returns investors would have received had they not paid any expenses. This is useful in our analysis to get a clear picture of whether or not $R^2$ is a predictor of performance. Gross return is calculated as follows:

$$gr_{i,t} = \frac{1+r_{i,t}}{1 - \frac{er_i}{12}} - 1$$

where, $r_{i,t}$ is the net return for month $i$ and $er_i$ is the expense ratio for the fiscal year that covers month $i$. This calculation assumes that the fees are determined based on monthly ending net assets.

### 6.1.1 Criteria for Including Funds

To conduct this study as thorough as possible, we need to ensure that our sample is consistent with the intention of the thesis. Morningstar categorizes funds according to their style, asset allocation, investment region etc. Hence, we have the following criteria for a fund to be included in our sample.

- The fund is an open-end mutual fund
- The fund domicile is Norway
- The fund base currency is Norwegian kroner (NOK)
- The fund asset allocation in equity is greater than 80%
- The fund invests more than 80% of its assets in the Norwegian stock market

From our research question, it is clear that we solely want to look at Norwegian funds that are publicly available. Further, we restrict the study to focus on investments in the stock market. This leads to including funds that have its domicile in Norway and invests at least 80% of its assets in Norwegian equity.[6] We set the limit at 80% to ensure that funds holding cash positions or small investments in global stocks are included. It goes without saying that we exclude funds that primarily invest in bills, bonds, combination funds or other funds. By restricting the sample to funds that invest primarily in Norwegian equities, we will get more sound results as the benchmark we use will be more suitable. We have cleared our sample funds containing the word “index” or similar. In addition Morningstar sorts funds on their investment style, thus, we have removed funds with the same investment style as index funds. We will eventually expand our sample to include index funds to get an, even more, comprehensive study.

[6] Also defined by the Norwegian Fund and Asset Management Association VFF. 2015. *Standard for informasjon og klassifisering av aksje- og kombinasjonsfond* [Online]. Available: http://vff.no/bransjestandarder [Accessed 18.12 2015].

### 6.1.2 Survivorship Bias & Sample Period

Survivorship bias in a sample can severely affect the results. That is if funds that are shut down or merged are excluded from the sample, an overestimation of the average performance may occur. This is due to the tendency that poorly performing funds are shut down. We include terminated and incepted funds within the sample period, thus avoiding survivorship bias in our dataset. [7]

Studies on the US mutual fund market, such as Brown et.al. (1992) and Brown and Goetzmann (1995), find that the survivorship bias is significant. On the Norwegian market, Sørensen (2010) provides evidence that surviving funds have outperformed dead funds. Kosowski et al. (2006) include only funds that have existed for five years in their analysis. This will increase the survivorship bias to some extent, by removing poorly performing funds. Fama and French (2010) omits funds that were not initiated five years before the end of their estimation period. Sørensen (2010) on the other hand includes all funds with at least one year of activity. He believes that including poorly performing and short-lived funds are important to achieve accurate and survivorship-bias free understanding of fund performance. Choosing of the sample period can be seen as a trade-off between applicable and relevant data and getting enough observations to obtain statistical significance. We choose to use a sample period from January 1996 to December 2014. Pre-1996 fund data is inadequate, and moreover, the Norwegian fund market were not mature. We believe this period is sufficient to achieve sound results as it includes both bull and bear markets.

### 6.1.3 Adjustments to the Sample

We adjust the sample such that we remove the first data point if a full month of daily returns is not available. This means that if a fund starts trading in the middle of a month, the first return is at the end of next month. Just like the first month, we adjust the last month in similar manner. We do this to avoid biased returns caused by not trading a full month. We exclude funds with less than 24 months of return, as this is the minimum observations needed to

[7] No funds were excluded due to the 24-month estimation window, expect funds incepted less than 24 month prior to sample end date.

conduct our methodology.[8] In the case of missing values, we calculated fictive NAV for the applicable months. We did this by calculating the average of the previous and next month. Funds missing more than two observations were excluded from our analysis.

### 6.1.4 Fund Dataset Summary

In total, our dataset comprises of 59 active funds and an additional 6 index funds. In the table presented in Appendix 6, we observe each fund and its lifespan, number of observations, asset under management (AUM) and operating fees. The numbers of observations for the funds range from minimum 37 to maximum 228. The majority of funds have 180 (mean of 183) observations or more which provide a solid sample. The largest fund in terms of AUM is DNB Norge with NOK 8.93 billion while the smallest fund is FORTE Norge with NOK 19 million. The average AUM is 1.7 billion. With regards to fees, the highest operating expense in our sample is 2.27% charged by Eika SMB, with a fee mean of 1.43%. Storebrand Norge Institusjon (0.2%) charges the lowest operating expense, due to the minimum deposit of 100 million NOK.

Because of our survivorship-bias free dataset, we include incepted funds and funds that are liquidated or merged during our analysis period. Hence, our dataset will vary in number of funds and observations as seen in table 2. The second column in the table below reports the number of funds existing each year. The third (fourth) column reports the number of funds incepted (liquidated or merged) each year. The last two years do not include any incepted funds because of our requirement of a 24-month estimation period.

[8] 24 months is the minimum amount of observations needed to conduct our rolling regression.

**Table 2: Sample size through sample period**

| Year | Number of funds | | |
|---|---|---|---|
| | End of year | Incepted | Liquidated |
| 1996 | 28 | 4 | 0 |
| 1997 | 31 | 3 | 0 |
| 1998 | 38 | 7 | 0 |
| 1999 | 39 | 1 | 0 |
| 2000 | 42 | 3 | 0 |
| 2001 | 46 | 4 | 0 |
| 2002 | 51 | 5 | 0 |
| 2003 | 53 | 2 | 0 |
| 2004 | 54 | 1 | 0 |
| 2005 | 55 | 1 | 0 |
| 2006 | 54 | 2 | 3 |
| 2007 | 53 | 0 | 1 |
| 2008 | 53 | 0 | 0 |
| 2009 | 53 | 0 | 0 |
| 2010 | 53 | 0 | 0 |
| 2011 | 55 | 2 | 0 |
| 2012 | 54 | 0 | 1 |
| 2013 | 51 | 0 | 3 |
| 2014 | 44 | 0 | 7 |

## 6.2 Benchmark Models

In our analysis, we use both the single-factor model and the Fama-French and Carhart four-factor model as benchmark models. Hereunder, we present our choice of factors and their sources.

### 6.2.1 Market Return

In order to capture the activeness and risk-adjusted returns of each fund the best way possible, we need to find an appropriate benchmark. Each fund states in its prospectus what their defined benchmark is. The main question is which proxy for market return we should use to capture the market as a risk factor. The benchmark should be as broad as possible and capture the return in the applicable investment universe.

The Norwegian Fund and Asset Management Association set certain requirements for a benchmark. These include such as, the benchmark must be possible to invest in, well-defined, observable and has the same risk- and investment profile as the fund. However, the most important requirement is that the benchmark and the fund are based in the same investment universe. [9]

Oslo Stock Exchange (OSE) provides several indexes that could be suitable when studying Norwegian funds. I.e. sector-specific indexes such as OSE10 Energy and OSE35 Health Care. With a more global perspective, the MSCI World Index or MSCI Nordic Index are applicable. In our case the most fitting ones are:

- OSEAX – Oslo Stock Exchange All Share Index includes all stocks on Oslo Stock Exchange.
- OSEBX – Oslo Stock Exchange Benchmark Index includes most traded shares listed on Oslo Stock Exchange. Often referred to as “The main index”.
- OSEFX – Oslo Stock Exchange Mutual Fund Index is a capped version of OSEBX.

Most funds state OSEFX as their benchmark and Morningstar use OSEFX as their universal benchmark for Norwegian funds. The OSEFX is a capped version of the Oslo Stock Exchange Benchmark Index (OSEBX). The capping rules comply with the UCITS (Undertakings for Collective Investment in Transferable Securities) directives for regulating investments in mutual funds. The maximum weight of a security is 10% of total market value of index and securities exceeding 5% must not combined exceed 40%.[10] To achieve the best basis of comparison we use the same benchmark for all funds in the sample. We determined our benchmark’s market proxy by testing different indices on our sample. We found that OSEFX achieved the highest overall $R^2$, and thus, is the best fit for our dataset. This method of benchmark selection is in line with Petajisto & Cremers (2009). The choice of benchmark will

[9]http://vff.no/assets/Bransjenormer/Bransjeanbefalinger/Bransjeanbefaling-kriterier-for-valg-av-referanseindekser-for-aksjefond.pdf

[10] http://www.oslobors.no/markedsaktivitet/#/details/OSEFX.OSE/overview

affect the results of our study, but because of the aforementioned the OSEFX will provide the most trustworthy results.

### 6.2.2 Risk-Free Rate and Risk Factors

We construct monthly excess return for each of the funds and the market returns by deducting the one-month risk-free proxy from the returns. This is an estimate of one-month risk-free rate based on NIBOR, acquired from Professor Bernt Arne Ødegaard's website. [11] The time-series of monthly returns for the remaining factors of Fama-French and Carhart, that is the size-, book-to-market - and momentum factor, are also gathered from Ødegaard's website. Ødegaard's data is a well-known source on Norwegian stock market data and used by several studies on Norwegian mutual funds. Ødegaard constructs these risk factors for OSE in the same way as French does for the US stock market. [12] The size factor (SMB) is the returns of a portfolio that take a long position in small companies and a short position in large companies. The book-to-market factor (HML) is the returns of a portfolio that have a long position in companies with high book-to-market value and a short position in companies with low book-to-market value. The momentum factor (UMD) factor is a portfolio that is long in winners and short in losers from the previous year.

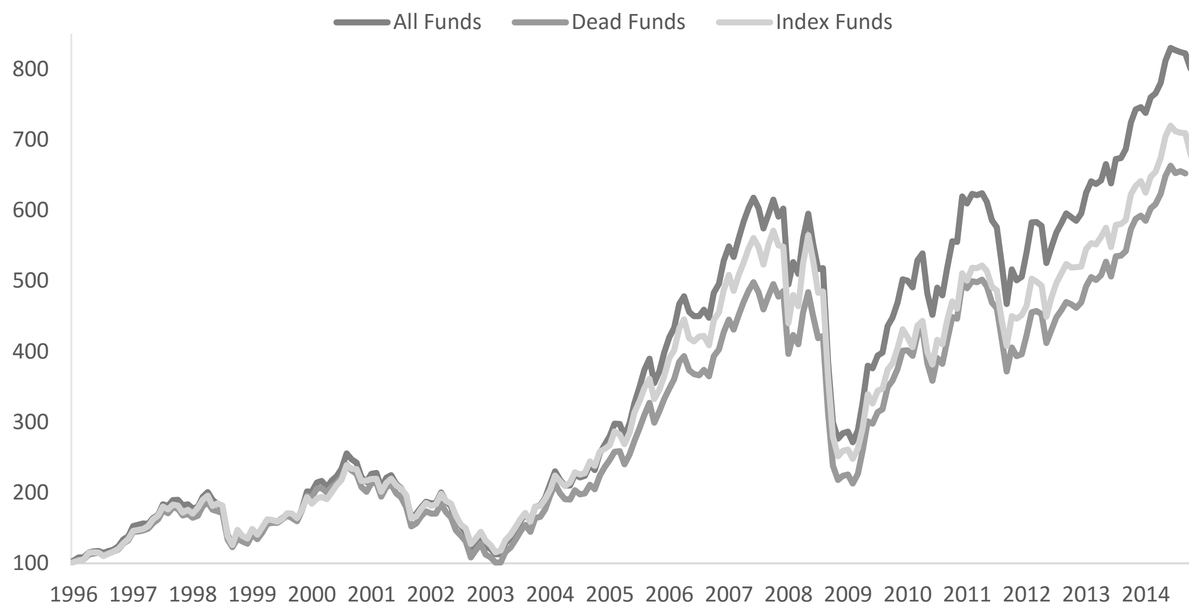
### 6.2.3 Summary Statistics

In the figure below, we have plotted the returns of all the funds in our sample, the index funds (≈OSEBX) and the dead funds. This illustrates the survivorship bias that would have been present if we had excluded the terminated funds. The returns of the dead funds have been substantially lower than the returns of an equally weighted portfolio of all funds.

[11] ØDEGAARD, B. A. *Asset pricing data at OSE* [Online]. Available: http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html [Accessed].

[12] FRENCH, K. R. *Current research returns* [Online]. Available: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html [Accessed 18.12 2015].

**Figure 6: Illustration of survivorship bias**




*Accumulated returns for all fund and dead funds, compared with index return*

In 2008, Næs et.al (2011) published a paper on known systematic risk factors on OSE. This research concludes with SMB and stock liquidity factor (LIQ) being present on OSE. Further, they claim that HML and UMD do not demand risk compensation, and is therefore not relevant for the Norwegian stock market. However, as stated by the Næs et.al. (2011), the reliability of these results are highly sensitive to the sample period. Therefore, we choose to use the FFC model as it is a common benchmark model in studies on fund performance, and also applied by Amihud and Goyenko (2013).

In the table below, we present the different return vectors. Mrkt is the market return (given by the OSEFX) excess of the risk-free rate (the 1-month proxy). SMB and HML are returns of the factor mimicking portfolios for size and book-to-market equity of Fama and French. UMD is the factor-mimicking portfolio for one-year return momentum. Column two reports yearly average return of the four portfolios. The third column reports the standard deviation of the return per year for each portfolio. Column four to seven reports the correlations between the factor portfolios.

**Table 3: Yearly average factor returns and SD and correlation matrix**

| | | | Correlations | | | |
|---|---|---|---|---|---|---|
| Risk Factor | Yearly Average Return | Standard Deviations | $R_m$ | *SMB* | *HML* | *UMD* |
| Mrkt | 8.63% | 22.58% | 1.00 | | | |
| SMB | 6.91% | 13.72% | -0.48 | 1.00 | | |
| HML | -1.96% | 15.71% | -0.20 | -0.04 | 1.00 | |
| UMD | 9.58% | 19.37% | -0.13 | 0.13 | -0.08 | 1.00 |

As we see from table 3, all factors except HML have quite high returns. The correlation between the factors are also relatively small which indicates that they do not capture the same risk.

# 7. Results

In this chapter, we present, comment and interpret our empirical results. We present the results separated into subsections based on research question I, II and III. In subsection one, we look at the degree of active management in Norway in the period under investigation. Then, in subsection two, we examine an investment strategy based on our measure of active management. Lastly, we investigate if we can identify fund characteristics effect on active management.

## 7.1 How Active are Norwegian Funds?

We start by addressing how active Norwegian equity mutual funds have been from 1996 to 2014. We use $R^2$ as a measure of active management and apply a four-factor model presented in chapter 5.1.1. The model includes the risk factors market return, SMB, HML and UMD. We do this to ensure conformity to similar studies. Second, to validate our result, we employ tracking error to measure active management. Furthermore, we look at index funds $R^2$ as a comparative basis in respect to the $R^2$ of active funds and "closet-indexers". Then, we consider fees and the degree of active management. Lastly, we compare our results with existing empirical literature.

### 7.1.1 Examining Active Management Using $R^2$

To examine active management among Norwegian mutual funds, we apply our two benchmark models and use $R^2$ as a measure of activeness. In the table below, we present the aggregate output from the time-series regressions of an equally weighted portfolio consisting of all funds in our sample.

**Table 4: Aggregate Output**

| Model | $R^2$ | α | Mrkt | SMB | HML | UMD |
|---|---|---|---|---|---|---|
| Single-Factor | 0.914 | 2.98% | 0.964 | | | |
| | | (3.30) | (60.54) | | | |
| FFC | 0.931 | 1.43% | 0.999 | 0.141 | -0.054 | 0.011 |
| | | (1.83) | (89.07) | (7.75) | (-3.78) | (0.93) |

*Aggregate output from the two regression models. The table shows results of an equally weighted portfolio of mutual fund returns regressed on the Single-factor model and the FFC four-factor model. Returns are gross of fees and alphas are annualized. $R^2$ is the average obtained from individual fund regressions. T-values are corrected according to Newey-West. The sample period is Jan. 1996 - Dec.2014.*

We see that the average $R^2$ is 0.914 when applying the single-factor model as the benchmark model. This number increases when we apply the four-factor model (FFC) resulting in an $R^2$ of 0.931. This means that on average about 7 % of the funds return variance is explained by something else than the risk factors in the FFC model. We see that all coefficients except the UMD are statistically significant. Norwegian fund manager's seems to load their portfolios on the SMB factor indicated by the coefficient of 0.141. We also note that the risk-adjusted gross return declines from 2.98% (3.30) to 1.43% (1.83) when applying the four-factor model rather than the single-factor. Rerunning the analysis with net returns, the alphas drop to 1.44% (1.64) and -0.08% (-0.10) for the respective models. Hence, we cannot claim that Norwegian equity mutual funds create significant risk-adjusted returns to its investors. This is in line with previous studies on the Norwegian mutual fund market, e.g. Sørensen (2010). In Table 5***: Individual Fund Output Using FFC Model*** we show the individual regression output for a selection of funds using the FFC model.

**Table 5: Individual Fund Output Using FFC Model**

| Rank/pctile | Date Span | $R^2$ | $r_i$-$r_m$ | α | Mrkt | SMB | HML |
|---|---|---|---|---|---|---|---|
| Most active | 199601-201412 | 0.785 | 3.91% | -0.53% | 1.022 | 0.448 | -0.244 |
| (Danske Inv. Vekst) | | | | (-0.19) | (25.24) | (6.83) | (-4.75) |
| 2 | 199601-201412 | 0.806 | 4.64% | 0.99% | 1.049 | 0.418 | -0.463 |
| (Storebrand Vekst) | | | | (0.34) | (24.99) | (6.16) | (-8.69) |
| 3 | 199706-201412 | 0.825 | 0.23% | -4.48% | 1.045 | 0.523 | -0.044 |
| (Nordea SMB) | | | | (-1.83) | (29.11) | (8.99) | (-0.97) |
| 10% | 200104-201412 | 0.852 | 5.10% | 1.51% | 1.171 | 0.588 | -0.082 |
| (DNB SMB) | | | | (0.52) | (27.90) | (7.91) | (-1.44) |
| 20% | 199803-201412 | 0.873 | 3.64% | 0.64% | 1.08 | 0.201 | -0.255 |
| (Atlas Norge) | | | | (0.26) | (31.02) | (3.58) | (-5.78) |
| Median | 199601-201412 | 0.953 | 4.17% | 3.19% | 0.967 | 0.014 | -0.107 |
| (Carnegie AksjeNorge) | | | | (2.64) | (56.40) | (0.50) | (-4.92) |
| 80% | 199601-201412 | 0.978 | 1.42% | 1.46% | 0.975 | 0.033 | -0.008 |
| (Nordea Avkastning) | | | | (1.82) | (85.06) | (1.77) | (-0.56) |
| 90% | 199601-201412 | 0.984 | 1.12% | 1.38% | 0.954 | -0.032 | 0.012 |
| (DNB Norge) | | | | (2.00) | (97.01) | (-2.01) | (0.95) |
| 3 | 199601-201402 | 0.985 | 0.82% | 1.26% | 0.964 | -0.009 | 0.005 |
| (DNB Norge Avanse I) | | | | (0.30) | (99.23) | (-0.55) | (0.43) |
| 2 | 199601-201402 | 0.985 | 1.85% | 1.96% | 0.959 | -0.006 | 0.006 |
| (DNB Norge I) | | | | (2.85) | (99.90) | (-0.37) | (0.52) |
| Least active | 199601-201412 | 0.985 | 2.01% | 1.55% | 1.007 | 0.038 | -0.015 |
| (Storebrand Norge) | | | | (2.26) | (103.16) | (2.41) | (-1.17) |
| Average | | 0.931 | 2.16% | 1.25% | 0.994 | 0.124 | -0.046 |

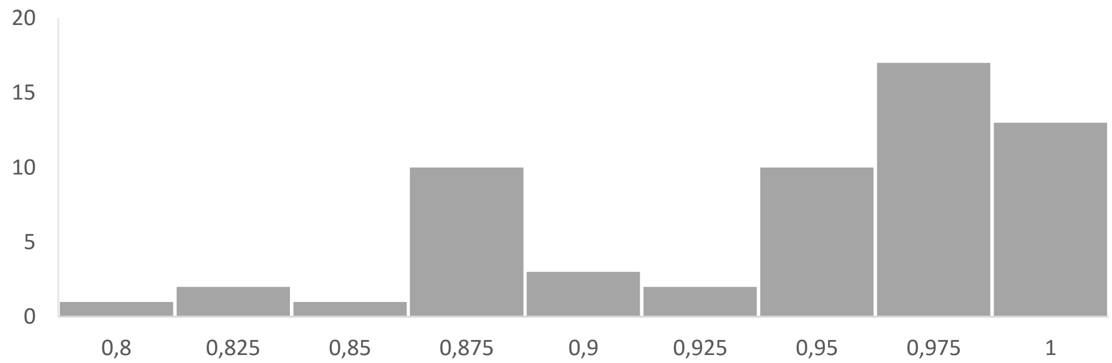
*The table shows individual fund and percentiles results employing the FFC model. Alphas are annualized. T-values are corrected according to Newey-West (1987). $R_i$-$r_m$ is the annualized risk-neutral return.*

By running the regression for each fund individually, it is possible to assess the activeness of each fund in our sample. The momentum factor (UMD) is omitted from the table, as it is insignificant for almost all funds. It is reasonable to think that this factor is not relevant in the Norwegian market, rather than the managers choose not to utilize this risk factor.

We find that the most active equity mutual fund in Norway from 1996-2014 has been Danske Invest Norge Vekst with an $R^2$ of 0.785. Its yearly risk-adjusted return is equal to -0.53% (risk-neutral yearly average return is 3.91%), though not significant. Then follows Storebrand Vekst and Nordea SMB with an $R^2$ of 0.806 and 0.825. We observe that many of the most active funds take more market risk than the benchmark. We find from both this output and further investigation, that funds that are more active in general have a market coefficient above 1. Indicating that these funds take active positions when it comes to market timing. The opposite is true for less active funds, which have a market coefficient similar to the index funds (as seen in Table 7). In addition, the more active funds load quite heavily on the SMB factor (most often significant). Whereas the average SMB coefficient is 0.124 for all funds, the most active half of our sample have an average coefficient of 0.224. Looking at the lowest $R^2$ quartile, the average SMB loading is 0.300. The size and liquidity of the Norwegian stock market might be a rationale for this result. To explain this, imagine a stock market comprising of five stocks. Stock A, B and C are large companies, D is mid-size and E is small cap with low liquidity. Due to the aforementioned UCITS regulations of fund management (The maximum weight of a security is 10% of total market value of index and securities exceeding 5% must not combined exceed 40%), funds have limited allocation options toward the large companies (A, B and C). If the fund managers wish to deviate from the benchmark, they are forced to take positions in the smaller company. Consequently, managers that want to deviate from the benchmark will get a bias towards small cap stocks, i.e. the SMB factor. In larger markets (NYSE etc.), a fund will more easily be able to construct a concentrated portfolio composed of several larger companies and still achieve a low $R^2$ score. As this section show, much of the proclaimed active management are accounted for by the SMB factor. As a consequence, loading in the SMB factor will not be ascribed to active management in our model.

The median $R^2$ score, here represented by Carnegie AksjeNorge, is 0.953. This means that half of the funds in our survivorship-bias free sample scores 0.953 or higher. This means that the FFC benchmark model explains 95% or more of the variation in returns for half of our sample of active funds. As discussed in section 3.6, a fund with an $R^2$ over 0.95 is categorised as a "closet-indexer”. These findings indicate that several Norwegian equity funds are essentially passive funds. In Figure 7, we illustrate the skewness in distributions of $R^2$ in our sample.

**Figure 7: $R^2$ Distribution of sample funds**




The histogram shows the number of funds within each $R^2$ interval.

We see that 50% of the Norwegian mutual funds have an $R^2$ higher than 0.95. This is consistent with what Professor Amihud found in the US market. His study revealed that the median fund in the US market had an $R^2$ of 93 %. "The great majority of funds are closet indexers," he says. "They tell you they are active funds and take your money but do something close to the index" (Wall Street Journal 2013 (Light, 2013)). A possible explanation for the lack of active management in Norway is found in Cremers et.al. (2015). They suggest that funds are more active when they face more competitive pressure from low-cost explicitly indexed funds. Hence, the low number of index funds in the Norwegian fund market might be an explanation of the scarcity of actively managed funds.

The least active fund in our analysis is Storebrand Norge with an $R^2$ of 0.985. This fund is creating an alpha of 2.55% (2.26), while not being especially loaded in any of the factors except the OSEFX. The competition for least active fund was quite hard as many funds scored just below 0.985. In general, the least active funds are not loaded in any particular degree towards the risk factors except the market. Since index funds represent a benchmark, they do not exploit the FFC risk factors in any particular degree. Therefore, it is natural that the least active funds are less exposed to the FFC factors.

### 7.1.2 Active Management Measured by Tracking Error

Due to the high share of “closet indexers”, we double check our results using tracking error (TE), introduced in section 3.4.3. TE and $R^2$ are both measures of return variance. Our main model will absorb exploitation of the FFC factors and such positions will not be ascribed as active management. Thus, potentially leading to higher $R^2$ than a corresponding TE measure. However, we do not find significant distinction in the different methods' result of activeness. The average TE for our sample is 6.52%, a number viewed by practitioners as low. In comparison, the index funds in our sample have a TE of 1.28%. As we sort all funds based on both $R^2$ and TE, excluding one extreme value, a fund on average moves two places using absolute values when changing ranking from $R^2$ to TE. This implies that the two different measures yield similar ranking of the funds concerning active management. More important it supports the fact that many Norwegian funds are "closet-indexers". As Table 6 shows, the different methods returns similar ranking of the funds in respect to their activeness/deviation to their benchmark. These findings support $R^2$ as our measure of activeness and indicate that our findings are robust against a change in measurement method.

**Table 6: Active Management Ranking Based on $R^2$ and TE**

| **Most Active** | | | | |
|---|---|---|---|---|
| **Ranking** | **Fund Name** | **TE** | **Fund Name** | **$R^2$** |
| 1 | StorebrandVekst | 15.19% | DanskeInvestNorgeVekst | 0.785 |
| 2 | DanskeInvestNorgeVekst | 13.76% | StorebrandVekst | 0.806 |
| 3 | GlobusAktivAcc | 13.61% | NordeaSMB | 0.825 |
| 4 | GlobusNorgeIIAcc | 13.36% | ParetoAksjeNorgeA | 0.846 |
| 5 | AlfredBergGambak | 12.53% | GlobusAktivAcc | 0.851 |
| 6 | NordeaSMB | 12.22% | DNBSMB | 0.852 |
| 7 | DNBSMB | 12.02% | ODINNorge | 0.857 |
| **Least Active** | | | | |
| 53 | DNBNorgeAvanseII | 3.06% | AlfredBergNorge | 0.983 |
| 54 | DNBNorge | 3.05% | DNBNorge | 0.984 |
| 55 | DNBNorgeIII | 3.03% | DNBNorgeIII | 0.984 |
| 56 | DNBNorgeI | 2.95% | DNBNorgeIV | 0.984 |
| 57 | StorebrandNorgeInstitusjon | 2.92% | DNBNorgeAvanseI | 0.985 |
| 58 | DNBNorgeAvanseI | 2.89% | DNBNorgeI | 0.985 |
| 59 | StorebrandNorge | 2.86% | StorebrandNorge | 0.985 |

*Ranking funds from most active management to least active management according to the two measures.*

### 7.1.3 Risk Factors Influence on Active Management

Figure 7 shows that the funds in our dataset are heavily skewed towards high $R^2$. Half of the funds are located in the area $R^2 > 0.95$. This observation supports the ongoing criticism of Norwegian funds, in that they barely deviate from their benchmark. Through this section, we analyse if the actively managed funds utilize the known risk factors in their pursuit to beat their benchmark, and as a consequence of this, the four-factor model absorbs this strategy resulting in a high $R^2$ and low alpha for these funds.

In this analysis, we introduce true index funds and compare them with the funds in our sample. An index fund is by definition a fund that imitate the index, and consequently, should score an $R^2$ close to 1.0. Index funds commonly charge low fees accordingly to its passive management. Hence, "closet-indexers" charging active management fees, might not be a worthwhile investment.

**Table 7: Loadings Active vs "Closet-Index" vs Index Fund**.

| | Regression statistics | | |
|---|---|---|---|
| Coefficients | Active | "Closet-Index" | Index |
| Market | 1.024*** | 0.975*** | 0.977*** |
| | (58.95) | (67.21) | (200.79) |
| SMB | 0.238*** | 0.023* | -0.001 |
| | (8.46) | (1.71) | (-0.24) |
| HML | -0.093*** | -0.010 | -0.003 |
| | (-4.22) | (-0.92) | (-0.64) |
| UMD | 0.007 | 0.011 | 0.001 |
| | (0.41) | (1.35) | (0.12) |
| Alpha(annualized) | 0.005 | 0.015** | -0.001 |
| | (0.38) | (2.59) | (-0.50) |
| $R^2$ | 0.888 | 0.972 | 0.997 |

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

$R^2$ is an average of the individual funds $R^2$ from the FFC-model. All other values is equally weighted returns regressed on the FFC-model. The benchmark for "active" and "closet-index" is OSEFX and the benchmark for "index" is OSEBX.

The index portfolio consists of an equally weighted portfolio of the Norwegian index funds available in the Norwegian market (n=6). We use OSEBX as this is the benchmark identified by index fund providers. In addition, we find that this index matches the movement of index funds the best. This method is in line with the benchmark identification method used by Petajisto & Cremers (2009). The active portfolio is constructed by the funds in our sample with an $R^2$-score less than 0.95 (n=29). The "closet-index" portfolio is an equally weighted portfolio of the fund in our sample that has an $R^2$-score higher than 0.95 (n=30).

As expected, the index funds are not loaded at all against the FFC factors. The FFC coefficients of “closet-index” funds are also small, with SMB as a nearly insignificant exception. We also observe that “closet-indexers” $R^2$ is not far from that of the true index funds. This may indicate that “closet-indexers” do not deliver the active management their fees imply. This is in line with the Financial Supervisory Authority of Norway criticism of Norwegian funds that charge active management fees, but cannot document their effort to actively beat the benchmark.[13]

If we then turn to the sample with low $R^2$ funds, we see that they have a heavier loading on the market factor and SMB factor. The higher market loading indicates that these funds are taking beta bets, taking on more market risk and potentially achieving higher returns. The higher SMB factor may indicate that the funds are deviating from their benchmark through exploiting the tendency of small companies outperforming large companies. This tendency is widely known, and it is based on the fact that smaller companies carry more risk than larger companies do. Because of this, such loadings will not provide a risk-adjusted alpha. Alternatively, the loading on SMB might come because of the competition in gathering superior information. Actively managed funds might, on the background of the efficient market hypothesis and the cost-income equilibrium, concentrate their analysis on smaller companies with fewer analysts following them. This could potentially explain some of the higher loadings in the SMB-factor. In addition, we have the “small market” argument from section 7.1.1, that also implies that active funds are “forced” into an SMB factor bias.

**Table 8: Single-Factor Loading**

| | Regression statistics | |
|---|---|---|
| Coefficients | Active | “Closet-Index” |
| Market | $0.963^{***}$ | $0.968^{***}$ |
| | (54.56) | (141.22) |
| Alpha$_{(annualized)}$ | $0.026^{*}$ | $0.018^{***}$ |
| | (1.77) | (3.22) |
| $R^2$ | 0.857 | 0.970 |

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

$R^2$ is an average of the individual funds $R^2$ from the FFC-model. All other values is equally weighted returns regressed on the FFC-model.

[13] http://www.finanstilsynet.no/no/Artikkelarkiv/Aktuelt/2015/2_kvartal/Aktiv-forvaltning-av-aksjefond--tematilsyn/

It is intriguing to see that the single-factor model alpha is higher for funds with $R^2 < 0.95$.This implies that active fund managers rely on the well-known risk factors to achieve higher returns. This may fool a naïve investor, in terms of higher absolute returns, but the risk-adjusted returns are lower. Active funds do not generate positive alpha when we adjust for the risk factors in our model. However, the "closet-indexers" do. This may indicate that “closet-indexers” have found the “secret sauce.”

### 7.1.4 Fees and Active Management

Discovering that much of the fund managers in our sample are relatively passive, we compare the degree of activeness with the fees associated with each fund. We introduce a new measure that we call *value for money* (VFM). This relates directly to active versus passive management. When charging higher fees, you expect the management to be active and potentially achieve risk-adjusted returns. The variable is a measure of the degree of active management you receive for the fee you pay, hence a higher value is better. *VFM* is calculated by the following formula:

$$VFM = \frac{(1 - R^2)}{Operating\ Fees}$$

The formula is straightforward and does not weight either of its components in any way. Hence, it assumes a linear relationship between activeness and fees, which might not be accurate in real life. However, it gives a good indication of whether you get what you pay for, that is active management and the opportunity to achieve risk-adjusted returns. As

show there is a vast amount of funds that are charging fees from 1.50-2.00% and manages the fund like an index fund. On the contrary, among the top 10 funds, we observe efforts of actual active management, in reference to their $R^2$ score. It is noteworthy that DNB has so many funds located in the lower part of the list. DNB is the fund provider that by far has most customers and accounts for a substantial part of the total amount invested in Norwegian funds. Why would anyone pay DNB 2% in yearly fees to manage the fund as an index fund, when they rather could buy an actual index fund with fees around 0.10%-0.30%? There is no guarantee that active management will yield higher returns. However, the managers should, at least, give the investors the opportunity of excess returns when charging "active fees". We see that there are indications that fund managers deprive investors of this opportunity. Cremers et. al.(2015) suggest that actively managed funds are more active and charge lower fees when they face more competition from true index funds. Hence, the lack of explicit index funds in Norway might be a reason for passive funds charging “active fees”. We do not want to further speculate on this, but we encourage others to further enlighten the field of fund management and fee levels in Norway.

**Table 9: Active Management to fee**

| Top 10 Fund Name | Fee ratio | $R^2$ | **VFM** | Net α | Bottom 10 Fund Name | Fee ratio | $R^2$ | **VFM** | Net α |
|---|---|---|---|---|---|---|---|---|---|
| Pareto Aksje Nor I | 0.50 | 0.859 | **0.28** | 1.96% | RF Aksjefond Acc | 2.00 | 0.967 | **0.02** | -0.44% |
| Globus Aktiv Acc | 0.80 | 0.851 | **0.19** | -6.40% | Alfred Berg Nor | 1.20 | 0.981 | **0.02** | 1.00% |
| Atlas Norge | 0.75 | 0.873 | **0.17** | -1.03% | DNB Nor (Avanse II) | 1.20 | 0.982 | **0.02** | -0.98% |
| ODIN Norge II | 0.90 | 0.861 | **0.15** | -1.60% | DNB Nor (III) | 1.09 | 0.984 | **0.01** | 0.75% |
| Pareto Investment | 0.50 | 0.938 | **0.12** | 1.28% | Alfred Berg Nor Etisk | 1.70 | 0.98 | **0.01** | -0.75% |
| Danske Inv. Nor | 1.75 | 0.785 | **0.12** | -2.27% | Nordea Avkastning | 2.00 | 0.978 | **0.01** | -0.56% |
| Storebrand Vekst | 2.00 | 0.806 | **0.10** | -1.02% | Storebrand Nor | 1.50 | 0.985 | **0.01** | 0.02% |
| Nordea SMB | 2.00 | 0.825 | **0.09** | -6.37% | DNB Nor | 1.80 | 0.984 | **0.01** | -0.57% |
| Pareto Aksje Nor A | 1.84 | 0.846 | **0.08** | -0.02% | DNB Nor (I) | 1.80 | 0.985 | **0.01** | -0.01% |
| DNB SMB | 2.01 | 0.852 | **0.07** | -0.00% | DNB Nor (Avanse I) | 1.81 | 0.985 | **0.01** | -0.57% |

*Alphas are net of fees. Alphas are almost exclusively insignificant. Institutional funds are not included as their fee level is incomparable to other funds due to a minimum investment of 100 million .VFM is the value for money metric.*

### 7.1.5 Comparison to Other Studies on Active Management

Post and Vethe’s (2012) study support our findings. They conducted a similar study on the Norwegian market, which indicated that many of the most popular Norwegian funds are merely "closet-indexers". Smørgrav and Næss (2011) used Active share (AS) as their measure of activeness. They found that 20% of funds are classified as "closet-indexers" while another 30% are close to being "closet-indexers". However, there are reasons to believe their findings are biased. Suppose a fund has the OSEFX as its stated benchmark and invests passively most of its assets in this index and the rest passively invested in the OSESX (Small Cap index), which on average outperforms the OSEFX. This fund will have a positive active share given that its portfolio deviates from its benchmark's portfolio (OSEFX), and hence it will be considered active, although it is in fact a passive indexer. On the other hand, $R^2$ from a risk factor model will identify this indexing and its $R^2$ will be closer to one. Thus, we believe Smørgrav and Næss are underestimating the number of "closet-indexers" and that our results are more descriptive of active management in the Norwegian fund market.

## 7.2 Picking Winners Based on Degree of Active Management

Now we construct portfolios based on preceding $R^2$ and alpha to see if fund activeness can predict risk-adjusted returns. The methodology used is explained thoroughly in chapter 5.1.2. Further, due to the two-sided profile of our fund sample, we do some adjustments to how many portfolios applied in the method. In addition, we conduct the same method using the single-factor model. This will adjust for the effect of risk factor loading by active managers.

### 7.2.1 Lagged $R^2$ as a Predictor of Performance

In this section, we examine if it is possible to use lagged $R^2$ as a predictor of performance. We have in total 59 funds included in this analysis. The number of funds each year differentiates, depending on the number of funds existing each year. Hence, the 16 portfolios do not have the same amount of funds each period, but since this is an equally weighted portfolio, it will not be a problem for the analysis.

$R^2_{t-1}$ and $alpha_{t-1}$ refer to the 24-month regression window preceding the investment period of one month. $R^2_{t-1}$ is listed in quartiles from left to right, low $R^2$ value to high $R^2$ value. $Alpha_{t-1}$ is listed in quartiles from top to bottom, low alpha value to high alpha value. The $R^2_{t-1}$ low-minus-high portfolio consists of a long position in funds with low $R^2$ value and a short position in funds with high $R^2$ value. The $alpha_{t-1}$ high-minus-low portfolio is long in high alpha value funds and short low alpha value funds. The values in the table are annualized monthly risk-adjusted alphas. In parenthesis, we observe the estimated Newey-West (1987) corrected t-statistics.

**Table 10: FFC Results**

**Portfolio alpha, sorting on lagged $\mathbf{R^2}$ and alpha**

| | $R^2{}_{t-1}$ | | | | | |
|---|---|---|---|---|---|---|
| $Alpha_{t-1}$ | Low | 2 | 3 | High | All | Low-High |
| Low | -0.025 | -0.004 | 0.015 | 0.011 | 0.002 | -0.035* |
| | (-1.11) | (-0.23) | (1.25) | (1.50) | (0.14) | (-1.66) |
| 2 | -0.024 | 0.023* | 0.006 | 0.025*** | 0.006 | -0.048** |
| | (-1.07) | (1.79) | (0.65) | (3.81) | (0.62) | (-2.23) |
| 3 | 0.014 | 0.029** | 0.019** | 0.018*** | 0.010 | -0.004 |
| | (0.68) | (2.19) | (2.53) | (2.60) | (1.47) | (-0.18) |
| High | 0.015 | 0.004 | 0.014 | 0.012* | 0.010 | 0.003 |
| | (0.90) | (0.38) | (1.52) | (1.96) | (1.10) | (0.21) |
| All | -0.003 | 0.013 | 0.014* | 0.016*** | 0.012 | -0.018 |
| | (-0.16) | (1.25) | (1.94) | (3.16) | (1.48) | (-1.25) |
| High-Low | 0.042** | 0.008 | -0.001 | 0.001 | 0.008 | |
| | (2.18) | (0.49) | (-0.06) | (0.21) | (0.70) | |

** $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$*

*In each cell (portfolio), we present the annualized alpha, using monthly gross returns. The t-statistics (parentheses) are estimated using robust standard errors (Newey and West, 1987).*

Looking at the "High-minus-Low" $alpha_{t-1}$ portfolios, we see that the portfolio performance increases as $R^2{}_{t-1}$ decreases. The highest return in this sample is located amongst these portfolios, more specifically in the "Low" $R^2{}_{t-1}$ quartile with an alpha of 4.2%. Thus far, it seems to be a possibility that the most active funds could be future winners.

A more in-depth review shows that there is no particular trend in the "High" $alpha_{t-1}$ portfolios, when moving from most active to least active. If we look at the "Low" $alpha_{t-1}$ portfolios, a more evident tendency appears. The more active funds seem to perform worse than the less active, especially the "Low" $R^2{}_{t-1}$ portfolio with alpha -2.5%, though not significant. It seems that the trend in the "High-minus-Low" $alpha_{t-1}$ portfolios is rather explained by the poor performance of "Low" $alpha_{t-1}$ portfolios, than the superior performance of "High" $alpha_{t-1}$ portfolios.

When looking at the $R^2{}_{t-1}$ quartiles without sorting for $alpha_{t-1}$ ("All"), we observe an increasing alpha when moving from left (low $R^2{}_{t-1}$) to right (high $R^2{}_{t-1}$). The four $R^2{}_{t-1}$ quartiles generates values of -0.3%, 1.3%, 1.4% and 1.6% respectively, whereas only 1.4% and 1.6% is significant. This indicates that less active funds create larger risk-adjusted returns, gross of fees. This is in line with findings from other studies on the Norwegian mutual fund market.

Sørensen (2010) states that active funds do not outperform the index funds. Since "closet-indexers" barely diverge from the benchmark, you would expect the same to apply for this category of funds. Hence, our findings support other studies on the subject in Norway saying that, considering the differences in fees, investors are better off investing in index funds.

A final evidence on $R^2$ as a predictor of performance is found in the "Low-High" $R^2_{t-1}$ column. The "Low" and "Second" $alpha_{t-1}$ quartiles generate negative returns, whilst the two highest $alpha_{t-1}$ quartiles are more or less zero. This indicates that investing in the most active and shorting the least active ones would generate negative returns. This is also indicated when not sorting for alpha with a value of -1.8%.

In general, the "High" $R^2$ portfolios have higher alphas and more significance than the rest. We do not find enough consistency in our results to conclude that $R^2$ is a predictor of performance. However, it indicates that the least active managed funds are generating the highest risk-adjusted returns.

Another takeaway from this analysis is on persistence in performance. We see that the most active funds ("Low" $R^2_{t-1}$), in combination with a "High-minus-Low" $alpha_{t-1}$ portfolio generates a significant positive alpha of 4.2%. This indicates that if you were to invest in the most active Norwegian funds you should go for past winners. However, it is likely that this result is due to funds with low alpha is performing worse than the funds with high alpha is performing well. This is in line with Sørensen (2010) and Carhart (1997), stating that persistence is more salient for poor performing funds than for well-performing funds. In addition, we see that the "Low-minus-High" $R^2_{t-1}$ portfolio for the two lowest $alpha_{t-1}$ quartiles gives a negative return. They obtain alphas of -3.5% and -4.8% (significant), which again indicates persistence in poor performing funds. Ranking solely on $alpha_{t-1}$ "All $R^2$" we see that there is a trend, though not significant, in the relationship between $alpha_{t-1}$ and alpha of the portfolios. This may indicate that performance persistence among fund is present, at least over a 2-year period.

Similar studies conducted on other markets also show inconsistent results on the relationship of low $R^2$ and alpha. However, a study conducted on the US market shows that there is a relationship between low $R^2_{t-1}$ and high alpha (Amihud and Goyenko, 2013). We do not observe the same relationship between low $R^2_{t-1}$ and alpha. On the contrary, we observe that alpha increases as $R^2_{t-1}$ increases. However, the results are not statistically significant and in general, the alphas is rather small or negative. We have done our analysis with shorter and longer estimation windows, as well as investment period, without achieving results that differ from what we have presented.

As a final remark, we believe that the analysis is suffering from the skewness towards high $R^2$ in our sample. We have divided the sample into four quartiles based on $R^2$. However, due to the many funds scoring in the upper 90's on $R^2$, quartile three and four, will barely differ from each other. This interferes with our purpose, which is to see whether you can pick winners based on their degree of activeness. In the next section, we will try to cater for this by sorting $R^2$ in two groups based on their $R^2$, active funds and “closet-index” funds.

### 7.2.2 Active Funds vs. “Closet-Indexers”

Due to the rather small data sample (59 funds) and the samples two-folded profile concerning the $R^2$ distribution, we conducted the same analysis splitting the funds into two categories based on their $R^2$-score. We divide between fund with $R^2 > 0.95$ and $R^2 < 0.95$. This segregation criteria splits the sample down the middle leaving $R^2 > 0.95 = 30$ funds, and $R^2 < 0.95 = 29$ funds. This allows us to get a more distinct view on how the actual active funds have been performing against the "closet-indexers". In other words, we manage to distinguish the activeness of funds more clearly and hence examine what we intended to. From the table we see that the results are quite similar to what we observe in Table 10. Again, we find high alphas with the high $R^2$ portfolio. The alphas in the $R^2 > 0.95$ sample are all higher and more statistically different from zero than that of the $R^2 < 0.95$ sample. Indicating the same as in the previous section, “closet-indexers” outperform the actively managed funds.

**Table 11: Active versus "closet-index"**

**Portfolio alpha, based on sorting on lagged $R^2$ and alpha**

| | $R^2_{t-1}$ | | | |
|---|---|---|---|---|
| $Alpha_{t-1}$ | Low | High | All | Low-High |
| Low | -0.025 | 0.011 | 0.002 | -0.036* |
| | (-1.19) | (1.30) | (0.18) | (-1.83) |
| 2 | 0.016 | 0.019*** | 0.006 | -0.003 |
| | (1.21) | (2.99) | (0.63) | (-0.26) |
| 3 | 0.008 | 0.016*** | 0.010 | -0.008 |
| | (0.57) | (2.80) | (1.49) | (-0.57) |
| High | 0.013 | 0.014* | 0.011 | -0.001 |
| | (1.08) | (1.84) | (1.08) | (-0.07) |
| All | 0.005 | 0.015** | 0.012 | -0.010 |
| | (0.38) | (2.59) | (1.48) | (-1.07) |
| High-Low | 0.039** | 0.003 | 0.008 | |
| | (2.10) | (0.31) | (0.72) | |

** $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$*

*In each cell (portfolio), we present the annualized alpha, using monthly gross returns. The t-statistics (parentheses) are calculated using robust standard errors (Newey and West, 1987).*

In both cases, we see that the portfolio providing the highest returns (also most statistically significant) is the portfolio constructed by the lowest $R^2$ quartile and a long-short position in high-low alpha (3.9%). This would suggest that investing in actively managed funds that achieve significant returns in the previous period (24 months), may be a winning strategy. However, it may be the negative return of the low portfolio (-2.5%) that is the main reason for this outcome.

As a concluding remark, we maintain our view of investing with regard to a funds activeness. The least active funds, that is $R^2 > 0.95$, outperforms the most active half of the Norwegian funds.

### 7.2.3 Single-Factor Model

As we show in section 7.1.3, fund managers expose themselves to the risk factors included in the four-factor model (FFC). Using the FFC-model, funds are not rewarded for their exposure to these risk factors. In section 3.6, we describe the different definitions of active management. If timing (beta-bets) is actually considered active management, the four-factor model will be improper. Therefore, we examine the same hypothesis as in 7.2.1. but this time, we use the single-factor model. That is, we only use the market factor (OSEFX index) as the explanatory variable in our model. The result is presented in Table 12***: Single-Factor Results***.

**Table 12: Single-Factor Results**

**Portfolio alpha, based on sorting on lagged $\mathbf{R^2}$ and alpha**

| $Alpha_{t-1}$ | $R^2{}_{t-1}$ Low | 2 | 3 | High | All | Low-High |
|---|---|---|---|---|---|---|
| Low | 0.004 | 0.010 | 0.020* | 0.019*** | 0.020 | -0.015 |
| | (0.14) | (0.62) | (1.84) | (3.11) | (1.52) | (-0.57) |
| 2 | 0.020 | 0.028** | 0.014 | 0.024*** | 0.015 | -0.004 |
| | (0.84) | (2.30) | (1.39) | (4.11) | (1.58) | (-0.19) |
| 3 | 0.021 | 0.028** | 0.010 | 0.027*** | 0.014* | -0.006 |
| | (0.95) | (2.32) | (1.19) | (4.13) | (1.79) | (-0.29) |
| High | 0.055** | 0.034*** | 0.019** | 0.012** | 0.027** | 0.042* |
| | (2.19) | (2.91) | (2.12) | (2.08) | (2.21) | (1.76) |
| All | 0.026 | 0.026** | 0.016** | 0.020*** | 0.025*** | 0.006 |
| | (1.24) | (2.54) | (2.18) | (4.17) | (2.67) | (0.31) |
| High-Low | 0.051** | 0.023 | 0.000 | -0.007 | 0.007 | |
| | (2.41) | (1.48) | (-0.03) | (-1.03) | (0.54) | |

** p < 0.10; ** p < 0.05; *** p < 0.01*

*In each cell (portfolio), we present the annualized alpha, using monthly gross returns. The t-statistics (parentheses) are calculated using robust standard errors (Newey and West, 1987).*

If we compare these results with the ones from Table 10 (7.2.1.), we observe much of the same pattern. However, there are some interesting differences. We observe a decreasing alpha moving from left to right in the "High-minus-Low" $alpha_{t-1}$ column. This is only a weak indication of low $R^2$ being a predictor of better performance, as the only significant alpha (5.1%) is found under the "Low" $R^2{}_{t-1}$ column.

Looking at the top quintile $alpha_{t-1}$ ("High") and the returns of the different $R^2{}_{t-1}$ portfolios, we see a significant decreasing alpha moving from most active to least active. This further strengthens the impression of low $R^2{}_{t-1}$ as a predictor of better performance. In fact, the "Low" $R^2{}_{t-1}$, "High" $alpha_{t-1}$ portfolio is producing the table's highest returns of 5.5%.

Examining the "Low" $alpha_{t-1}$ row, we see the opposite, where alpha increases moving from left to right. The second, third and "All" $alpha_{t-1}$ rows provides a lot more ambiguous result.

In general, the "High" $R^2_{t-1}$ column is generating the most significant returns, with exception of the "High" $alpha_{t-1}$ row.

Further, we turn our attention to the theoretical portfolio that has a long position in low $R^2_{t-1}$ quintile funds and a short position in high $R^2_{t-1}$ quintile funds. The returns of this portfolio are presented in the rightmost column of the table. We see that the alphas in this column is more or less zero, for all the portfolios in the bottom three quartiles of lagged alpha. However, an exception is the top quintile $alpha_{t-1}$, which has a positive and significant alpha of 4.2%. This indicates that $R^2_{t-1}$ predicts winners amongst the previous best performing funds.

We notice from the lagged $R^2$ columns, that alpha is less dependent on the preceding alpha as the lagged $R^2$ increases. Meaning that the distance between winners and losers amongst active funds is bigger than that of less active funds. Thus, it looks like investors have more to gain from looking at past performance when choosing more actively managed funds. Amongst the least active funds, past performance does not seem to predict any particular alpha in the next period. This trend is easily observed in the “High-minus-Low” alpha row.

The table gives  an interesting insight in the relationship between lagged $R^2$ and alpha. We see that the more active a fund is, the more you should emphasise on preceding performance when selecting which fund to invest. Among the preceding best performing funds it may seem like $R^2$ indeed is a predictor of performance. However, a low or high, $R^2_{t-1}$ do not consistently lead to higher returns. Thus, we cannot conclude with lagged $R^2$ being a credible predictor for future performance.

The ambiguous results derived from the previous sections motivated us to divide our dataset into periods with different economics cycles and market conditions. In the dataset period between 01.1996 and 12.2014, we observe three major events affecting the world’s financial markets. The Asia crisis (1997-1998), the dotcom bubble (2002) and the financial crisis (2008). We have used these events as points of shift when looking at the activeness among the funds. We conducted the methodology from section 7.2.1 (Appendix 7) and get very similar results in each period as we do in the overall study. Concluding with that over longer time periods (24 months) financial cycles do not provoke a significant change in active management of funds.

### 7.2.4 Comparison with Other Predictors of Performance

$R^2$ and Active Share (AS) are both measures of active management and are therefore potential predictors of performance. Our findings regarding performance are inconsistent with the findings in both Amihud & Goyenko (2013) and Cremers & Petajisto (2009). Amihud & Goyenko finds that $R^2$ is a significant predictor of fund performance, where the most active funds outperform the less active ones. Cremers & Pejajisto uses AS as a measure of activeness and finds evidence supporting Amihud & Goyenko. However, these are both studies on the US market. In Norway, Smørgrav and Næss (2011) conducted a study on the Norwegian market using AS. They imply that funds that are more active achieve higher risk-adjusted returns than less active funds. However, there is no clear pattern showing increasing alphas when AS increases. The only indication they find is that the high-low AS portfolio has a positive alpha of 0.67%, though not significant. We believe that the results are sensitive to what sample period we investigate and that this might explain some of the differences in results. Lastly, our results are more in line with other performance studies on the Norwegian market (Sørensen, 2010). After reviewing Smørgrav and Næss, we do not find a reason to believe that our findings are counterfactual, but rather result of different methodology and sample period. Furthermore, Cremers et. al. (2015) finds no evidence of R2 being a predictor of performance. As their study include European markets, including Norway, we find these results as a better comparison to ours.

## 7.3 Fund Characteristics Impact on Activeness

In this last section, we examine the effects of fund characteristics on its degree of active management. By fund characteristics, we mean attributes that the fund or fund management possess. In particular, we look at fund expenses, fund size, fund age, portfolio turnover[14] and manager tenure. Also, we look at different investment styles. We regress each characteristic for each fund on a transformed measure of active management, $TR^2$ (as described in section 5.1.3). The regression is run using panel data and the fixed effects estimator.

[14] This is a measure of the fund's trading activity, which is computed by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets.

## 7.3.1 The Determinants of Fund's $R^2$

We regress $TR^2_{j,t}$ on lagged fund characteristics obtained from Morningstar and Børsprosjektet (NHH). Since $R^2$ is estimated with a 24-month estimation period, we here use nine non-overlapping periods of 24 month from 1998 to 2014. The fund characteristics are end of the year before the beginning of the 24-month estimation period. The implications of fund characteristics is estimated by a panel regression with style dummy variables, shown in the equation below. The standard errors are clustered by fund.

$$TR^2_{i,t} = \beta_0 + \beta_1 Fees_{i,t-1} + \beta_2 \ln(Size)_{i,t-1} + \beta_3 (\ln(size))^2_{i,t-1} + \beta_4 \ln(age)_{i,t-1} + \beta_5 \ln(tenure)_{i,t-1} + \sum_{n-1}^{9} y_{nt}\, StyleDummy_{i,t-1} + \varepsilon_t,$$

In Table 13, we present the result. The coefficient of fees is negative, suggesting that management that is more active is associated with higher fees. Active funds gather and process vast amounts of information, an activity investors not easily can replicate and thus a cost they are willing to incur. The coefficient is significant thus linking active management with higher fees, as logically expected. However, as we saw in chapter 7.1.5., some funds charge high fees without engaging in active management.

The negative coefficient of fund age suggest that older funds are more active and selective than younger funds. This is somewhat strange if we think of survival bias. The hypothesis behind the survivorship bias is that poor performing funds will be euthanized. Active funds perform poorly, thus they should be replaced more often. Subsequently leading to lower age among low $R^2$ funds. Moreover, saying that older funds are more actively managed could be in line with what Chevalier and Ellison (1999) finds. Although, this will only be true if longer fund age is somewhat equal to longer tenure. Their study claims that junior managers tend to "avoid unsystematic risk when selecting their portfolio." Meaning that managers with short tenure choose higher $R^2$ investment strategies, leading to portfolios with higher systematic risk. However, the tenure coefficient is barely positive and insignificant, indicating that there is no such relationship present in our sample. We encourage further addressing of the matter.

When looking at the two size-related variables we observe that $R^2$ is an increasing and concave function of fund size. This is evident from the positive and negative coefficients of ln(size) and $[\ln(\text{size})]^2$, respectively. Large funds are forced to broaden their investments because of liquidity issues that arises from having large investment allocated over few stocks. That is, selling large volumes of a company's shares could provoke an unintentional decline in the share price, and even limit the possibility to sell because the lack of counterparts in the marketplace (Amihud et al., 2005). In addition, a positive relationship between $R^2$ and fund size may reflect managers' pursuit of status among their peers in managing a large fund (Van Binsbergen et al., 2008). Managers of small funds will try to improve their status by increasing their funds' size by choosing a more idiosyncratic investment strategy. Consequently resulting in smaller funds choosing strategies that lead to lower $R^2$. However, the t-statistics for the size coefficients are very low thus makes these considerations far from conclusive.

**Table 13: Determinants of $R^2$**

| *Explanatory variables, lagged* | *Dependent variable:* $TR^2_{j,t}$ |
|---|---|
| Fee | -0.607 (-4.57) |
| ln(size) | 0.018 (0.05) |
| $[\ln(\text{size})]^2$ | -0.0001 (-0.02) |
| ln(fund age) | -0.443 (-4.31) |
| ln(manager tenure) | 0.040 (0.61) |
| *Style dummy variables* | |
| Small Growth | 0.009 (0.03) |
| Small Blend | -0.397 (-1.21) |
| Small Value | -0.458 (-1.51) |
| Mid Growth | 0.226 (0.90) |
| Mid Blend | 0.023 (0.09) |
| Mid Value | -0.115 (-0.51) |
| Large Growth | N/A |
| Large Blend | 0.131 (0.55) |
| Large Value | 0.190 (0.80) |
| $R^2$ | 0.25 |

*$TR^2$ is estimated with a 24-month estimation period, using nine non-overlapping periods of 24 months from 1998 to 2014. The fund characteristics are end of the year before the beginning of the 24-month estimation period. T-values are presented in parentheses The $R^2$ presented in the table is this regression model's coefficient of determination.*

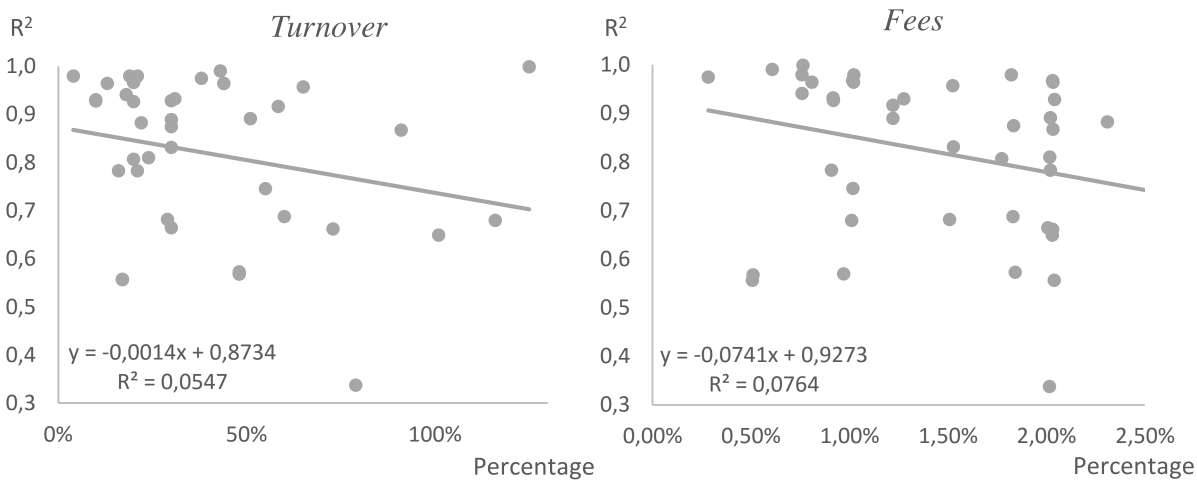
In the lower part of the table, we see how different investment styles ascribes to $R^2$. Morningstar Direct defines the different fund styles, and we have adopted their style definition. The large growth style is omitted, as there are not enough funds in our dataset that fulfil the style specifications. None of the dummies is significant, so we can only consider the coefficients as indication. As we saw in 7.1.1, active funds have a tendency to invest in small cap stocks, as seen by the negative coefficient in Table 13. A positive coefficient for the large style dummies indicates that these fund types are associated with higher $R^2$. High $R^2$ funds will have a portfolio composition close to that of the benchmark. Thus, it will include positions in the largest companies at OSE. Overall, the dummy coefficients are conforming with our previous findings.

### 7.3.2 A Snapshot of the Present Norwegian Market

In this section, we look at the Norwegian fund market today (end of our sample). Unlike the previous analysis, we will in this section present an overview of how fund characteristics affects activeness in the most recent years (2013-2014). We use the same methodology as previously where we use lagged funds characteristics. Hence, the graphs show end 2012 fund characteristics and $R^2$ calculated from January 2013 to December 2014.

Academia suggests that portfolio turnover is a measure of active management, and it is reasonable to believe that funds that are more active have higher turnover. Wermers (2000) find that funds with higher turnover outperform funds with lower turnover. However, turnover itself cannot produce excess returns. Excess returns are only obtained by a portfolio diverging from a benchmark (in our case the FFC-model). In recent years, Norwegian funds' activeness have a positive association with turnover. Norwegian funds, in general, seems to have a turnover around 20-40%, implying that Norwegian funds in general have a buy-hold strategy (Lawton, 2009).

**Figure 8: Scatter Plot Fund Characteristics, Turnover & Fees**

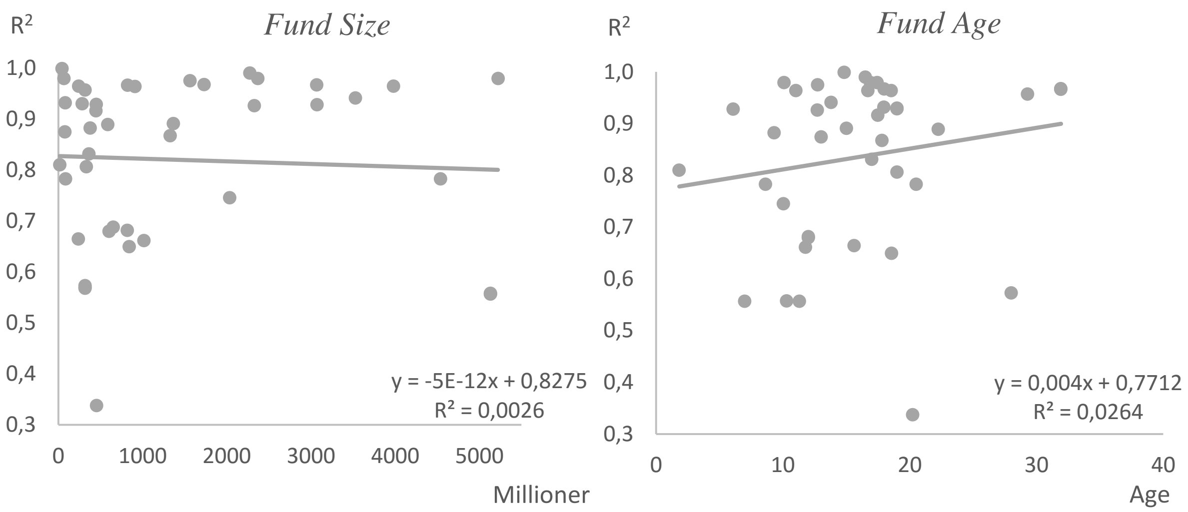



*The graphs show end 2012 fund characteristics and $R^2$ calculated from January 2013 to December 2014*

There should be a relation between fees and active management since market analysis is resource intensive. As expected, we find that higher fees relate positively to lower $R^2$. This is also in line with the panel regression. It is noteworthy that some funds still charge high fees while conducting passive management (funds located north east in the scatter plot). Investors should avoid these funds, and rather choose cheaper index funds. Even though The Financial Supervisory Authority of Norway criticized Norwegian funds for their lack of active management, there are still funds acting as "closet-indexers". This result is conforming to our results from section 7.1.

Amihud & Goyenko (2013) indicate that there is a negative relation between fund size and $R^2$. In this period, fund size has a slightly negative and insignificant coefficient, which yields an inconclusive answer to whether it affects a funds activeness in the recent years. We found the same relationship in our panel data regression.

**Figure 9: Scatter Plot Fund Characteristics, Size & Age**

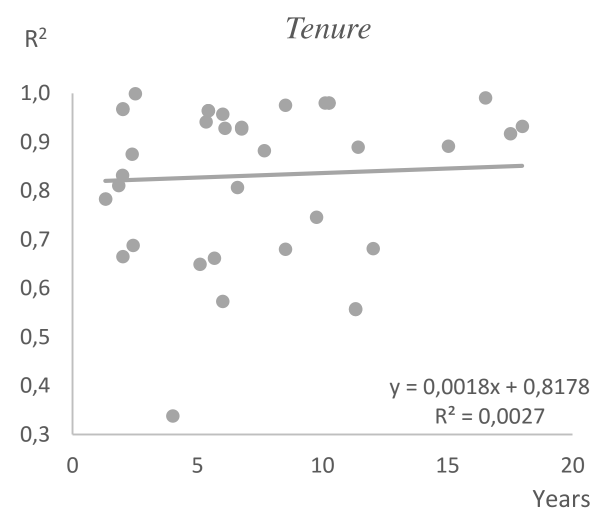



*The graphs show end 2012 fund characteristics and $R^2$ calculated from January 2013 to December 2014*

The relationship between fund age and $R^2$ is positive. This is as expected since the fund age coefficient for the whole sample period is positive and significant.

Tenure has a slightly positive line of regression implying that Norwegian funds nowadays are more active when the manager is less experienced. This supports our findings from the panel regression and the aforementioned theory, although the coefficient is insignificant.

**Table 14: Scatter plot fund Characteristics, Tenure**




*The graphs show end 2012 fund characteristics and $R^2$ calculated from January 2013 to December 2014*

# 8. Conclusion

Active fund management has been around since dawn and accounts for a substantial part of the equity fund market. In this thesis, we apply the determination of coefficient, or $R^2$, from a multifactor regression model as our measure of active management. Through a comprehensive empirical study of historical returns, we show that Norwegian fund managers might not be as active as they should. We find that half of our sample scores an $R^2$ of 0.95 or above, indicating that they are "closet-indexers". Comparing funds with $R^2$ less than 0.95, "closet-indexers" and true index funds, we find great similarities between the latter two, whilst the first group differ with more significant loading on the risk factors. The SMB factor absorbs most of the deviation from the market benchmark and reduces active management in general. We observe that many of the "closet-indexers" charge fees in line with the actively managed funds, meaning that many investors incur avoidable charges. Therefore, we would encourage investors to make use of their consumer power and be more critical of the fee levels charged by different funds.

Amihud and Goyenko (2013) conclude with a low $R^2$ being a predictor of better future performance. By using a rolling regression with a 24 months estimation window, we find no consistency indicating that low $R^2$ is a credible predictor of better performance in the Norwegian fund market. We find that high $R^2$, in general, outperform low $R^2$ portfolios when applying a four-factor model. When using the single-factor model, thus allowing utilization of the risk factors in active management, low $R^2$ seems to predict higher future performance among preceding winners. Interestingly, this relationship vanishes as we look at funds that performed poorly in the past period. Meaning that investor have more to gain from looking at past performance when investing in an actually active fund.

Examining the effects of fund characteristics on its degree of active management, we mostly find insignificant relationships. Across funds, higher activeness is only positively associated with expenses and fund age. Indicating that older funds are more active, and that fund, in general, do not charge fees unwarranted. However, as pointed out above, the latter should be considered wisely. Investment style coefficients suggest that funds that have a low $R^2$ invest in small size stocks while funds with high $R^2$ invest in large- and mid-size stocks. This is coherent with the apparent presence of loadings on the SMB factor.

Depending on your risk preference, if you only are looking for a broad market exposure, you should invest in index funds. If you are looking for a fair chance to beat the benchmark and competing funds, you should go for past winners among the most actively managed quartile of funds.

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# Appendices

### Appendix 1- Assumptions for using OLS

There are seven underlying assumptions for use of the OLS method on time series data.

1. The regression model is linear in the parameters and it is correctly specified.

2. X2 and X3 are uncorrelated with the error term (ε).

3. The error term u has a zero mean value, that is
$$E(\varepsilon_i) = 0$$

4. Homoscedasticity: This assumption is known as constant variance. The variance of the error variable $\sigma^2(\varepsilon)$ , is required to be constant. When this requirement is violated, the condition is called heteroscedasticity

5. Independent random variable: The random variables are not correlated (not all equal to the same constant) with one another, so that is,
$$E(u_i u_j) = 0, \;\; i \neq j$$
Breach of this assumption is autocorrelation.

6. No exact collinearity exist between X2 and X3

7. For hypothesis testing, the error term ε follows the normal distribution with mean zero and (homoscedastic) variance $\sigma^2$ that is, $\varepsilon_i \sim N(0, \sigma^2)$.

We would like to note that even if some of the assumptions are violated the method could still be used. The OLS will be able to estimate the parameters, however the standard errors will be less credible and thus affect the validity of hypothesis testing.

## Appendix 2 - Normality tests

| Funds | Autocorrelation DW-estimate | lower bound | Upper bound | Heteroscedasticity B-P p-value | Normality Ryan-Joiner p-value |
|---|---|---|---|---|---|
| Alfred Berg Aktiv | 1.590 | 1.728 | 2.272 | 0.283 | 0.000 |
| Alfred Berg Aktiv II | 1.647 | 1.679 | 2.321 | 0.000 | 0.004 |
| Alfred Berg Gambak | 1.530 | 1.728 | 2.272 | 0.000 | 0.000 |
| Alfred Berg Humanfond | 1.663 | 1.679 | 2.321 | 0.031 | 0.000 |
| Alfred Berg Norge + | 1.494 | 1.679 | 2.321 | 0.001 | 0.000 |
| Alfred Berg Norge Classic | 1.933 | 1.728 | 2.272 | 0.799 | 0.000 |
| Alfred Berg Norge Etisk | 1.644 | 1.592 | 2.408 | 0.001 | 0.000 |
| Atlas Norge | 1.672 | 1.728 | 2.272 | 0.000 | 0.000 |
| Carnegie Aksje Norge | 1.978 | 1.728 | 2.272 | 0.000 | 0.000 |
| Danske Invest Norge I | 1.966 | 1.728 | 2.272 | 0.000 | 0.000 |
| Danske Invest Norge II | 1.967 | 1.728 | 2.272 | 0.000 | 0.000 |
| Danske Invest Norge Vekst | 1.688 | 1.728 | 2.272 | 0.000 | 0.000 |
| Danske Invest Norske Aksjer | 1.770 | 1.679 | 2.321 | 0.083 | 0.000 |
| Danske Invest Norske Aksjer | 1.739 | 1.579 | 2.421 | 0.001 | 0.000 |
| Delphi Norge | 2.213 | 1.728 | 2.272 | 0.042 | 0.000 |
| DNB Norge | 1.910 | 1.728 | 2.272 | 0.001 | 0.000 |
| DNB Norge (Avanse I) | 1.896 | 1.728 | 2.272 | 0.869 | 0.000 |
| DNB Norge (Avanse II) | 1.873 | 1.728 | 2.272 | 0.935 | 0.000 |
| DNB Norge (I) | 1.768 | 1.728 | 2.272 | 0.047 | 0.000 |
| DNB Norge (III) | 1.836 | 1.728 | 2.272 | 0.002 | 0.000 |
| DNB Norge (IV) | 1.676 | 1.592 | 2.408 | 0.001 | 0.000 |
| DNB Norge Selektiv | 1.834 | 1.728 | 2.272 | 0.649 | 0.000 |
| DNB Norge Selektiv (II) | 1.820 | 1.679 | 2.321 | 0.011 | 0.000 |
| DNB Norge Selektiv (III) | 1.834 | 1.728 | 2.272 | 0.011 | 0.000 |
| DNB SMB | 1.666 | 1.679 | 2.321 | 0.017 | 0.057 |
| Eika Norge | 1.535 | 1.592 | 2.408 | 0.018 | 0.000 |
| Eika SMB | 1.795 | 1.679 | 2.321 | 0.001 | 0.001 |
| Fondsfinans Norge | 1.698 | 1.592 | 2.408 | 0.009 | 0.000 |
| FORTE Norge | 2.147 | 1.336 | 2.664 | 0.728 | 0.299 |
| Globus Aktiv Acc | 1.718 | 1.566 | 2.434 | 0.156 | 0.723 |
| Globus Norge II Acc | 1.698 | 1.579 | 2.421 | 0.084 | 0.845 |
| Handelsbanken Norge | 1.757 | 1.728 | 2.272 | 0.706 | 0.000 |
| Holberg Norge | 1.622 | 1.679 | 2.321 | 0.065 | 0.036 |
| KLP AksjeNorge | 1.843 | 1.679 | 2.321 | 0.041 | 0.000 |
| NB Aksjefond | 1.935 | 1.728 | 2.272 | 0.690 | 0.000 |
| Nordea Avkastning | 2.227 | 1.728 | 2.272 | 0.007 | 0.000 |
| Nordea Kapital | 2.245 | 1.728 | 2.272 | 0.761 | 0.000 |
| Nordea SMB | 1.865 | 1.728 | 2.272 | 0.000 | 0.202 |
| Nordea Vekst | 2.097 | 1.728 | 2.272 | 0.010 | 0.000 |
| ODIN Norge | 2.031 | 1.728 | 2.272 | 0.002 | 0.000 |
| ODIN Norge II | 1.500 | 1.592 | 2.408 | 0.003 | 0.000 |
| Pareto Aksje Norge A | 1.619 | 1.592 | 2.408 | 0.004 | 0.000 |
| Pareto Aksje Norge B | 1.602 | 1.592 | 2.408 | 0.001 | 0.000 |
| Pareto Aksje Norge I | 1.635 | 1.679 | 2.321 | 0.017 | 0.000 |
| Pareto Investment Fund A | 1.942 | 1.728 | 2.272 | 0.347 | 0.000 |
| Pareto Investment Fund B | 1.938 | 1.728 | 2.272 | 0.347 | 0.000 |
| Pareto Investment Fund C | 1.936 | 1.728 | 2.272 | 0.345 | 0.000 |
| PLUSS Markedsverdi | 2.006 | 1.728 | 2.272 | 0.000 | 0.000 |
| RF Aksjefond Acc | 1.698 | 1.592 | 2.408 | 0.000 | 0.005 |
| RF Plussfond Acc | 1.694 | 1.378 | 2.622 | 0.623 | 0.069 |
| Storebrand Aksje Innland | 2.092 | 1.728 | 2.272 | 0.724 | 0.000 |
| Storebrand Norge | 2.268 | 1.728 | 2.272 | 0.000 | 0.000 |
| Storebrand Norge H | 1.632 | 1.592 | 2.408 | 0.001 | 0.000 |
| Storebrand Norge I | 1.801 | 1.679 | 2.321 | 0.064 | 0.000 |
| Storebrand Norge Institusjon | 1.913 | 1.249 | 2.751 | 0.764 | 0.174 |
| Storebrand Optima Norge | 1.791 | 1.679 | 2.321 | 0.082 | 0.000 |
| Storebrand Vekst | 1.878 | 1.728 | 2.272 | 0.022 | 0.000 |
| Storebrand Verdi | 1.868 | 1.728 | 2.272 | 0.008 | 0.000 |
| Terra Norge | 1.547 | 1.679 | 2.321 | 0.000 | 0.000 |

**Appendix 3 - Breusch and Pagan Lagrangian multiplier test for random effects**

$TR^2$ [Fundid,t] = Xb + u[Fundis] + e[Fundid,t]

Estimated results:

| | Var | sd = sqrt(var) |
|---|---|---|
| $TR^2$ | 0.409293 | 0.63976 |
| e | 0.190077 | 0.435978 |
| u | 0.148181 | 0.384943 |

| | | |
|---|---|---|
| Test: | Var(u) = | 0 |
| chibar2 (01) | = | 72.9 |
| Prob > | chibar2 = | 0.00000 |

**Appendix 4 – Hausman test**

| | Coefficients | | | |
|---|---|---|---|---|
| | (b) | (B) | (b-B) | sqrt(diag(V_b-V_B)) |
| | fixed | random | Difference | S.E. |
| fee | -0.313 | -0.313 | -3.89E-15 | . |
| lnsize | 0.28541 | 0.28541 | -2.19E-13 | . |
| lnsize2 | -0.0083 | -0.0083 | 5.45E-15 | . |
| lnage | -0.027 | -0.027 | 1.28E-14 | . |
| lntenure | -0.033 | -0.033 | -1.08E-15 | 0 |

b = consistent under H0 and Ha; obtained from xtreg
B = Inconsistent under Ha, efficient under H0; obatained from xtreg

Test: H0: differences in coefficients nor systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 0.00
chi2 < 0 ==> model fitted on these data fails to meet the asymptopic assumptions of the Hausman test; see suest for a generalized test

**Appendix 5: Robust Breusch-Pagan test (Robust Hausman test)**

| tr2 | Coef. | Std. Err. | z | P> \|z\| | [95% Conf. Intervall] | |
|---|---|---|---|---|---|---|
| fee | -0.31303 | 0.10756 | -2.91 | 0.004 | -0.52383 | -0.10222 |
| lnsize | 0.28541 | 0.53185 | 0.54 | 0.592 | -0.75700 | 1.32783 |
| lnsize2 | -0.00829 | 0.01349 | -0.61 | 0.539 | -0.03473 | 0.01814 |
| lnage | -0.02705 | 0.07279 | -0.37 | 0.71 | -0.16971 | 0.11562 |
| lntenure | -0.03295 | 0.05130 | -0.64 | 0.521 | -0.13349 | 0.06759 |
| _cons | 1.27396 | 5.22918 | 0.24 | 0.808 | -8.97505 | 11.52297 |
| sigma_u | 0.38494245 | | | | | |
| sigma_e | 0.43597838 | | | | | |
| rho | 0.43807024 (fraction of variance due to u_i) | | | | | |

Test of over identifying restrictions: fixed vs random effects

Cross-section time-series model: xtreg re

Sargan-Hansen statistic 30.438 Chi-sq(5) P-value = 0.0000

# Appendix 6: Sample of funds

| Fund Name | Date Span | Observations | AUM (NOK Millions) | Operating fee (%) |
|---|---|---|---|---|
| Alfred Berg Aktiv | 199601-201412 | 228 | 452 | 1.50 |
| Alfred Berg Aktiv II | 199710-201209 | 180 | 16 | 1.60 |
| Alfred Berg Gambak | 199601-201412 | 228 | 877 | 1.80 |
| Alfred Berg Humanfond | 200001-201412 | 180 | 95 | 1.80 |
| Alfred Berg Norge + | 199801-201403 | 195 | 832 | 0.70 |
| Alfred Berg Norge Classic | 199601-201412 | 228 | 883 | 1.20 |
| Alfred Berg Norge Etisk | 200204-201403 | 144 | 75 | 1.70 |
| Atlas Norge | 199803-201412 | 202 | 43 | 0.75 |
| Carnegie Aksje Norge | 199601-201412 | 228 | 479 | 1.20 |
| Danske Invest Norge I | 199601-201412 | 228 | 512 | 2.00 |
| Danske Invest Norge II | 199601-201412 | 228 | 895 | 1.25 |
| Danske Invest Norge Vekst | 199601-201412 | 228 | 322 | 1.75 |
| Danske Invest Norske Aksjer Inst I | 200005-201412 | 176 | 3006 | 0.90 |
| Danske Invest Norske Aksjer Inst II | 200612-201412 | 97 | 5351 | 0.90 |
| Delphi Norge | 199601-201412 | 228 | 913 | 2.00 |
| DNB Norge | 199601-201412 | 228 | 7326 | 1.80 |
| DNB Norge (Avanse I) | 199601-201402 | 218 | 2171 | 1.81 |
| DNB Norge (Avanse II) | 199601-201409 | 225 | 75 | 1.20 |
| DNB Norge (I) | 199601-201402 | 218 | 2787 | 1.80 |
| DNB Norge (III) | 199603-201412 | 226 | 140 | 1.09 |
| DNB Norge (IV) | 200212-201412 | 145 | 8929 | 0.75 |
| DNB Norge Selektiv | 199605-201412 | 224 | 924 | 2.01 |
| DNB Norge Selektiv (II) | 200201-201412 | 156 | 283 | 1.01 |
| DNB Norge Selektiv (III) | 199601-201412 | 228 | 4214 | 0.80 |
| DNB SMB | 200104-201412 | 165 | 1118 | 2.01 |
| Eika Norge | 200310-201412 | 135 | 1276 | 2.00 |
| Eika SMB | 199805-201309 | 185 | 42 | 2.27 |
| Fondsfinans Norge | 200301-201412 | 144 | 2115 | 1.00 |
| FORTE Norge | 201104-201412 | 45 | 19 | 2.00 |
| Globus Aktiv Acc | 199812-200604 | 89 | N/A | 0.80 |
| Globus Norge II Acc | 199812-200610 | 95 | N/A | 2.00 |
| Handelsbanken Norge | 199601-201412 | 228 | 1765 | 2.00 |
| Holberg Norge | 200101-201412 | 168 | 603 | 1.50 |
| KLP AksjeNorge | 199904-201412 | 189 | 4715 | 0.75 |
| NB Aksjefond | 199609-201308 | 205 | 104 | 2.27 |
| Nordea Avkastning | 199601-201412 | 228 | 1806 | 2.00 |
| Nordea Kapital | 199601-201412 | 228 | 4111 | 1.00 |
| Nordea SMB | 199706-201412 | 211 | 154 | 2.00 |
| Nordea Vekst | 199601-201412 | 228 | 882 | 2.00 |
| ODIN Norge | 199601-201412 | 228 | 4874 | 2.00 |
| ODIN Norge II | 200406-201412 | 127 | 105 | 0.90 |
| Pareto Aksje Norge A | 200210-201412 | 147 | 1873 | 1.84 |
| Pareto Aksje Norge B | 200601-201412 | 108 | 912 | 2.01 |
| Pareto Aksje Norge I | 200110-201412 | 159 | 4426 | 0.50 |
| Pareto Investment Fund A | 199601-201412 | 228 | 232 | 1.80 |
| Pareto Investment Fund B | 199601-201412 | 228 | 23 | 0.95 |
| Pareto Investment Fund C | 199601-201412 | 228 | 150 | 0.50 |
| PLUSS Markedsverdi | 199601-201412 | 228 | 117 | 0.90 |
| RF Aksjefond Acc | 199711-200702 | 112 | N/A | 2.00 |
| RF Plussfond Acc | 200202-200605 | 52 | N/A | 2.00 |
| Storebrand Aksje Innland | 199608-201412 | 221 | 1569 | 0.60 |
| Storebrand Norge | 199601-201412 | 228 | 386 | 1.50 |
| Storebrand Norge H | 200511-201405 | 103 | 535 | 0.28 |
| Storebrand Norge I | 200005-201412 | 176 | 3929 | 0.28 |
| Storebrand Norge Institusjon | 201101-201401 | 37 | 760 | 0.20 |
| Storebrand Optima Norge | 200101-201412 | 168 | 323 | 1.00 |
| Storebrand Vekst | 199601-201412 | 228 | 632 | 2.00 |
| Storebrand Verdi | 199801-201412 | 204 | 1416 | 2.00 |
| Terra Norge | 199805-201309 | 185 | 605 | 2.20 |
| Alfred Berg Indeks I | 200411-201412 | 98 | 256 | 0.08 |
| Carnegie Norge Indeks | 199601-201412 | 228 | 13 | 0.80 |
| DNB Norge Indeks | 201009-201412 | 52 | 644 | 0.32 |
| KLP AksjeNorge Indeks | 200510-201412 | 111 | 8472 | 0.10 |
| KLP AksjeNorge Indeks II | 200810-201412 | 75 | 862 | 0.20 |
| PLUSS Indeks | 199601-201412 | 228 | 28 | 0.70 |

**Appendix 7: Period dependent results**

| $Alpha_{t-1}$ | $R^2{}_{t-1}$ Low | 2 | 3 | High | All | Low-High |
|---|---|---|---|---|---|---|
| Low | -0.060 | -0.039 | -0.055** | 0.004 | -0.042 | -0.064 |
| | (-1.19) | (-1.08) | (-2.17) | (0.33) | (-1.27) | (-1.45) |
| 2 | -0.059 | 0.003 | -0.025 | 0.009 | 0.000 | -0.067 |
| | (-1.12) | (0.12) | (-1.09) | (0.70) | (-0.02) | (-1.38) |
| 3 | 0.002 | -0.006 | 0.000 | 0.012 | 0.012 | -0.009 |
| | (0.05) | (-0.20) | (-0.00) | (1.08) | (0.73) | (-0.20) |
| High | 0.099** | -0.003 | 0.035 | 0.032** | 0.038** | 0.065* |
| | (2.44) | (-0.12) | (1.65) | (2.66) | (2.10) | (1.76) |
| All | 0.005 | -0.010 | -0.006 | 0.015 | 0.012 | -0.006 |
| | (0.13) | (-0.44) | (-0.33) | (1.56) | (0.93) | (-0.34) |
| High-Low | 0.168*** | 0.038 | 0.095*** | 0.028** | 0.083*** | |
| | (3.23) | (1.00) | (3.31) | (2.17) | (2.83) | |

** p < 0.10; ** p < 0.05; *** p < 0.01*

*Portfolio returns Period 1 (01.1998-03.2003): Results using gross returns.*

| $Alpha_{t-1}$ | $R^2{}_{t-1}$ Low | 2 | 3 | High | All | Low-High |
|---|---|---|---|---|---|---|
| Low | -0.053 | -0.055 | -0.020 | -0.003 | -0.034 | -0.050 |
| | (-1.33) | (-1.68) | (-1.01) | (-0.22) | (-1.37) | (-1.35) |
| 2 | -0.024 | 0.019 | 0.014 | 0.024* | 0.013 | -0.047 |
| | (-0.73) | (0.81) | (0.73) | (1.85) | (0.86) | (-1.39) |
| 3 | 0.081 | 0.041 | 0.017 | 0.029** | 0.029** | 0.051 |
| | (1.69) | (1.68) | (0.99) | (2.16) | (2.07) | (1.14) |
| High | 0.058 | 0.056** | 0.050*** | 0.032** | 0.064*** | 0.026 |
| | (1.66) | (2.60) | (3.48) | (2.32) | (3.08) | (0.77) |
| All | 0.018 | 0.017 | 0.018 | 0.021* | -0.003 | 0.019 |
| | (0.58) | (0.87) | (1.26) | (1.94) | (-0.11) | (1.17) |
| High-Low | 0.117*** | 0.117*** | 0.071*** | 0.035** | 0.100*** | |
| | (3.18) | (3.35) | (3.58) | (2.24) | (4.31) | |

** p < 0.10; ** p < 0.05; *** p < 0.01*

*Portfolio returns Period 2 (02.2003-05.2008): Results using gross returns.*

| $Alpha_{t-1}$ | $R^2{}_{t-1}$ | | | | | |
|---|---|---|---|---|---|---|
| | Low | 2 | 3 | High | All | Low-High |
| Low | -0.082*** | -0.031 | 0.003 | -0.006 | -0.034* | 0.033 |
| | (-2.94) | (-1.46) | (0.21) | (-0.80) | (-1.71) | (0.94) |
| 2 | -0.041 | -0.003 | 0.017 | 0.009 | -0.002 | 0.003 |
| | (-1.30) | (0.25) | (1.45) | (1.03) | (-0.15) | (-0.07) |
| 3 | 0.012 | 0.015 | 0.021* | 0.010 | 0.017 | -0.050 |
| | (0.37) | (0.67) | (1.82) | (1.13) | (1.63) | (-1.61) |
| High | 0.052 | 0.034 | 0.031** | 0.019* | 0.038* | -0.077*** |
| | (1.41) | (1.40) | (2.40) | (1.80) | (1.93) | (-2.97) |
| All | -0.012 | 0.006 | 0.018* | 0.009 | 0.012 | -0.021 |
| | (-0.48) | (0.37) | (1.88) | (1.34) | (0.93) | (-0.85) |
| High-Low | 0.144*** | 0.067** | 0.027* | 0.025** | 0.074*** | |
| | (3.82) | (2.30) | (1.74) | (2.26) | (3.54) | |

** $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$*

*Portfolio returns Period 3 (02.2009-12.2014): Results using gross returns.*