Norwegian School of Economics
Bergen, Spring, 2019

Value Creation Through Industry Concentrated Fund Portfolios

An empirical study of the Norwegian fund market

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Master Thesis, MSc in Economics and Business Administration,
Financial Economics

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Abstract

Although financial theory recommends investors to diversify their holdings across industries to reduce their overall unsystematic risk, some fund managers hold their portfolios concentrated in specific industries. This thesis study the relation between the industry concentration and the performance of actively managed Norwegian equity funds in the period from 2006 through 2017. By dividing funds into portfolios by their industry concentration, we analyze whether fund managers can create value by concentrating their portfolios in specific industries.

Overall, we find that Norwegian equity funds, on average, perform better than a comparable benchmark but in lack of statistical evidence, we cannot conclude whether they are able to cover their costs. Furthermore, our results are in contrast with previous literature and indicate that funds with diversified portfolios achieve higher gross returns than funds with concentrated portfolios after controlling for risk using various models and performance measurements. The difference is higher when looking at net returns, as more concentrated funds charge higher management fees. These findings indicate that investment ability is more evident among Norwegian managers who hold their portfolios diversified between industries.

Acknowledgements

This master's thesis has been part of our master's degree with a specialization in finance at the Norwegian School of Economics. The master's thesis has, at times, been tough and demanding, but all in all, it has given us great learning outcomes. This experience will hopefully serve us well into our careers. We want to take this opportunity to express our gratitude to our supervisor Andreas Ørpetveit, for useful guidance, his availability and constructive feedback along the way. Additionally, we also want to thank André Wattø Sjuve for his help and valuable input throughout the period. Finally, we also want to thank the Norwegian School of Economics which provides us access to the databases of Datastream, Bloomberg and Børsprosjektet.

Norges Handelshøyskole

Bergen, 01.06.2019

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Contents

List of figures

List of tables

1 Introduction

1.1 Background

Recently, there has been a remarkable growth in the mutual fund industry. For instance, according to Gjerde and Sættem (1991), there was only one mutual fund invested on the Oslo Stock Exchange (OSE) before 1982. In the same year, mutual fund investment with tax rebate was introduced in Norway. The rebate led to an increase in mutual funds and the total market value was 290 million NOK by the end of the year. In the past decades, the number of funds, and their value have continued to rise rapidly in the Norwegian market. As we illustrate in Figure 2, the total value in the Norwegian fund market was 1.138 trillion NOK at the end of 2017. Due to historically low interest rates in savings accounts, actually lower than inflation, investors have been forced to look for other options for their savings. This has led households and retail investors having much of their capital managed by mutual funds.

As a result of the great growth, numerous empirical studies have been conducted toward active management. The previous literature has tried to provide answers to different questions – the most common is whether mutual funds can create risk-adjusted alphas (net of expenses) to their investors. Beginning with Jensen (1968), many empirical studies suggest that actively managed mutual funds, on average, underperform the market and various risk-adjusted benchmarks. However, this does not preclude the possibility of superior performance by a subset of mutual funds.

Financial theory recommends investors to diversify their holdings across industries to reduce their overall unsystematic risk. Fund managers, however, might want to hold concentrated portfolios in specific industries. These managers might believe that these industries will outperform the overall market, or they have superior information in these industries. Studies suggest that active funds that outperform benchmarks cause high money inflows, while underperforming funds are not penalized equivalently. This is root to an exciting investment prospect, the potential conflict of interests between the investors and managers. Fund managers can have incentives to take highly risky bets in specific industries trying to achieve extreme returns, while the investors, on the other hand, might not want to hold this high risk into their portfolios.

One crucial question is how active management should be defined? According to Chen (2018), active managers rely on analytical research, forecasts, and their judgment and experience in making investment decisions on what securities to buy, hold and sell. To be able to perform active management successfully, the market has to be efficient on a sufficient weak form. If this is not the case, all information is already reflected in the market prices of the stocks, i.e., there is nothing more to gather from stock picking over following the market precisely. In other words, while passive managers deal with the market to harvest risk premiums, active managers trade against the market, in addition to harvesting assumed mispricing. An active manager can create value to his portfolio in two ways, market timing or stock picking. *Market timing* is a strategy that determines when to be invested in the market, and when you should hold cash or interest rate securities. The purpose is to try to get most of the highs and the long-term returns you get from being invested in stocks while avoiding deep and worthwhile downturns. *Stock picking* involves active bets on individual stocks. For example, betting only in one firm from a specific industry. Despite evidence suggesting that actively managed funds, on average, do not outperform low-cost index funds, many fund managers still take active bets.

1.2 Purpose

The literature claims that managers can beat the market by keeping concentrated portfolios and investing in industries they have faith in. The aim of this thesis is to investigate whether managers who specialize in industries can outperform the market by answering the following:

"Can Norwegian fund managers create value by concentrating their portfolios in specific industries?"

To answer this question, we use t-tests, different regression models and performance measurements, based on a dataset including actively managed Norwegian equity funds during the period from 2006 through 2017. The Industry Concentration Index (ICI), defined by Kacperczyk, Sialm and Zheng (2005), is used to measure the industry concentration of the included funds. From this, funds are divided into equally weighted portfolios based on their industry concentration. The performance evaluation throughout the thesis is based on risk and returns from these portfolios.

Despite there has been written several master theses dealing with fund performance, we do not find research similar to our study towards the Norwegian equity market. This has been the main trigger for this thesis. We want to investigate whether the results from the Norwegian market support the previous literature, that industry concentrated equity funds perform better than diversified ones. We believe a study from the Norwegian market, comparing our results to other financial markets, for instance, the U.S market, could be exciting as markets have different characteristics. The OSE is relatively small, compared to, for example, NYSE.[1] The number of listed companies also vary significantly between the exchanges. For instance, there were 227 listed companies on the OSE and 3,130 listed companies on NYSE per December 2017.[2] Also, OSE is characterized by its high commodity exposure, which can make it more volatile than other major stock exchanges. Furthermore, we hope that our thesis could contribute to the Norwegian investors´ assessment between active and passive management.

1.3 Structure

Aside from the reference list and appendix, this thesis consists of seven chapters. The rest of this thesis is structured as follows: Chapter 2 will give a brief introduction to the fund market and the related literature. In chapter 3, we present relevant theory of which this thesis is built upon. Chapter 4 describes our data material and methods we used to collect these data. In chapter 5, we describe the methodology behind our results before we in chapter 6, give a presentation and discussion of these results. Finally, in chapter 7, we present our conclusion and discuss the limitations and possible extensions of our study.

[1] New York Stock Exchange.

[2] The numbers are retrieved from the web site of Oslo stock exchange https://www.oslobors.no/Oslo-Boers/Statistikk/Fakta-og-noekkeltall/2017-Fakta-og-noekkeltall-desember-2017 and the web site of New York Stock Exchange https://www.nyse.com/publicdocs/nyse/data/Monthly_Consolidated_Volume_by_Symbol_201712.pdf?fbclid=IwAR0ALucVq6S2VeE0gqR7Ipy-jjxtOzJPepNJLD-YFG1L9zRAaGUkUCZMER0.

2 Fund market and related literature

In this chapter, we give an overview of the fund market, and we also provide an introduction to the related literature for this study.

2.1 Mutual funds

A mutual fund is a financial investment vehicle, in which many investors join forces to invest their capital in the securities market. Saving in funds have several advantages over other forms of saving. The most important advantage, according to the stock industry, is the professional management of your money. Investors buy funds because they do not have the necessary experience or time to manage their portfolios. Diversification is another argument – the idea is to invest in many assets so that a gain in other assets minimizes a loss in a particular investment. Large equity funds typically have hundreds of different stocks in many various industries. It would not be possible for a private investor to build such a portfolio with a small amount of money. Because of the benefit of high liquidity, a fund will also allow you to convert stocks into cash at any time. You can buy and sell units at any time – for just about the amount you want. In addition, funds may be the saving that offers the most protection to investors through strict government regulations, both nationally and internationally.

The return on an investment depends on the risk you are willing to undertake, and thus, which mutual fund you should choose. Returns beyond the risk-free interest rate can, therefore, be interpreted as a compensation for the risk one is willing to take, but there is, however, no guarantee that one will receive this compensation. A mutual fund may charge a management fee to pay for their expenses. The fund can have high returns, but if the costs are too high, the investor will not benefit from the investment.

Mutual funds are classified within different categories, which makes it clear and easy to compare returns, risks and costs between comparable funds. In the Norwegian market, we have four main types of funds. *Money market funds* invest only in highly liquid instruments, such as certificates of deposit and treasury bills. *Fixed income funds* buy investments that pay a fixed rate of return, such as government bonds and high-yield corporate bonds. They aim to have money income to the fund regularly, mostly through the interest that the fund earns. *Combination funds* invest in a mix of equities and fixed income securities. The managers of these funds want to achieve the perfect distribution between the risk in the stock market and the safety of the fixed income market. *Equity funds* invest in stocks, where at least 80 % of the unitholders' capital is invested in the stock market. They are divided into different groups according to where the fund's assets must be invested. The investment may, for instance, be geographically limited (Norway, the Nordic region or Europe) or to the industry (Health Care, Financials or Information Technology). Further, a Norwegian equity fund is defined as a fund that invests a minimum of 80 % of total assets in stocks listed on the OSE (Verdipapirfondenes forening, 2019).

Equity funds generate the highest expected return, but they also come with the highest risk. The annual average excess return on Norwegian stocks from 1976 to 2010, has been 11.6 % adjusted for tax and price increases (Bøhren & Michalsen, 2012). In this thesis, we only include equity funds. We find this exciting because this type of fund has the highest fluctuations in return. Figure 1 illustrates the relationship between expected return and risk for the different funds.

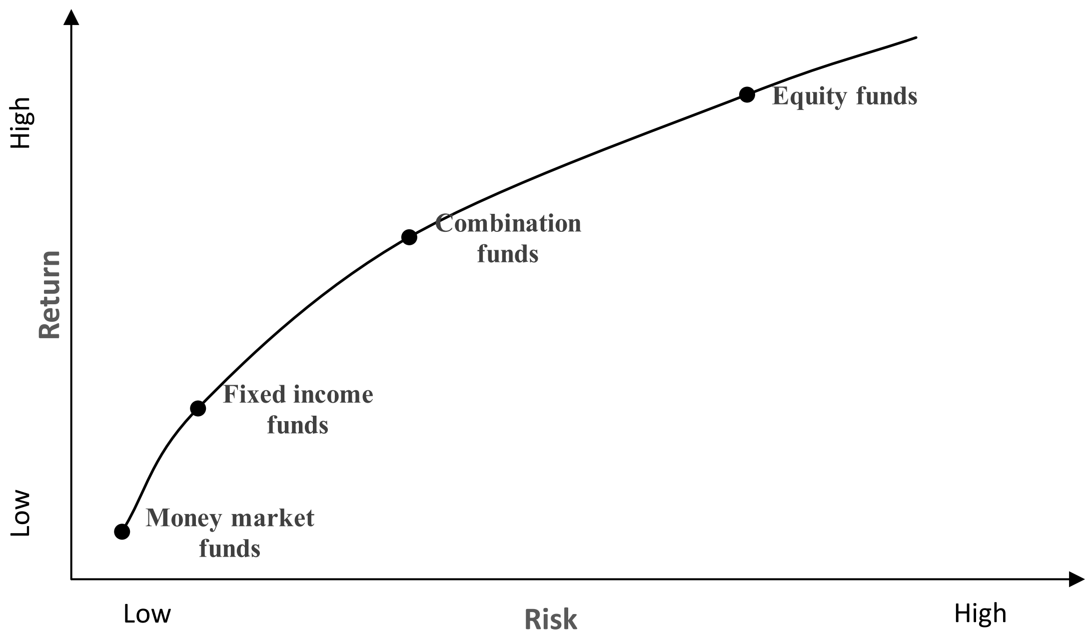

Figure 1 Expected risk and return for different fund types

2.2 Norwegian fund market

To illustrate the recent growth in the Norwegian fund market, we have plotted the development in AUM for different fund types in Figure 2.[3] The illustration shows that the market has grown from 342 billion NOK to 1.138 trillion NOK during the period from 2006 through 2017. This implies a total growth of 232 % over the 12 years. Equity and fixed income funds consist of the largest shares in the market.

Although fund investments have increased largely in Norway, Norwegian investors have a low share of their fortune placed in mutual funds compared to private investors in the rest of Europe. For instance, in 2014, 5 % of Norwegian households' wealth was invested in funds and stocks, roughly half of the average level in Sweden of 10 % (Wiig, 2014). In Norway, the combination of strong growth in house prices and the favorable tax rules has made real estate a desirable saving and investment object.

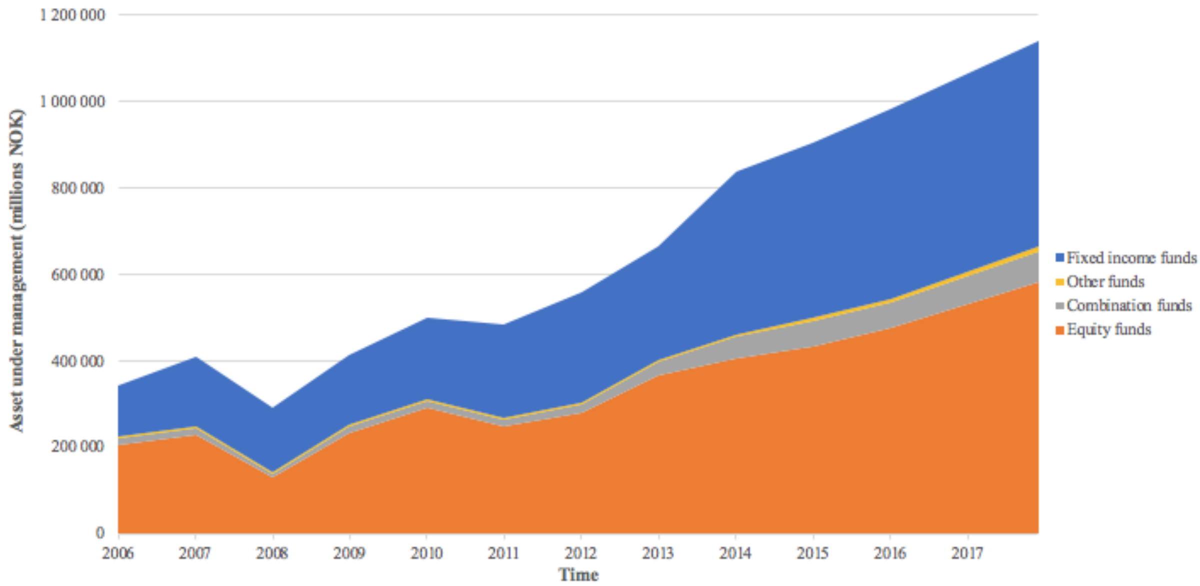

Figure 2 Norwegian fund market from 2006 through 2017

[3] The numbers are retrieved from the web site of Verdipapirfondenes forening https://vff.no/historisk-statistikk.

2.3 Market events

Throughout history, we have observed different corrections in the financial markets, including the Norwegian market. Some events have been greater than others, and these will primarily be remembered for a long time. To examine the Norwegian fund performance, these market events become an interesting topic for both academics and investors. Figure 3 illustrates the development of both the NOVIX[4] and the OSEFX.[5] The developments are based on the closing values on each trading day for both the NOVIX and the OSEFX. During the period covered by this thesis, there have been different global and local market events that had a big impact on the Norwegian market. NOVIX and OSEFX tend to move in opposite directions.

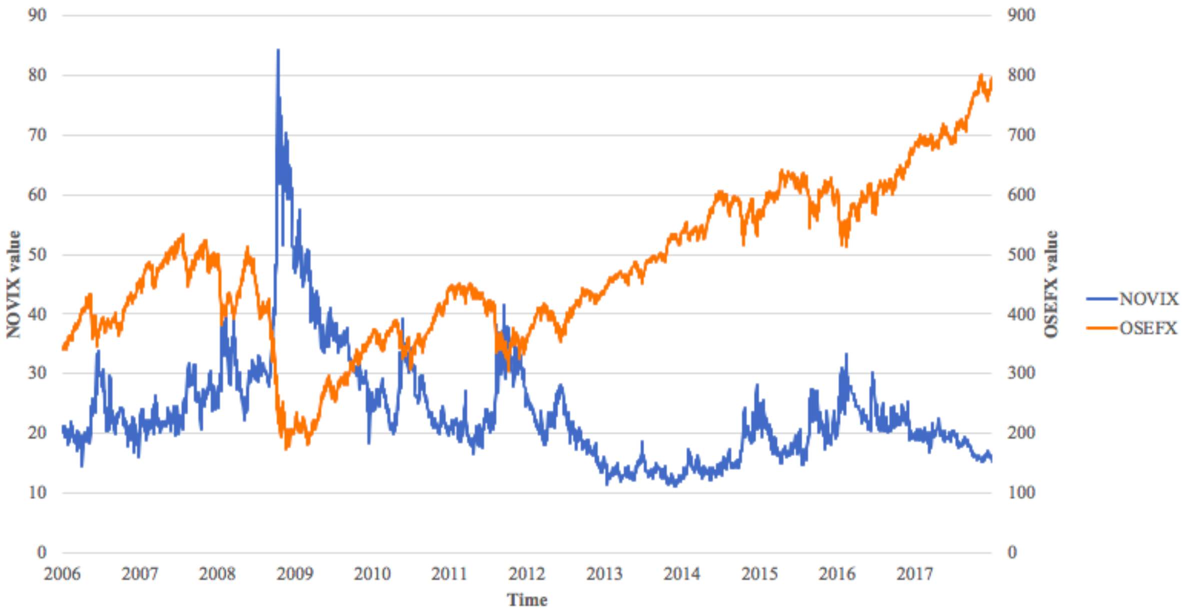

Figure 3 Development in the NOVIX and the OSEFX from 2006 through 2017

2.3.1 Financial Crisis

In 2008 the world economy faced the worst crisis since the Great Depression of the 1930s. The crisis first started in 2007 when the high housing prices in the U.S finally turned

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[4] Bugge, Guttormsen, Ringdal & Molnár (2016) introduced the NOVIX, which is an implied volatility index for the Norwegian equity index, OBX, and is based on the CBOE Volatility Index known as the VIX. The volatility numbers are retrieved from the web site of NOVIX https://novix.xyz/intra.html.

[5] The Oslo Stock Exchange Mutual Fund Index

decisively downward. This trend spread quickly, first to the U.S financial sector, and then outward to the global financial markets. Several financial institutions, such as Lehmann Brothers and big banks, had to bail out to prevent a possible collapse of the world's financial system. The global equity market experienced a dramatic fall of approximately 40 %, while the condition at the OSE was even worse – the main index fell by 54 % (Oslø Børs, 2008).

2.3.2 Debt Crisis

As Figure 3 illustrates, there were two events in the period between 2010 and 2012. The first event is known as the EU Debt Crisis, which mainly occurred with a link to the Financial Crisis. The European governments had to rescue troubled banks in their countries during the Financial Crisis, which led to increased national debt. The second event started in August 2011 and is known as the U.S Credit-Rating Downgrade. Standard & Poor`s triggered this event when they for the first time in history downgraded the U.S long-term debt assessment from AAA to AA+ (Appelbaum & Dash, 2011). This downgrading was done due to political risks and rising national debt.

2.3.3 Oil Crisis

Another market event started at the end of 2014. China's brake, shale oil revolution and an OPEC shock were among the main reasons for the crisis (Fredriksen & Johansen, 2015). As a result of the crisis from 2014 to 2016, tens of thousands of workers within the energy sector lost their jobs, and we also faced the longest drop in the oil price through history. Since the energy sector is a major component of the OSEFX index, many academics predicted a steep fall in the OSEFX. In contrast, we faced a different development; the index went from having a stable to an unstable growth in the period between 2014 and 2016.

2.4 Related literature

According to the Efficient Market Hypothesis (EMH), Malkiel and Fama (1970) point out that fund managers are not able to outperform a benchmark index because stock prices have already incorporated all available information. EMH operates with three forms of market efficiency; weak, semi-strong and strong form. Within the *weak form*, it is assumed that all information about historical development but nothing more, is reflected in the stock price. Historical prices will, therefore, have no prediction value. *Semi-strong form* implies that prices reflect all publicly available information. Everything other than inside information will be without prediction value. *Strong form* states that inside information is also reflected in the price. As all information is reflected, the price will be equal to the real value of the asset. It will not be possible to beat the market, and active management will be worthless.

Although studies similar to the one from Jensen (1968) suggest that actively managed mutual funds, on average, underperform the market, these results can vary widely between financial markets. For instance, Forbrukerrådet (2018) showed that actively managed Norwegian equity funds targeted on the OSE – as a group – yielded a positive annual abnormal return of 0.86 % net of expenses.

Berk and Green (2004) discuss why both return before (gross) and after (net) expenses are informative. Looking at the gross returns enables us to evaluate the investment ability of the fund managers better, since managers with better skills may charge higher fees. On the other hand, investors are interested in net returns. Further, they also suggest that the size of a fund may affect its ability to outperform the benchmark. They explain many stylized facts related to fund performance using a model with rational agents. In their model, active skilled managers do not outperform passive benchmarks after deducting expenses because of a competitive market for capital provision combined with decreasing returns to scale in active management.

A related study "Does fund size erode performance? Liquidity, organizational diseconomies and active money management" was done by Chen, Hong, Huang, and Kubik (2004). They find that smaller funds tend to outperform larger funds due to diseconomies of scale. While the size of the fund negatively affects its performance, it is possible that a wide dispersion of holdings across many industries also may erode its performance.

Kacperczyk et al. (2005) studied the relation between the industry concentration and the performance of actively managed U.S. mutual funds from 1984 to 1999. Based on 1,771 actively managed diversified equity funds, they find that, on average, more concentrated funds perform better after controlling for risk and style differences using various performance measures. Their findings suggest that investment ability is more evident among managers who hold portfolios concentrated in a few industries. For example, based on the Carhart (1997) four-factor model, they find that the most diversified fund portfolio generates an abnormal return of 0.09 % per quarter, while the most concentrated fund portfolio generates an abnormal return of 0.53 % per quarter, before expenses.

Hiraki, Liu and Wang (2015) based their work done by Kacperczyk et al. (2005) and examine the relation between country and industry portfolio concentration and performance using a dataset of 389 international equity funds over the period 1993 to 2009. Their results suggest that industry concentrated funds outperform diversified funds in all size groups. For instance, the average return difference between industry concentrated and diversified funds is 0.33 %, 0.17 %, and 0.19 % per month in the small, medium, and large fund groups, respectively. Their results support the findings from Kacperczyk et al. (2005).

3 Theory

In this chapter, we present relevant theory used throughout this thesis. Some variables are included in several models and performance measurements; therefore, we choose to explain these variables only the first time they are presented.

3.1 Modern Portfolio Theory

Modern Portfolio Theory (MPT) was introduced by Harry Markowitz (1952). MPT argues that an investment's risk and return characteristics should not be viewed alone but should be evaluated by how the investment affects the overall portfolio´s risk and return. According to MPT, an investor can construct a portfolio of multiple assets that will maximize return for a given level of risk or minimize the risk for a given level of expected return. Further, MPT assumes that investors are risk-averse and have mean-variance preferences, meaning they prefer the least risky portfolio for a given level of return. This implies that an investor will take on more risk only if compensated by the higher expected return. One of the essential parts of the MPT is the efficient frontier, which lies above the minimum-variance portfolio. This frontier is the set of optimal portfolios that offer the highest expected return for a defined level of risk. For any portfolio below the minimum-variance portfolio, there is a portfolio with the same standard deviation and a higher expected return positioned directly above it.

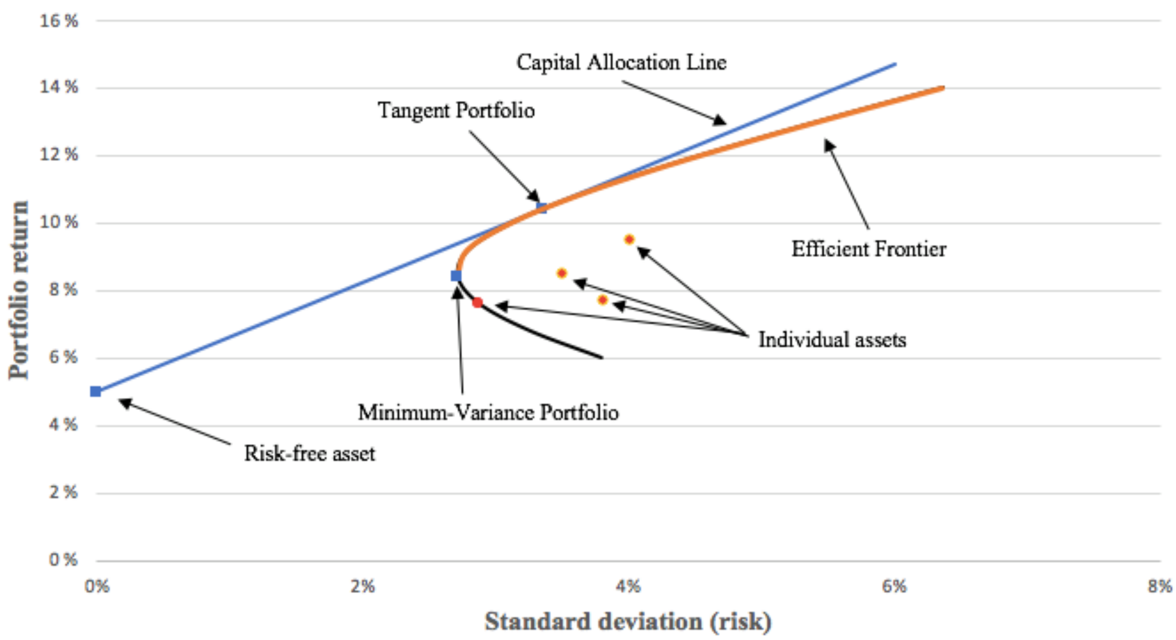

Figure 4 Portfolio optimization

Capital Allocation Line (CAL), is a graph showing all feasible risk-return combinations of a risky and risk-free asset. The CAL that is supported by the optimal portfolio, the tangent portfolio, is tangent to the efficient frontier. This CAL dominates all available alternative lines. This portfolio maximizes the Sharpe Ratio (SR).[6] Where to be on the CAL depends on the individual investor's risk aversion, and thus, which combination of risk-free and risky assets he or she should hold.

3.2 Capital Asset Pricing Model

Explaining cross-sectional returns has over several years been the foundation of many studies within the finance field. Markowitz set the foundation of the Capital Asset Pricing Model (CAPM), in the work he did on MPT. CAPM was developed in the 1960s by Sharpe (1964), Lintner (1965) and Mossin (1966). The model was considered as a breakthrough in modern financial economics. It considers the relationship between the expected return of an asset or portfolio and its systematic risk, measured by beta (β). Its main argument is that the equilibrium return on all risky assets is a function of its covariance to the market portfolio. CAPM builds on assumptions that simplify reality. Lintner (1965) add to the assumptions about homogeneous expectations among investor-related risks and returns, and that they can place or borrow at a risk-free interest rate. CAPM is expressed as:

$$E(r_i) = r_f + \beta_{i,m}\left(E(r_m) - r_f\right) \tag{1}$$

where,

$E(r_i)$ = expected return on asset or portfolio i

r_f = risk-free rate

$\beta_{i,m}$ = the sensitivity of r_i to change in market risk premium

$E(r_m)$ = expected market return

From formula (1), we observe that only systematic risk is relevant and reflected in pricing. An investor cannot diversify systematic risk away. Unsystematic risk is connected to each company and can be diversified by investing widely in the market. Rational investors will

[6] See section 3.5.1 for explanation

hold the market portfolio, as this is perfectly diversified and provides the best return per unit risk (SR). All combinations of risk-free assets and the market portfolio are efficient, as the combinations have the same SR as the market portfolio and form the Capital Market Line (CML).

Beta measures the volatility of an individual asset or portfolio i in comparison to the market. Beta is given by:

$$\beta_i = \frac{\mathrm{Cov}(r_i, r_m)}{\mathrm{Var}(r_m)} \tag{2}$$

where,
$\mathrm{Cov}(r_i, r_m)$ = covariance between the return on asset or portfolio i and the market return
$\mathrm{Var}(r_m)$ = the variance of the market

- If beta = 1, the portfolio moves with the market.
- If beta < 1, the portfolio is less volatile than the market.
- If beta > 1, the portfolio is more volatile than the market.

However, the CAPM has been criticized in several areas. First, many of the assumptions that the model is based on are, in reality, unrealistic. This fact weakens the model's relevance in the real world. The model assumes, among other things, that a risk-free asset exists. Even if, for example, treasury bills are considered risk-free, there will always exist a certain risk of default. Furthermore, it is assumed that investors can borrow and place at the same interest rate. In the real world, there will always be a spread between lending and borrowing rates. It is also problematic to define the market portfolio. Usually, a broad market index is used as the market portfolio. Unfortunately, one will never manage to replicate the total market with all the assets that exist.

3.3 Fama and French´s three-factor model

Since its introduction in the 1960s, the CAPM has been the basis for a big number of financial studies. More recently, many academics argue that the CAPM alone fails to explain all the cross-sectional returns. Numerous factors have been proposed as complements and alternatives to the original model. Fama and French (1993) introduced their three-factor model to explain the cross-sectional returns better. They showed that the three-factor model could explain over 90 % of the returns of the diversified portfolio, compared with the average 70 % given by the CAPM. Ever since the introduction, it has commonly been used as a benchmark-model. Fama and French added two risk factors into the traditional CAPM. From this, the three-factor model is expressed as:

$$r_i = r_f + \beta_{i,m}(r_m - r_f) + \beta_{i,SMB} SMB + \beta_{i,HML} HML \tag{3}$$

where,
r_i = return on asset or portfolio i
r_m = market return
SMB = size factor
$\beta_{i,SMB}$ = the sensitivity of r_i to change in size factor
HML = value factor
$\beta_{i,HML}$ = the sensitivity of r_i to change in value factor

The betas explain the correlation between the asset or portfolio i returns and the corresponding factors. Small Minus Big *(SMB)* is a size effect based on a market capitalization of a company. It is calculated by taking the difference between the return of a portfolio of stocks holding small companies, and a portfolio of stocks holding large companies. High Minus Low *(HML)* is a value factor. It accounts for the spread in returns between value and growth stocks, i.e., the difference between the return of a portfolio of stocks with high book-to-market ratio ($\frac{B}{M}$), and the return of a portfolio of stocks with low book-to-market ratio ($\frac{B}{M}$).

3.4 Carhart´s four-factor model

Jegadeesh (1990) documented that in the short term, there is momentum in equity returns. The stocks that have yielded good (poor) returns in recent months sustained a high (low) return also the next month. The research by Jegadeesh and Titman (1993) confirmed the results and showed that the momentum effect lasts for 3 to 12 months. They found significant positive autocorrelation. Buying a portfolio of stocks that was ranked among the top 30 % in the previous year, and short-selling a portfolio of stocks that ranked among the bottom 30 % in the previous year (Winners – Losers), yields a positive risk-adjusted return in the coming year. The result laid the foundation for the Carhart (1997) four-factor model, which is an extended version of the well-known CAPM and three-factor model. In addition to the three-factor model of Fama and French (1993), Carhart (1997) extended the model by incorporating Jegadeesh and Titman (1993) one-year momentum factor. The four-factor model is expressed as:

$$r_i = r_f + \beta_{i,m}(r_m - r_f) + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \beta_{i,MOM}MOM \quad (4)$$

where,
MOM = momentum factor
$\beta_{i,MOM}$ = the sensitivity of r_i to change in momentum factor

3.5 Risk-adjusted performance measurements

A key lesson for fund managers is always that returns mean nothing unless put side by side with the undertaken risk. According to the CAPM, the expected return of a portfolio is dependent on its beta. This indicates that a fund manager can increase the expected return by taking a higher systematic risk; in other words, increasing the portfolio's beta. It is therefore not particularly useful to assess a manager's performance by looking exclusively at average returns. Distinguishing between those managers who achieve high returns based on their ability to stock picking and market timing, against those who achieve high returns solely due to higher risk, is very difficult. To assess the performance of different portfolios, one must, therefore, adjust for risk before comparison makes sense. One of the easiest ways to adjust returns concerning risk is to compare the return on funds that have equal risk. Nevertheless, such comparisons may be misleading because some managers concentrate on specific subgroups that are not comparable.

3.5.1 Sharpe Ratio

Sharpe Ratio (SR) was introduced by Sharpe (1966) and is a performance measurement for mutual funds. The ratio tells how much compensation an investor is getting for the additional risk he or she is bearing for not holding a risk-free asset. SR is calculated by dividing the portfolio's excess return by the standard deviation of the portfolio´s excess return. To indicate whether the fund performed better or worse compared to the market, the SR is often plotted against the CML. If the fund's SR is above (below) the CML, it performed better (worse) compared to the market. SR formula is given by:

$$SR_i = \frac{r_i - r_f}{\sigma_i} \tag{5}$$

where,

SR_i = Sharpe Ratio of portfolio i

σ_i = standard deviation of portfolio i´s excess return

3.5.2 Treynor Ratio

The Treynor Ratio (TR), sometimes called the reward-to-volatility, was developed by Treynor (1965). The ratio measures how much excess return that was generated for each unit of systematic risk taken on by a portfolio. It is calculated by dividing the portfolio's excess return by the portfolio's beta. While SR considers total risk, the TR only uses systematic risk. A high TR indicates that the fund has a higher systematic risk-adjusted return compared to a fund with a lower TR. TR formula is given by:

$$TR_i = \frac{r_i - r_f}{\beta_i} \tag{6}$$

where,

TR_i = Treynor Ratio of portfolio i

β_i = beta of portfolio i

3.5.3 Jensen´s alpha

Jensen´s alpha (α) was developed by Jensen (1968) when he in an article wanted to investigate if there was a possibility that some fund managers were able to beat the market over a longer period. The α is a measurement of risk-adjusted performance that represents the average return of a portfolio above or below the return predicted by the CAPM. In other words, one can claim that this measurement tests the fund managers´ ability to achieve higher returns than expected by the CAPM. In efficient markets, we expect the α to be equal to zero, and superior managers exist only if the α significantly differ from zero.

We can find α by:

$$E(r_i) = \alpha_i + r_f + \beta_{i,m}\left(E(r_m) - r_f\right) \tag{7}$$

by restructuring the formula, the α is given by

$$\alpha_i = E(r_i) - \left(r_f + \beta_{i,m}\left(E(r_m) - r_f\right)\right) \tag{8}$$

where,
α_i = alpha for portfolio i

- If $\alpha > 0$, the portfolio has outperformed the market on a risk-adjusted basis.
- If $\alpha < 0$, the portfolio has underperformed the market on a risk-adjusted basis.

3.5.4 Information Ratio

The Information Ratio (IR) is a measurement of portfolio returns above the returns of a benchmark, compared to the volatility of those returns. The ratio is calculated by dividing the portfolio return in excess of the benchmark return by the Tracking Error (TE).[7] The higher the IR, the higher the active return of the portfolio, given the amount of risk taken, and the better the manager has performed. Low IR indicates the opposite. IR formula is given by:

$$IR_i = \frac{r_i - r_m}{TE_i} \tag{9}$$

where,
IR_i = Information Ratio of portfolio i
TE_i = Tracking Error of portfolio i

[7] TE is a measurement of standard deviation of the divergence between the portfolio return and the benchmark return.

3.6 Industry Concentration Index

We use Kacperczyk et al. (2005) definition to measure the industry concentration, ICI, based on the fund holdings. ICI for fund *i* is defined as the sum of the squared deviations of the value weights for each of the *n* different industries held by the fund, relative to the industry weights of the market portfolio. ICI is expressed as:

$$ICI_i = \sum\nolimits_{j=1}^{n} \left(w_j - \bar{w}_j\right)^2 \tag{10}$$

where w_j it the weight of the fund holdings in industry *j* and $\bar{w}_j$ the weight of the market in industry j. ICI measures how much a fund portfolio deviates from the market portfolio. The index can take values between zero and two. ICI is equal to zero if a fund has the same industry composition as the market portfolio and increases as a fund becomes more concentrated in a few industries. The maximum value occurs if the fund and the market portfolio invest all their holdings in one industry each. For instance, the fund invests all its holdings in the financial sector, and the market portfolio invests all its holdings in the energy sector.

As stated by Kacperczyk et al. (2005), ICI is related to the Herfindahl-Hirschmann Index (HHI).[8] The ICI can be thought of as a market-adjusted HHI. There are two main reasons why the ICI is better suited than HHI. First, the industry weights of the total market vary over time. The ICI takes this variation into account by adjusting for the time-varying industry weights in the market portfolio. Second, a fund can have a lower HHI than the entire market portfolio if it is more equally invested in different industries. The ICI is not subject to this problem because the market portfolio has the lowest possible index value of zero.

[8] See Appendix A for full explanation of HHI

4 Data

In this chapter, we present our data material and how we have collected this data. Furthermore, we explain the choice of analysis period and how we have shared the dataset into two periods. Finally, we present descriptive statistics for our dataset.

4.1 Data sources

To carry out a quantitative analysis, it is necessary to obtain a large amount of credible data. Using the Norwegian School of Economics accesses to the databases of Morningstar, Børsprosjektet and Datastream have ensured this. The data material consists of 51 actively managed Norwegian equity funds in the period from January 2006 to December 2017. This period is exciting to investigate as it contains more recent data than previous related studies conducted toward other financial markets. Furthermore, we believe it is interesting to do such a study in recent times so that the results reflect the market as of today. The material contains monthly observations and covers a period of 144 months in total. We consider two sample periods, 2006 to 2017 and 2010 to 2017. In addition to the full sample period, we investigate a period which emphasizes the most recent years, which also do not contain the Financial Crisis. Note that the most recent sample period is short, which can make it difficult to measure performance with high significant precision. It is not the number of observations by itself that matters, but the length of the sample period. To avoid problems due to survivorship bias, we included funds that have been closed or merged during the sample period. In Appendix B, we present a full overview of the included funds.

4.2 Funds information

From Morningstar, monthly data for Norwegian equity funds invested on the OSE was downloaded. For each fund, the material includes return series, expense ratios, sector weights and Asset Under Management (AUM). Figure 5 presents an overview of the development of average sector weights for all included funds. The Energy sector dominated the fund’s portfolio holdings before the Oil Crisis. In more recent years, the average holdings still consist of a large amount in the Energy sector, but the Financial sector also accounts for a large share. In 2017, these two sectors constituted more than 40 % of the total holdings, which partly can indicate the concentration on the OSE. Note that the Real Estate sector started in September 2016.

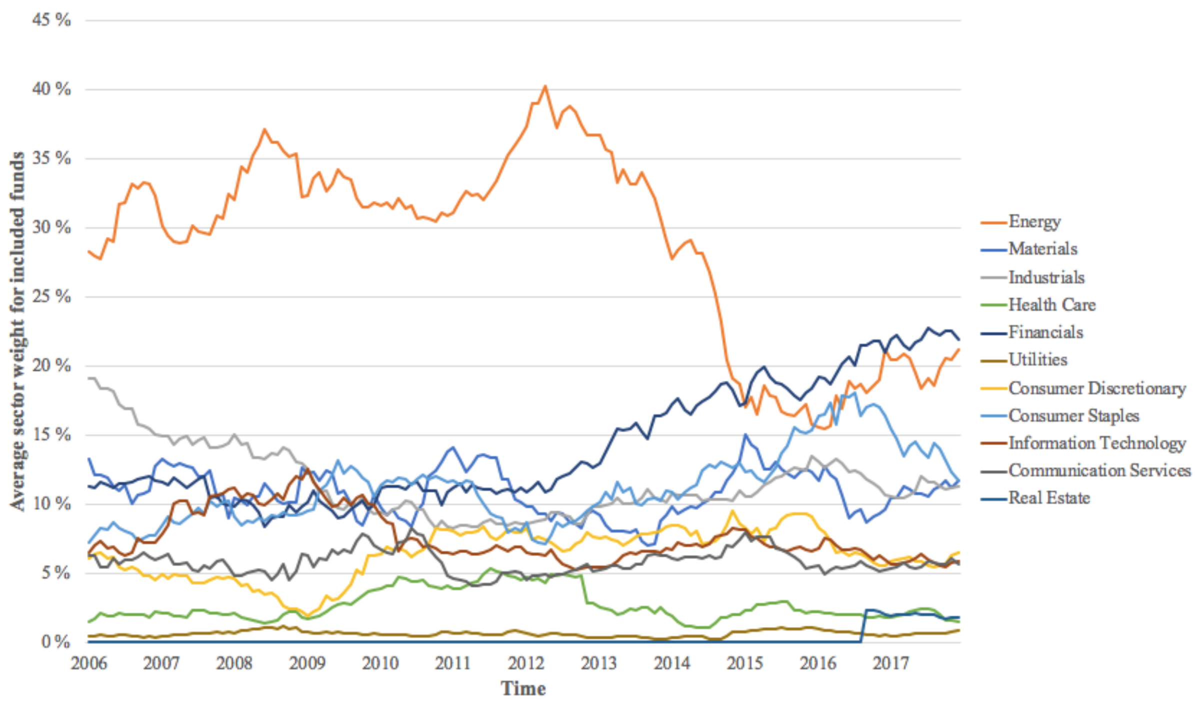

Figure 5 Average sector weights for all included funds

4.3 Reference index

Equity funds use a benchmark as a guideline for their investments in addition to comparing their performance. The included funds mainly use the OSEFX as a benchmark. OSEFX started in 2001 and is a capped version of the OSEBX.[9] OSEFX, like funds, is regulated with requirements for diversification and risk. The capping rules comply with the UCITS[10] directives for regulating investments in mutual funds. The maximum weight of a security is 10 % of the total market value of the index, and securities exceeding 5 % must not exceed 40 % together. The OSEFX index is adjusted for dividend payments ("Oslo Børs Mutual Fund Index," n.d.).

An alternative to the OSEFX will be the OSEAX.[11] This index contains all companies on the OSE and is also adjusted for dividends. A replication of the OSEAX implies trading in many illiquid stocks that cannot be done without high transaction costs. Due to this, OSEAX does not appear to be a reachable benchmark. Following the discussion, we use the OSEFX as a benchmark. The return history of OSEFX was downloaded from Børsprosjektet. OSEFX's quote development is plotted in both Figure 3 and 7. Note that there will usually be low

[9] The Oslo Stock Exchange Benchmark Index
[10] Undertakings Collective Investments in Transferable Securities
[11] The Oslo Stock Exchange All Share Index

expenses related to managing the benchmark index so that these expenses will have little impact on the findings. Thus, we do not take these expenses into account.

4.4 Sectors on the Oslo Stock Exchange

From Datastream, we downloaded additional data about the OSEFX. The data contains information about which companies OSEFX holds, with their associated weights. To classify which sector the companies belong to, we use a sector classification based on the GICS.[12] The GICS hierarchy begins with 11 sectors and is followed by 24 industry groups and 69 industries.[13] Forward in this thesis, we will use the 11 sectors from the GICS as a proxy for industries. These can sometimes be referred to as another since the related literature from Kacperczyk et al. (2005) and Hiraki et al. (2015) refers to these sectors as industries. In Table 1 we present the 11 sectors per December 2017.

Table 1 Sectors on the OSE

This table summarizes the 11 sectors on the OSE with their associated number of companies and share of OSEFX. In addition, OSEFX's market weight in each sector is reported. The presented information is per December 2017.

OSE number	Sector	Number of companies	Share of OSEFX	OSEFX holdings
OSE10	Energy	50	29.41 %	21.41 %
OSE15	Materials	7	4.12 %	14.05 %
OSE20	Industrials	35	20.59 %	7.52 %
OSE25	Consumer Discretionary	9	5.29 %	6.61 %
OSE30	Consumer Staples	10	5.88 %	13.69 %
OSE35	Health Care	8	4.71 %	0.51 %
OSE40	Financials	16	9.41 %	20.55 %
OSE45	Information Technology	25	14.71 %	4.49 %
OSE50	Communication Services	2	1.18 %	8.35 %
OSE55	Utilities	2	1.18 %	0.44 %
OSE60	Real Estate	6	3.53 %	2.39 %

From Datastream, we downloaded the industry indices OSE10, OSE15, OSE20, OSE25, OSE30, OSE35, OSE40, OSE45, OSE50, OSE55 and OSE60. Each OSE number is a classification number that provides information about which sector each company belongs to. To get a document that gave us the benchmark with different sector weights, we merged OSEFX's portfolio-holdings with the industry indices by each company's unique ISIN-number. In addition, we also downloaded quotes development for each industry index.

[12] Global Industry Classification Standard is developed and implemented by MSCI and Standard & Poor's and is mainly based on where companies generate their income (Oslo Stock Exchange, etc.).
[13] See Appendix C for a total overview of the GICS classification.

4.5 Risk factors

As mentioned, we use the OSEFX as a benchmark, i.e., market portfolio. We calculate the market risk factor by taking the return of the OSEFX in excess of the risk-free rate. Furthermore, the size, value and momentum factors used in the thesis are constructed by Bernt Arne Ødegaard.[14] He constructed these factors toward the Norwegian market, using raw stock market data from the OSE Data Service. From this data, he calculated the different time series. Quote from Ødegaard´s web site: "Asset pricing factors for the Oslo Stock Exchange similar to those developed by Eugene Fama and Ken French". The fact that the OSE let him publish these data, we find the factors reliably and have no doubt about using them in our analysis.

4.6 Descriptive statistics

The included funds may differ in characteristics, such as size, expenses and age. Panel A in Table 2 presents fund characteristics for our data collection. The average actively managed fund has an ICI of 4.38 % and ICI2 of 4.68 %. ICI has a range from 0.1 % to 55.17 % while ICI2 has a range from 0.09 % to 112.86 %. These wide ranges indicate huge variation due to concentration. In Panel B, we present a correlation matrix between the ICI measures and different fund characteristics. From the matrix, we observe several statistically significant correlations between the characteristics. Interestingly we find a negative correlation between age and the two ICI measures. As expected, we also observe a positive correlation between AUM and age. In addition, we observe a positive correlation between the two concentration indices and the expense ratio. This indicates that more concentrated funds seem to charge higher management fees.

[14] The factors were downloaded from Bernt Arne Ødegaard's web site http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html, and the numbers are expressed at a monthly frequency

Table 2 Descriptive statistics

This table summarizes descriptive statistics from the data collection. Panel A presents the fund characteristics of the most relevant variables from the actively managed equity funds. Panel B reports a correlation matrix between the main variables. The ICI is given by $ICI_{i,t} = \sum_{j=1}^{11}(w_{j,t} - \overline{w}_{j,t})^2$, where *ICI* for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $w_{j,t}$, relative to the sector weights of the OSEFX, $\overline{w}_{j,t}$. The ICI2 is given by $ICI2_{i,t} = \sum_{j=1}^{11}\left(\left(\frac{w_{j,t}}{t_{uc,t}}\right) - \overline{w}_{j,t}\right)^2$, where $ICI2$ for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $\left(\frac{w_{j,t}}{t_{uc,t}}\right)$, relative to the sector weights of the OSEFX, $\overline{w}_{j,t}$. Where $t_{uc,t}$ is the sum of the fund's total holdings without unclassified stocks and cash at time *t*. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Panel A: Fund characteristics

	Mean	Median	Min	Max
Monthly gross return (%)	.96	1.5	-29.94	22.3
Monthly expense ratio (%)	.13	.13	.02	.49
AUM (millions)	1089.2	503.61	3.7	11824.48
ICI (%)	4.38	2.58	.1	55.17
ICI2 (%)	4.68	2.6	.09	112.86
Age (years)	14.59	14	0	36.83

Panel B: Correlation matrix

	Gross return	Expense ratio	AUM	Age	ICI	ICI2
Monthly gross return	1					
Monthly expense ratio	0.142***	1				
AUM	0.0199	-0.174***	1			
Age	0.0128	0.0462***	0.146***	1		
ICI	-0.0192	0.204***	-0.0153	-0.195***	1	
ICI2	-0.0199	0.188***	-0.0169	-0.199***	0.956***	1

5 Methodology

Through this chapter, we explain the methods used to study whether Norwegian funds manage to create value through industry concentrated portfolios. Further, we try to emphasize the link between the presented theory from chapter 3 and how it is implemented.

5.1 Industry Concentration Index

To determine the ICI for the individual funds, we adjust formula (10) to our dataset. Specifically, we assign each stock held by a fund to one of 11 sectors from the GICS. As mentioned, these sectors are used as proxy for industries. ICI for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the equity fund, relative to the sector weights of the OSEFX. ICI is calculated by:

$$ICI_{i,t} = \sum_{j=1}^{11} \left(w_{j,t} - \bar{w}_{j,t}\right)^2 \tag{11}$$

where $w_{j,t}$ is the weight of the equity fund holdings in sector *j* at time *t* and $\bar{w}_{j,t}$ is the weight of the OSEFX in sector *j* at time *t*. As the dataset includes monthly sector weights, the ICI is calculated at the end of each month. The index will be used for portfolio construction, which we will explain in section 5.3.

5.2 Industry Concentration Index 2

In our data material, we obtained one problem. Some funds have unclassified stockholdings and cash. In Figure 6, we illustrate this problem. We plot the mean of both unclassified stockholdings and cash, during the period from 2006 through 2017.

To capture the mentioned problem, we expand formula (11) by making an Industry Concentration Index 2 (ICI2). ICI2 will be used for robustness checks to our main results using ICI. This index will eliminate the effect that a fund's total holdings will not amount to 100 % when we remove unclassified stockholdings and cash. ICI2 for fund *i* at time *t,* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the equity fund, relative to the sector weights of the OSEFX.

ICI2 is calculated by:

$$ICI2_{i,t} = \sum_{j=1}^{11}\left(\left(\frac{w_{j,t}}{t_{uc,t}}\right) - \overline{w}_{j,t}\right)^2 \tag{12}$$

where $w_{j,t}$ is the weight of the equity fund holdings in sector *j* at time *t*, $t_{uc,t}$ is the sum of fund total holdings without unclassified stocks and cash at time *t* and $\overline{w}_{j,t}$ is the weight of the OSEFX in sector *j* at time *t*. $t_{uc,t} < 1$ for the funds with unclassified stockholdings or cash at time *t*.

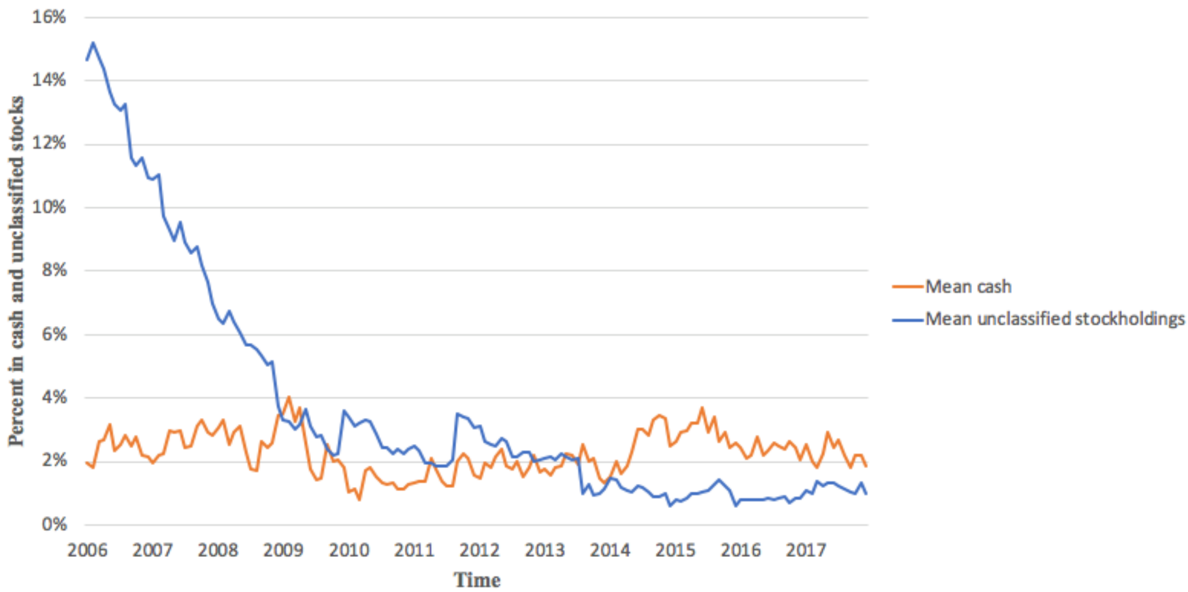

Figure 6 Development for unclassified stockholdings and cash from 2006 through 2017

5.3 Portfolio construction

5.3.1 Equally Weighted Portfolio

An Equally Weighted Portfolio (EWP), is, in general, a portfolio consisting of assets that are weighted equally and summed to one. Hence, $w_{i,EWP} = \frac{1}{N}$ with respect to $\Sigma_{i=1}^{N} w_{i,EWP} = 1$. In our case, w_{i,EWP_i} is the weight for fund i in the EWP_i and N is the number of funds included in the EWP_i.

First, we split our dataset into four decile portfolios according to the ICI at the end of each month. Second, the funds within each decile portfolio are given the same weights so that each decile sum to one, i.e., we make four EWPs. Decile 1 accord to the most diversified portfolio and Decile 4 is the most concentrated. The EWPs are rebalanced monthly based on the ICI. This makes it possible for a fund to change between two portfolios from one month to another; for instance, Alfred Berg Aktiv can switch between two EWPs from one month to another. For each EWP, we compute the equally weighted (EW) average return for each month.

5.3.2 Size portfolio

To further analyze the diseconomies of scale discussed by Berk and Green (2004) and Chen et al. (2004), we investigate whether the effect of ICI depends on the fund size. The results in chapter 6 toward size portfolios are compiled in two steps. First, we split the funds into four equally sized quintiles, based on their AUM at the end of each month. Second, we split the funds within each size quintile into four equal-sized deciles, according to their ICI. Quintile 1 represents the size portfolio of the smallest fund, while Quintile 4 report the portfolio including the largest funds. As for the EWPs, we compute the EW monthly average return for each decile portfolio, and the portfolios are rebalanced at the end of each month.

5.4 Active return

To analyze whether an EWP can beat the benchmark, we compute the active return, which is defined as the mean return difference between the EWP and the benchmark. The idea behind this is that the benchmark captures the risk of an EWP in a one-to-one basis, i.e., the EWP has a beta of one relative to its actual benchmark. We calculate the active return for all EWPs in the following way:

$$\mathcal{A}_{i,t} = \bar{r}_{i,t} - r_{m,t} \tag{13}$$

where $\mathcal{A}_{i,t}$ is the active return for EWP_i at time t, $\bar{r}_{i,t}$ is the average return of EWP_i at time t and $r_{m,t}$ is the return of the OSEFX at time t. To examine whether the return difference between the two samples is statistically significant, one can use different methods – we choose to use a t-test[15] for this. A such test can have three different outcomes. The active return can be equal to, greater than or less than zero, i.e., the test is two-sided. We have formulated the following hypothesis:

H_0: $\mathcal{A}_i = 0$
H_1: $\mathcal{A}_i \neq 0$

If we fail to reject the null hypothesis looking at gross $\mathcal{A}$, it indicates that the fund managers in the EWPs cannot create higher return than the market. Further, if we fail to reject the null hypothesis looking at net $\mathcal{A}$, it indicates that the fund managers are not able to cover their costs, and thus, do not add value to their investors portfolio. On the other hand, if we reject the null hypothesis, the opposite applies.

5.5 Regression models

Based on the EW average monthly returns, using different regression models, we test whether the Jensen´s alpha (α), referred to as alpha in chapter 6, is different from zero or not. Such test can have three different outcomes; the constant coefficient can be equal to, greater than or less than zero, i.e., the test is two-sided. The hypotheses for the regressions are formulated as follows:

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

If we fail to reject the null hypothesis looking at gross α, it indicates that the managers in the EWPs are not able to create value above the market. Further, if we fail to reject the null hypothesis looking at net α, it indicates that the managers in the EWPs are not able to cover their costs, and thus, do not possess investment abilities that are good enough to add value to their investors. If we reject the null hypothesis, the opposite applies. All regressions are performed based on OLS.[16]

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[15] See Appendix D for full explanation of t-test.

[16] Ordinary least squares (OLS) is a type of linear least squares method for estimating the unknown parameters in a linear regression model. The method corresponds to minimizing the sum of square differences between the observed and predicted values.

The regressions will decompose the fund's excess return into an alpha term, a beta term and a residual term. The α is the part of the return that is not generated by the risk factors considered. We will interpret the α as a measurement of managers' ability to generate abnormal returns. The betas can be seen as the part of the return that is caused by the fund's exposures to the risk factors. The sign of beta tells how the fund is tilted toward the risk factors; for instance, a positive SMB-beta implies that the portfolio has a small-cap tilt. Further, a market beta coefficient above (below) one, requires borrowing (lending) at the risk-free rate. This can potentially incur additional costs due to leverage. We will not take these costs into account in our analysis. The residual, ε, indicates all variation that the rest of the model cannot explain.

5.5.1 CAPM

As outlined in section 3.5.3, Jensen´s alpha (α) can be estimated by an extension of the original CAPM formula. Using the CAPM, which allows for a beta difference between the active funds and the benchmark, we will estimate the α. Some adjustments from formula (8) have been necessary for the implementation – the regression model is given by:

$$\bar{r}_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,m}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{14}$$

where the dependent left-hand variable, $\bar{r}_{i,t} - r_{f,t}$, is the average return of EWP_i in excess of the risk-free rate at time *t* and the independent variable is the return of the OSEFX in excess of the risk-free rate at time *t*. We have now added the complication that the α is a true excess return (zero-cost portfolio). $\varepsilon_{i,t}$ is the regression residual at time *t*.

5.5.2 Factor models

CAPM has been criticized in the past decades. Regression based on formula (14) limits itself to the explanatory power of the risk premium and the systematic risk for a benchmark. To adjust for return differences due to style and risk factors, we add different risk factors to our regression model. By expanding formula (14), we consider the three-factor model and the four-factor model when estimating α, that is – we run the following regressions:

$$\bar{r}_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,m}(r_{m,t} - r_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{i,t} \tag{15}$$

$$\bar{r}_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{i,m}\left(r_{m,t} - r_{f,t}\right) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \varepsilon_{i,t} \tag{16}$$

where the left-hand dependent variable, $\bar{r}_{i,t} - r_{f,t}$, is the average return of EWP_i in excess of the risk-free rate at time *t*, the right-hand independent variables are the risk factor returns at time *t* and $\varepsilon_{i,t}$ is the regression residual at time *t*.

5.6 Risk-adjusted performance measurements

Performance measurements reported in chapter 6 are calculated using standard techniques, but a review is provided to give an overview. We will use the SR, TR and IR to evaluate the risk-adjusted returns. The measurements are calculated by customizing the formulas presented in section 3.5, which we will explain in detail below.

5.6.1 Sharpe Ratio

To evaluate how much compensation the EWPs get compared to the underlying portfolio risk, we calculate the SR. The implemented formula is in accordance with formula (5) and is given by:

$$SR_{i,t} = \frac{\bar{r}_{i,t} - r_{f,t}}{\sigma_{i,t}} \tag{17}$$

where $\bar{r}_{i,t} - r_{f,t}$ is the average return of EWP_i in excess of the risk-free rate at time *t,* and $\sigma_{i,t}$ is the standard deviation of the excess return of EWP_i at time *t*.

5.6.2 Treynor Ratio

While SR considers total risk, the TR measures the excess return per unit of systematic risk. We calculate the measurement in accordance with formula (6), by the following:

$$TR_{i,t} = \frac{\bar{r}_{i,t} - r_{f,t}}{\beta_{i,t}} \tag{18}$$

where $\bar{r}_{i,t} - r_{f,t}$ is the average return of EWP_i in excess of the risk-free rate at time t, and $\beta_{i,t}$ is the beta of the EWP_i at time t, i.e., the measurement of $EWP_i's$ volatility of returns relative to the OSEFX. We use the estimated betas retrieved from the CAPM regressions, according to formula (14).

5.6.3 Information Ratio

The IR measures a portfolio's return in excess of the benchmark, i.e., the active return, per extra unit of risk that follows by deviating from the market portfolio. In accordance with formula (9), we calculate IR by:

$$IR_{i,t} = \frac{\bar{r}_{i,t} - r_{m,t}}{TE_{i,t}} \tag{19}$$

where $\bar{r}_{i,t} - r_{f,t}$ is the average return of EWP_i in excess of the OSEFX return at time t, and $TE_{i,t}$ is the standard deviation of the excess return at time t.

6 Results

In this chapter, we present the results from the analysis. The methods presented in chapter 5 are used to examine whether Norwegian fund managers can create value through industry concentrated fund portfolios or not. The average expenses, according to each decile portfolio, are only reported once – in Table 4.

Before we start discussing our results, we want to study some general trends in the Norwegian market. In Figure 7, we present the development of an EWP containing all of the included Norwegian equity funds relative to the OSEFX from 2006 through 2017. Developments are before deducting expenses and are indexed to 100 at the beginning of the period. The market had a significant setback during the Financial Crisis, where the benchmark had a sharper fall than the EWP. In the more recent period, both the equity funds and the benchmark have seen steady growth.

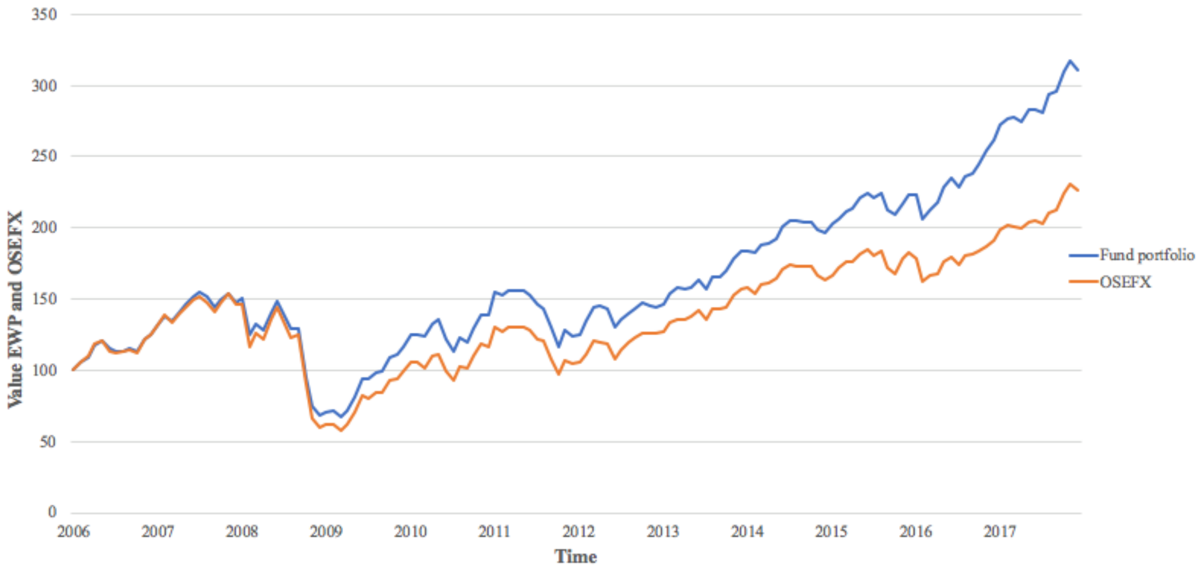

Figure 7 Development of an EWP and the OSEFX from 2006 through 2017

A decomposition of portfolio performance at sector level can in part explain the overall performance of the active funds. Figure 8 illustrates the monthly quote development for the 11 sectors and Table 3 gives an overview of return information for each sector during the period. As for Figure 7, the sector developments are indexed to 100 at the beginning of the period. Through the period, sectors like Consumer Staples, Communication Services, Utilities and Financials have created high returns, while the Energy, Information Technology and Industrial sector have generated a more gently development. Consumer Staples has had the very best growth, and especially since the Oil Crisis, the development has been great. The sector has yielded an absolute return of 444 % during the period.

The average return of the EWP has been higher than for the benchmark throughout the whole period. Particularly between the crises and after the Oil Crisis, the EWP has generated a higher return than the OSEFX. Active funds ability to time their investments and pick the right stocks after the various crises, seem to be the main reason that partly explains the outperformance of the OSEFX. For example, if the funds have been better than the benchmark to keep sectors that have generated high returns, such as Consumer Staples or Communication Services, they may have generated higher returns than the benchmark. Although the EWP of all funds, on average, has generated a higher absolute return than the OSEFX, it is hard to say whether the returns are statistically significant and caused by skill rather than luck.

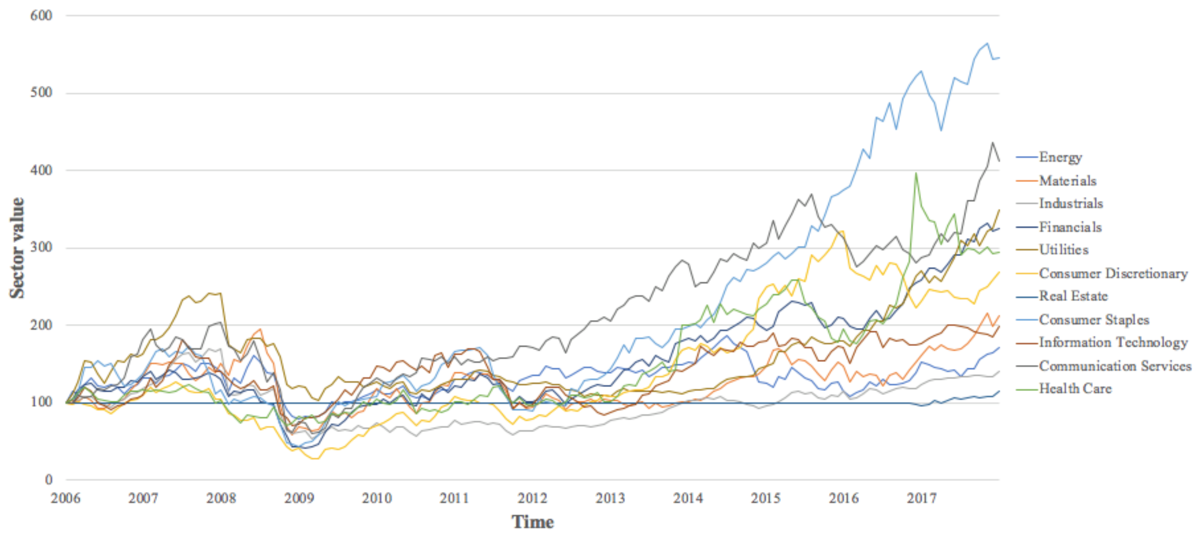

Figure 8 Quote development for the 11 sectors from 2006 through 2017

Table 3 Return information for the sectors

This table summarizes monthly geometric and absolute return information for the 11 sectors from the GICS in the period from 2006 to 2017. The monthly geometric return is calculated by: $R^G = \left(\frac{P_{T,i}}{P_{0,i}}\right)^{\frac{1}{144}} - 1$. The absolute return is calculated by: $R^A = \left(\frac{P_{T,i}}{P_{0,i}}\right) - 1$. Where $P_{T,i}$ is the quote value for sector *i* per December 2017 and $P_{0,i}$ is the quote value for sector *i* per January 2006. Note that the Real Estate sector started in September 2016, and thus the return history is short.

OSE number	Sector	Monthly return	Absolute return
OSE10	Energy	0.38 %	71.82 %
OSE15	Materials	0.52 %	111.40 %
OSE20	Industrials	0.23 %	39.80 %
OSE25	Consumer Discretionary	0.69 %	168.97 %
OSE30	Consumer Staples	1.18 %	444.76 %
OSE35	Health Care	0.75 %	194.65 %
OSE40	Financials	0.82 %	225.49 %
OSE45	Information Technology	0.48 %	99.33 %
OSE50	Communication Services	0.99 %	311.41 %
OSE55	Utilities	0.87 %	248.11 %
OSE60	Real Estate	0.83 %	14.10 %

6.1 Active return

We want to test whether the return difference between each EWP and the OSEFX are significantly different from zero or not. Table 4 summarizes results from our t-tests toward active return and reports both the gross and net returns. Overall, the negative performance difference between the most concentrated and diversified portfolios increases if we study the net returns because highly concentrated funds charge higher expenses than diversified funds.

In general, when looking at net returns, there is a lack of significant values. Even though we find positive values, there is only one decile in the two panels that are significantly different from zero at the 10 % level. This indicates that we fail to reject the null hypothesis and cannot conclude whether fund managers are able to cover their costs or not.

Looking at gross returns, we find significant values. In Panel A, we find Decile 1 to Decile 3 significant while Decile 1 and Decile 2 are significant in Panel B. From these results, we can reject the null hypothesis and conclude that some of the deciles portfolios can outperform the market. For both panels, we find Decile 2 to perform best, with a monthly active return of 0.261 % and 0.191 % respectively. Further, we also observe that the fourth decile has a lower active return compared to the first decile. These results suggest that the diversified fund portfolios tend to perform better than the concentrated portfolios. Another interesting finding is that Decile 2 has a higher active return and lower expenses compared to All Funds in both panels. In Panel A we find these values significant, which indicates that the funds within Decile 2 have performed better than the average funds included.

Assuming the benchmark captures the proper risks, the active funds in total have positive values in both panels. Furthermore, in lack of significant values, we can only conclude that All Funds has beaten the OSEFX by 0.188 % per month before expenses for the whole period, and that diversified funds tend to create higher active returns than the concentrated ones.

Table 4 Active return

This table summarizes active return, before and after expenses, for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI, which is given by $ICI_{i,t} = \sum_{j=1}^{11}(w_{j,t} - \overline{w}_{j,t})^2$, where *ICI* for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $w_{j,t}$, relative to the sector weights of the OSEFX, $\overline{w}_{j,t}$. The active returns and expenses are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. T statistics are shown in parentheses.

	Before expenses	Expense ratio	After expenses
Panel A: 2006 to 2017			
All Funds	0.188**	0.127	0.061
	(2.152)	-	(0.697)
Decile 1	0.196***	0.105	0.090
	(3.229)	-	(1.485)
Decile 2	0.261***	0.116	0.145*
	(3.489)	-	(1.938)
Decile 3	0.190*	0.139	0.051
	(1.967)	-	(0.530)
Decile 4	0.152	0.148	0.004
	(0.992)	-	(0.027)
Decile 4 – Decile 1	-0.044	0.043	-0.086
	(-0.265)	-	(-0.523)
Panel B: 2010 to 2017			
All Funds	0.149	0.122	0.027
	(1.602)	-	(0.292)
Decile 1	0.172***	0.097	0.075
	(3.052)	-	(1.318)
Decile 2	0.191**	0.111	0.080
	(2.436)	-	(1.014)
Decile 3	0.154	0.138	0.016
	(1.493)	-	(0.156)
Decile 4	0.141	0.141	0.001
	(0.808)	-	(0.004)
Decile 4 – Decile 1	-0.031	0.043	-0.074
	(-0.166)	-	(-0.401)

6.2 Regression results

In this section we present the regression results. Furthermore, we also present the portfolio's tilt toward the included risk factors, and finally, we examine the results related to size portfolios.

6.2.1 CAPM

Table 5 summarizes regression results from the CAPM. Both the gross and net alphas are reported.

Starting with All Funds in Panel A, we observe a monthly alpha of 0.237 % and 0.111 % before and after expenses, respectively. Further, we find a higher gross alpha for Decile 4 compared to Decile 1. The fourth decile outperforms the first decile by only 0.008 % per month. Due to higher expenses for the concentrated funds, the difference after expenses is negative. However, the differences are not statistically significant. Overall, the second decile has the highest alpha, both before and after expenses.

In Panel B, we observe lower monthly alphas than in Panel A. Comparing the deciles; we now find the fourth decile to perform best before expenses, with a monthly gross alpha of 0.238 %. However, this value is not significant. Similar to Panel A, the most concentrated funds outperform the diversified funds before expenses but underperforms after. This indicates that fund managers in the concentrated portfolios charge to high expenses, and in lack of statistically significant values, we cannot conclude whether they have investment abilities to cover their costs.

In general, due to a beta below one in our risk-adjusted regression model, we observe higher alphas compared to the active return. Comparing the difference in net alphas between Decile 4 and Decile 1, we find negative values, but they are not significant. This suggests that concentrated funds tend to underperform the diversified ones. Furthermore, we reject the null hypothesis looking at the gross alphas – which indicates that Norwegian fund managers are able to create value above the market. Looking at net alphas, we still find positive values, but in lack of statistical significance, we can only reject the null hypothesis for some deciles. This indicates that we do not have enough evidence to support the findings from

Forbrukerrådet (2018). Whether the fund managers create value to their investors or not is an open question.

Table 5 CAPM

This table summarizes alphas, before and after expenses, using the CAPM, for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI, which is given by $ICI_{i,t} = \sum_{j=1}^{11} (w_{j,t} - \bar{w}_{j,t})^2$, where *ICI* for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $w_{j,t}$, relative to the sector weights of the OSEFX, $\bar{w}_{j,t}$. The alphas are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The standard errors of the regressions are given in parentheses.

	Before expenses	After expenses
Panel A: 2006 to 2017		
All Funds	0.237***	0.111
	(0.073)	(0.073)
Decile 1	0.227***	0.122**
	(0.053)	(0.053)
Decile 2	0.294***	0.179***
	(0.068)	(0.068)
Decile 3	0.242***	0.010
	(0.083)	(0.008)
Decile 4	0.234*	0.008
	(0.132)	(0.013)
Decile 4 – Decile 1	0.008	-0.035
	(0.142)	(0.142)
Panel B: 2010 to 2017		
All Funds	0.204**	0.083
	(0.088)	(0.088)
Decile 1	0.198***	0.101*
	(0.055)	(0.055)
Decile 2	0.233***	0.122
	(0.075)	(0.075)
Decile 3	0.211**	0.007
	(0.099)	(0.009)
Decile 4	0.238	0.009
	(0.167)	(0.015)
Decile 4 – Decile 1	0.040	-0.003
	(0.176)	(0.176)

6.2.2 Three-factor model and four-factor model

Table 6 summarizes the regression result from the three-factor model and the four-factor model. We report both the gross and net alphas.

Starting with Panel A, we observe that the concentrated funds tend to underperform the diversified funds in both the three-factor model and the four-factor model. Comparing Decile 4 relative to Decile 1, we find the monthly gross alphas in the three-factor model to be

0.096 % and 0.208 %, while the four-factor model gives 0.182 % and 0.182 %, respectively. Only Decile 1 is statistically significant. The monthly difference, before expenses, between the fourth and first decile, is -0.112 % and 0.001 % in the three-factor model and the four-factor model, respectively. The differences are not significant. Looking at net alphas, there is a lack of significant values.

In Panel B, we also observe that the most concentrated funds tend to underperform the most diversified funds in both the three-factor model and the four-factor model. Comparing Decile 4 to Decile 1, we find the monthly gross alphas to be 0.093 % and 0.181 % in the three-factor model, and 0.116 % and 0.150 % in the four-factor model, respectively. Only Decile 1 is statistically significant. The monthly difference between the fourth and the first decile is -0.088 % and -0.034 % before expenses in the three-factor model and the four-factor model, respectively. Although there are negative differences, we do not find these significant. Similar to Panel A, the evidence that fund managers possess investment abilities that are good enough to add value to their investors' portfolios is lacking.

For both the three-factor model and the four-factor model, we observe positive gross and net values. In lack of significant net values, we cannot conclude whether the fund managers are able to cover their costs. The alphas of the most diversified fund portfolios exceed the most concentrated fund portfolios. This result does not support the findings from Kacperczyk et al. (2005) and Hiraki et al. (2015). However, despite negative differences, we do not find these values statistically significant.

Table 6 Three-factor model and four-factor model

This table summarizes alphas, before and after expenses, using the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. The table includes different portfolios of funds for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI, which is given by $ICI_{i,t} = \sum_{j=1}^{11}(w_{j,t} - \overline{w}_{j,t})^2$, where *ICI* for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $w_{j,t}$, relative to the sector weights of the OSEFX, $\overline{w}_{j,t}$. The alphas are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The standard errors of the regressions are given in parentheses.

	Before expenses		**After expenses**	
	Three-factor	Four-factor	Three-factor	Four-factor
Panel A: 2006 to 2017				
All Funds	0.169**	0.172**	0.043	0.045
	(0.069)	(0.073)	(0.069)	(0.073)
Decile 1	0.208***	0.182***	0.103*	0.076
	(0.054)	(0.057)	(0.054)	(0.057)
Decile 2	0.261***	0.225***	0.145**	0.108
	(0.068)	(0.071)	(0.068)	(0.071)
Decile 3	0.174**	0.159*	0.037	0.022
	(0.078)	(0.082)	(0.078)	(0.082)
Decile 4	0.096	0.182	-0.050	0.036
	(0.118)	(0.122)	(0.118)	(0.122)
Decile 4 -Decile 1	-0.112	0.001	-0.153	-0.040
	(0.130)	(0.135)	(0.130)	(0.135)
Panel B: 2010 to 2017				
All Funds	0.139*	0.114	0.018	-0.007
	(0.083)	(0.092)	(0.083)	(0.092)
Decile 1	0.181***	0.150**	0.084	0.052
	(0.056)	(0.061)	(0.056)	(0.061)
Decile 2	0.199**	0.148*	0.088	0.039
	(0.076)	(0.084)	(0.076)	(0.083)
Decile 3	0.146	0.090	0.008	-0.048
	(0.093)	(0.102)	(0.093)	(0.102)
Decile 4	0.093	0.116	-0.046	-0.024
	(0.153)	(0.169)	(0.153)	(0.169)
Decile 4 -Decile 1	-0.088	-0.034	-0.130	-0.076
	(0.163)	(0.180)	(0.162)	(0.180)

6.2.3 Risk factors

To examine the risk and style characteristics of the decile portfolios, we report the factor loadings of the four-factor model before expenses in Table 7. Looking at All Funds in Panel A, actively managed funds have significant tilts toward the market and size factor, but not toward the value and momentum factor. This indicates a lower exposure to the market relative to the OSEFX, and overweight in small firms. Comparing concentrated to diversified funds, we observe that concentrated funds tend to hold more small companies and exhibit less momentum in their returns than diversified funds.

In Panel B, All Funds have similar tilts toward the factor loadings as in Panel A. Further; concentrated funds also tend to hold more small companies than diversified funds.

Table 7 Factor estimates for the four-factor model

This table summarizes the factor loadings using the Carhart (1997) four-factor model for different portfolios of funds for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI, which is given by $ICI_{i,t} = \sum_{j=1}^{11}(w_{j,t} - \bar{w}_{j,t})^2$, where *ICI* for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $w_{j,t}$, relative to the sector weights of the OSEFX, $\bar{w}_{j,t}$. The first column reports the four-factor alphas, and the remaining four columns report the factor loadings using returns before expenses. Alphas are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The standard errors of the regressions are given in parentheses.

	Alpha	Market beta	Size beta	Value beta	Momentum beta
Panel A: 2006 to 2017					
All Funds	0.172**	0.960***	0.122***	0.021	-0.002
	(0.073)	(0.016)	(0.024)	(0.019)	(0.017)
Decile 1	0.182***	0.960***	0.033*	0.017	0.020
	(0.057)	(0.012)	(0.018)	(0.015)	(0.014)
Decile 2	0.225***	0.970***	0.065***	-0.002	0.028
	(0.071)	(0.016)	(0.023)	(0.019)	(0.017)
Decile 3	0.159*	0.963***	0.133***	0.030	0.011
	(0.082)	(0.018)	(0.027)	(0.022)	(0.020)
Decile 4	0.182	0.951***	0.261***	0.039	-0.066**
	(0.122)	(0.027)	(0.040)	(0.033)	(0.029)
Decile 4 – Decile 1	0.001	-0.001	0.227***	0.023	-0.086***
	(0.135)	(0.029)	(0.044)	(0.036)	(0.033)
Panel B: 2010 to 2017					
All Funds	0.114	0.984***	0.138***	0.020	0.016
	(0.092)	(0.024)	(0.031)	(0.024)	(0.024)
Decile 1	0.150**	0.985***	0.045**	0.012	0.019
	(0.061)	(0.016)	(0.021)	(0.016)	(0.016)
Decile 2	0.148*	0.974***	0.065**	-0.006	0.031
	(0.084)	(0.022)	(0.029)	(0.022)	(0.022)
Decile 3	0.090	0.991***	0.155***	0.033	0.034
	(0.102)	(0.027)	(0.035)	(0.027)	(0.027)
Decile 4	0.116	0.987***	0.289***	0.034	-0.014
	(0.169)	(0.045)	(0.058)	(0.045)	(0.044)
Decile 4 – Decile 1	-0.034	0.002	0.244***	0.023	-0.033
	(0.180)	(0.047)	(0.061)	(0.048)	(0.047)

6.2.4 Size portfolios

To analyze the effect of ICI due to the size of the funds and performances, we present the results from the EW size portfolios in Table 8. The table summarizes the monthly gross alphas, using the four-factor model. Note that each decile within the size quintiles has a low number of funds, which can give impact to the statistical significance.

Starting with All Funds in Panel A, we observe that small funds tend to outperform large funds. We find the monthly gross alpha to be 0.237 % and 0.102 %, for the smallest and largest size quintile, respectively. Only Quintile 1 being statistically significant.
Further, in Panel A, we observe positive performance difference between the fourth and first decile within Quintile 1, while the difference is negative for the larger size quintiles. However, none of these differences is statistically significant. In addition, we observe a lower average ICI in the smallest quintile, compared to the largest one.

From Panel B, we also observe that the smallest size quintiles outperform the largest quintiles for All Funds. The monthly gross alphas are 0.142 % and 0.069 % for the lowest and highest quintile, respectively. However, these alphas are not significant. Similar to Panel A, Quintile 2 tend to perform best. Comparing the difference between the diversified and concentrated funds in the different size portfolios, we observe the same results as in Panel A – the difference is only positive for the smallest size quintile.

Our findings support the results from Chen et al. (2004), that small funds tend to outperform large funds. This indicates that Norwegian equity funds suffer from diseconomies of scale. While concentrated portfolios perform better than diversified for the smallest funds, diversification seems to be better for most funds.

Table 8 Size portfolios using the four-factor model

This table summarizes alphas, before expenses, using the Carhart (1997) four-factor model, for both the period of 2006 to 2017 and 2010 to 2017. First, we split the funds into four equally sized quintiles, based on their AUM at the end of each month. Second, we split the funds within each size quintile into four equal-sized deciles according to their lagged ICI, which is given by $ICI_{i,t} = \sum_{j=1}^{11}(w_{j,t} - \bar{w}_{j,t})^2$, where *ICI* for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $w_{j,t}$, relative to the sector weights of the OSEFX, $\bar{w}_{j,t}$. The alphas are expressed at a monthly frequency. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The standard errors of the regressions are given in parentheses.

	Quintile 1	Quintile 2	Quintile 3	Quintile 4
Panel A: 2006 to 2017				
Average AUM (millions)	128.33	439.87	926.63	2875.69
Average ICI (%)	4.56	4.48	3.28	5.15
All Funds	0.237***	0.240***	0.158*	0.102
	(0.081)	(0.091)	(0.080)	(0.075)
Decile 1	0.228***	0.279***	0.191**	0.198**
	(0.076)	(0.090)	(0.078)	(0.079)
Decile 2	0.258***	0.326***	0.057	0.085
	(0.091)	(0.097)	(0.077)	(0.076)
Decile 3	0.101	0.224*	0.264**	0.020
	(0.131)	(0.131)	(0.114)	(0.112)
Decile 4	0.347**	0.136	0.112	0.092
	(0.146)	(0.183)	(0.133)	(0.124)
Decile 4 – Decile 1	0.119	-0.143	-0.079	-0.106
	(0.165)	(0.204)	(0.155)	(0.147)
Panel B: 2010 to 2017				
Average AUM (millions)	149.60	517.18	1123.92	3358.80
Average ICI (%)	4.60	3.93	2.56	3.16
All Funds	0.142	0.230*	0.087	0.069
	(0.115)	(0.120)	(0.092)	(0.088)
Decile 1	0.162*	0.252**	0.131	0.181**
	(0.096)	(0.104)	(0.087)	(0.077)
Decile 2	0.180	0.186	0.069	0.082
	(0.121)	(0.124)	(0.089)	(0.083)
Decile 3	-0.041	0.350**	0.069	0.005
	(0.191)	(0.166)	(0.131)	(0.134)
Decile 4	0.229	0.119	0.037	0.062
	(0.201)	(0.250)	(0.159)	(0.162)
Decile 4 – Decile 1	0.068	-0.133	-0.094	-0.120
	(0.224)	(0.271)	(0.181)	(0.179)

6.3 Risk-adjusted performance measurements

In this section, we will look at how the EWPs perform, using performance measurements presented in section 5.6. Such measurements can help us refine the image of the risk associated with the return achieved. To assess the performance of different portfolios, one must adjust for risk before comparison makes sense. There are many methods used for this. The performance measurements you choose will be able to provide different rankings for the portfolios. In Table 9, we present an overview of the fund portfolio´s performance results.

We report two different rankings, one between the OSEFX and the All Funds portfolio, and one between the different decile portfolios.

Table 9 Performance measurements

This table summarizes the Sharpe, Treynor and Information Ratios for both the period of 2006 to 2017 and 2010 to 2017. The table report two different rankings, one between the All Funds and the OSEFX, and one between the different decile portfolios.

Panel A: 2006 to 2017								
Portfolios	**Sharpe Ratio**		**Treynor Ratio**		**Information Ratio**		**Overall rank**	
	SR	Rank	TR	Rank	IR	Rank	Sum	Rank
OSEFX	0.086	2	0.005	2	-	-	4	2
All Funds	0.128	1	0.008	1	0.180	-	2	1
Decile 1	0.125	4	0.008	4	0.270	2	10	4
Decile 2	0.136	1	0.008	1	0.291	1	3	1
Decile 3	0.129	2	0.008	3	0.164	3	8	2
Decile 4	0.126	3	0.008	2	0.083	4	9	3
Panel B: 2010 to 2017								
Portfolios	**Sharpe Ratio**		**Treynor Ratio**		**Information Ratio**		**Overall rank**	
	SR	Rank	TR	Rank	IR	Rank	Sum	Rank
OSEFX	0.133	2	0.007	2	-	-	4	2
All Funds	0.171	1	0.009	1	0.134	-	2	1
Decile 1	0.171	3	0.009	4	0.255	1	8	2
Decile 2	0.178	1	0.009	2	0.203	2	5	1
Decile 3	0.172	2	0.009	3	0.125	3	8	2
Decile 4	0.170	4	0.010	1	0.067	4	9	4

From the table, we observe positive ratios for all portfolios, including the benchmark. In general, actively managed funds have higher values for the SR and TR compared to OSEFX. This indicates that active managers are more compensated for the undertaken risk than the OSEFX.

According to SR, Decile 2 and Decile 3 are the best performing deciles in both periods – Decile 2 is the overall best, with 0.136 and 0.178 in the two periods, respectively. This reflects how much Decile 2 achieves in excess return over the risk-free rate per unit of risk it undertakes. Generally, we find higher values in Panel B compared to Panel A. One explanation for this could be the Financial Crisis, where all funds on average, including the benchmark, had negative returns. In addition, the market was exposed to more unstable and extreme returns. This led to a higher difference in fund performance between each fund, i.e., higher standard deviation during the full sample period. The risk-free rate has also decreased in more recent years. Based on the SR, a partly diversified portfolio seems to gain most from the undertaken risk.

Similar to the SR, we observe the highest TR values in the more recent sample period. Also here, this could be explained by the Financial Crisis. Higher excess return over the risk-free rate for our fund portfolios in recent years, is the main reason for the development. According to TR, Decile 1 has the weakest performance in both periods. Although we do not find any clear pattern in the ranking for the different decile portfolios, Decile 4 performs best in Panel B, with 0.010 in excess return per unit of systematic risk it undertakes. However, the ratios deviate minimally between the deciles.

In general, we find higher IR values in Panel A compared to Panel B. This indicates that in the more recent sample period, the funds achieve lower excess return over the benchmark return, or that the active management comes with higher portfolio risk compared to the benchmark. From the ranking, we find the diversified deciles to perform best in both periods. In the recent period, they achieve 0.255 and 0.203, respectively. These numbers indicate the additional return per unit of additional unique risk they undertake, by deviating from the OSEFX. In addition, we observe that Decile 4 has the weakest performance in both periods. According to IR, diversified portfolios tend to be better than concentrated portfolios in the Norwegian market.

Overall, we find Decile 2 and 3 to perform best in the overall ranking for both panels. Decile 2 is the very best, which indicates that fund managers in this decile have generated the best risk-adjusted abnormal returns. Hence, the result suggests that a partial diversified sector portfolio seems to have the best performance in the Norwegian market throughout the period.

6.4 Robustness checks

Overall, analyzing the results using ICI2, we find very similar rankings for the decile portfolios compared to the results using ICI. This indicates that the problem due to unclassified stockholdings and cash do not have any impact on our findings. Both the alphas and their statistical significance deviate minimally between the results using the two concentration indices. As expected, we observe small changes in the results from the more recent period, as the portion of unclassified stocks and cash are almost gone after 2010. In Table 10, we present the regression results from the three-factor model and the four-factor model using EWPs sorted by ICI2. Both gross and net alphas are reported. For the other robustness results, see Appendix E. As Table 10 shows, we find very similar results as presented in section 6.2.2. We still find that the diversified funds tend to outperform concentrated funds. However, the difference is still insignificant, and we cannot conclude whether diversified funds outperform the concentrated.

Table 10 Three-factor model and four-factor model (using ICI2)

This table summarizes alphas, before and after expenses, using the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. The table includes different portfolios of funds for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI2, which is given by $ICI2_{i,t} = \sum_{j=1}^{11}\left(\left(\frac{w_{j,t}}{t_{uc,t}}\right) - \bar{w}_{j,t}\right)^2$, where $ICI2$ for fund i at time t is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $\left(\frac{w_{j,t}}{t_{uc,t}}\right)$, relative to the sector weights of the OSEFX, $\bar{w}_{j,t}$. Where $t_{uc,t}$ is the sum of the fund's total holdings without unclassified stocks and cash at time t. The alphas are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The standard errors of the regressions are given in parentheses.

	Before expenses		**After expenses**	
	Three-factor	Four-factor	Three-factor	Four-factor
Panel A: 2006 to 2017				
All Funds	0.169**	0.172**	0.043	0.045
	(0.069)	(0.073)	(0.069)	(0.073)
Decile 1	0.218***	0.193***	0.113**	0.088
	(0.055)	(0.058)	(0.055)	(0.058)
Decile 2	0.201***	0.175**	0.083	0.057
	(0.072)	(0.076)	(0.072)	(0.076)
Decile 3	0.179**	0.171**	0.044	0.036
	(0.078)	(0.082)	(0.078)	(0.082)
Decile 4	0.101	0.176	-0.047	0.028
	(0.118)	(0.123)	(0.118)	(0.123)
Decile 4 – Decile 1	-0.117	-0.0176	-0.160	-0.060
	(0.131)	(0.137)	(0.131)	(0.136)
Panel B: 2010 to 2017				
All Funds	0.139*	0.114	0.018	-0.007
	(0.083)	(0.092)	(0.083)	(0.092)
Decile 1	0.179***	0.151**	0.082	0.059
	(0.056)	(0.061)	(0.056)	(0.061)
Decile 2	0.198**	0.151*	0.086	0.039
	(0.078)	(0.086)	(0.078)	(0.085)
Decile 3	0.131	0.082	-0.004	-0.054
	(0.094)	(0.103)	(0.094)	(0.103)
Decile 4	0.112	0.122	-0.029	-0.018
	(0.152)	(0.168)	(0.151)	(0.168)
Decile 4 – Decile 1	-0.067	-0.029	-0.110	-0.071
	(0.161)	(0.179)	(0.161)	(0.179)

6.5 Discussion

Following the results, despite there is a lack of significant net values, the Norwegian market seems to be a market where it is possible to achieve abnormal returns through active management. However, we find no evidence that industry concentration seems to pay off in this market.

Even though financial theory recommends investors to diversify their holdings across industries to reduce their overall unsystematic risk, a considerable part of Norwegian funds is betting against their chosen benchmark with a more industry concentrated portfolio. OSE is characterized by a small investment universe where there can be information imperfections and mispricing. Our results indicate that more concentrated fund portfolios achieve positive alphas, but few of the net values are significant. This leads us to the idea that there is a large spread in the returns achieved for the more concentrated funds. Negative differences between the most concentrated and diversified fund portfolios indicate that there are also difficulties in creating higher returns through an industry concentrated portfolio compared to a diversified portfolio.

In contrast to global funds, Norwegian funds which solely invest in the Norwegian market could have problems due to investment opportunities. They will have a low number of possible investments. More importantly, the number of companies within each industry is vastly uneven and, in some industries, highly limited. For example, in 2017, there were only two companies in the Utility and Communication Service sectors, while companies within the Energy and Industrial sector dominated the rest of the OSE. Hence, OSE itself is a concentrated and volatile stock exchange, and its small universe is one of the main reasons why industry concentration seems challenging.

The uneven distribution of companies within the different sectors makes it difficult for Norwegian managers to achieve abnormal returns by industry concentration. If they choose to concentrate their portfolios in an already dominating industry, this will require unusual large industry-holdings as the market already has a considerable part of its holdings invested in this industry. The different alternative, which is larger stockholdings in the smaller industries, requires either larger holdings in companies they already own or new investments in companies that are "second best" alternatives. Such strategies are highly risky and have the possibility of a huge upside, but also a really low downside. While it is possible to outperform the market this way, it is difficult to do it consistently, which is reflected in our results. These strategies are likely to increase the portfolio risk more than it is compensated.

The breadth of the market is essential, but also the depth has a lot to say. Many of the attractive companies in the Norwegian market have a low market capitalization and possibly low stock turnover per day. This, combined with the Norwegian market being relatively narrow, makes it even riskier to concentrate their portfolio in a few industries. The risk of not being able to trade their shares as fast as they want could have a significant impact on the returns achieved. The liquidity on OSE could, therefore, be a problem for concentrated portfolios. This problem is more prominent in small stock exchanges compared to larger stock exchanges, for instance, the NYSE.

Furthermore, size is problematic for fund managers; not only does more AUM tend to make the market move against you when you try to build a position, but there are theoretically only some good investment opportunities and fewer and fewer as your requirements for the size of an investment increase. Large-scale funds with a limited universe are more likely to face challenges related to their size compared to large-scale global funds because their universe is limited by the number of the companies they invest in – especially on a small stock exchange like OSE. This can partly explain why it could be challenging to concentrate portfolios into industries for large funds in the Norwegian market.

When we control for the size, we observe that small funds perform better than larger funds. OSE – like other stock exchanges – is characterized by diseconomies of scale. Furthermore, we do not find a clear link between industry concentration and the fund size. Small funds have the advantage of being able to invest a higher share of the fund's capital in the “best ideas” regardless of the size of the investable companies. Hence, fewer good investment objects are needed to achieve a desirable return for the fund. For example, a fund with AUM of 100 million NOK could invest 10 million NOK in a company that has a small market cap while a fund with AUM of 1,000 million NOK must invest 100 million NOK to get the same exposure. Thus, a small SMB fund focusing on small companies in the Norwegian market can benefit compared to a large SMB fund in the same market. Most funds, besides the rules on the max size in the fund, also have limits on how much of a company the fund can own.

Furthermore, large funds will also be more affected by the depth of the market. OSE is not liquid enough for large funds to be able to invest in attractive medium-sized companies and at the same time, have adequate liquidity in its investments. In global stock exchanges, this problem will be limited as the selection of companies is much higher.

An active fund with a low ICI, categorized as diversified, will have similar industry-holdings as its benchmark but may differ entirely from the benchmark in companies invested within each industry. While our results indicate that more diversified fund portfolios perform better than more concentrated portfolios, it is possible that this is because some fund managers have better stock picking abilities, not solely because they are more diversified across industries. This is not something we can detect with our industry concentration index, and this will be discussed further in section 7.2.

There are two main takeaways in why industry concentration can be challenging on the OSE; First, OSE is characterized by a small investment universe which limits the number of possible investments. Second, industry concentration on an already commodity-focused stock exchange will entail very high risk and can thus go beyond a funds' investment strategy.

7 Conclusion and limitations

7.1 Conclusion

Whether active management creates value or not, has been a big debate among practitioners and academics. Using a dataset of Norwegian equity funds from 2006 through 2017, we investigate whether Norwegian fund managers can create value by deviate from a passive benchmark and concentrating their portfolios in specific industries.

Our analyses have provided several exciting findings. The regression analyses and t-tests suggest that Norwegian fund managers, on average, can create value above the OSEFX before deducting expenses. After deducting expenses, we still find positive alphas in our results, but the statistical evidence that fund managers, in general, have sufficient skill to cover their costs is lacking. Therefore, we do not have enough evidence to conclude whether investors get value added to their portfolios, but the Norwegian market seems to be efficient on a sufficient weak form. Hence, it could be possible to achieve abnormal return through active management. Comparing differences between return in the concentrated fund portfolios to the diversified portfolios, we overall find that the most diversified fund portfolios tend to perform best. We do, however, note that these differences are not significant.

The main takeaway from the regression analyses and t-tests suggests that there is no evidence that concentrated portfolios seem to perform better than diversified ones. These findings are robust when controlling for unclassified stockholdings and cash using ICI2. There are neither differences in results from the two periods. Further, investigating the diseconomies of scale, we do not find a clear pattern between industry concentration and the size of a fund. Although smaller funds perform better than larger funds, we find no evidence whether this is due to concentration or not. In addition, examining the risk and style characteristics of the decile portfolios, we observe that concentrated funds tend to hold more small companies and exhibit less momentum in their returns than diversified funds.

When risk-adjusting the returns using performance measurements, we obtained positive ratios for all portfolios. In the overall ranking, the most concentrated fund portfolios have a poor performance with low ratios, while Decile 2 is the best performing decile in both periods. Although it is more difficult to draw a clear conclusion from the performance measurements, a partly diversified portfolio seems to be most compensated for the undertaken risk.

In contrast with previous literature, we do not find evidence that funds with more industry concentrated portfolios perform better than funds with diversified portfolios. To answer our research question, we argue that Norwegian fund managers are not able to create value by concentrating their portfolios in specific industries.

7.2 Limitations and further research

We have made our best efforts to minimize limitations through the thesis, but certain aspects of it need to be addressed. While our results provide exciting insight, we believe our thesis can be expanded. Therefore, we aim to give an outline of some limitations and aspects that could be further researched.

We have only included risk factors in connection with our regression models in the thesis. A proposal for further research may be to go into more depth on whether other risk factors are relevant for Norwegian equity funds. However, it is difficult to define what is a relevant risk. Several different models can be used to analyze fund performance. For instance, Fama and French (2015) expanded their three-factor model, where they included the two risk factors, Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA). It is, therefore, conceivable to believe that other models are better suited to investigate factors that influence the performance of Norwegian equity funds.

To investigate fund concentration, we have in this thesis, contribute to the concentration measure, ICI, defined by Kacperczyk et al. (2005). For further research, we believe that a Security Concentration Index (SCI) could be interesting to include. In contrast to focusing on the total industry weight, the SCI could measure the relative size of the bets the manager is placing in the firms held. In other words, SCI could, therefore, measure the fund's concentration in a more specific way by introducing the holding differences in specific firms. The results from such analysis could, therefore, be more suited to investigate if the fund performance can be due to either stock picking or market timing.

Finally, it would also be exciting to extend our thesis, including all mutual funds invested on the OSE, not just the Norwegian equity funds. Due to insignificant results in our difference regressions, we believe an expanded data material of more individual funds and an expanded period, would help to achieve more significant values.

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Appendix

A: Herfindahl-Hirschman Index

The Herfindahl-Hirschman Index (HHI) is a commonly accepted measurement of market concentration. The HHI index is expressed as:

$$HHI = \sum_{i=1}^{n} s_i^2 \tag{A.1}$$

where s_i represents a firm's market share – the overall equation squares them up and then sums them up for each firm in a market. The more firms (n) present in a market or the more balanced their market shares are, the lower the sum (*HHI*) is. For example, in a market with four firms with respectively shares of 15 %, 35 %, 20 %, and 30 %, the HHI is 2,750 ($15^2 + 35^2 + 20^2 + 30^2 = 2{,}750$).

The HHI takes into account the relative size distribution of the firms in a market. It approaches zero when a market is occupied by a large number of firms of relatively equal size, and it reaches its maximum of 10,000 points when there is a monopoly market. The HHI increases both as the number of firms in the market decreases and as the disparity in size between those firms increases.

B: Included funds

Table B.1 Fund overview

This table summarizes information about the included funds. Start and end date, average annual gross return, average annual expense ratio, average monthly AUM (millions NOK) and average monthly ICI are reported.

Fund name	Start	End	Gross return	Expense ratio	AUM	ICI
Alfred Berg Aktiv	Mar 2006	Dec 2017	11.58 %	1.52 %	559.40	2.06 %
Alfred Berg Aktiv II	Jan 2006	Sept 2012	8.28 %	1.56 %	40.60	2.65 %
Alfred Berg Gambak	Mar 2006	Dec 2017	14.68 %	2.95 %	1172.80	3.39 %
Alfred Berg Humanfond	Jan 2006	May 2015	11.60 %	1.81 %	83.12	1.95 %
Alfred Berg Norge +	Jan 2006	Mars 2014	11.00 %	0.71 %	1021.30	1.43 %
Alfred Berg Norge Classic	Jan 2006	Dec 2017	12.36 %	1.21 %	797.20	1.17 %
Alfred Berg Norge Etisk	Jan 2006	Mars 2014	10.57 %	1.73 %	83.71	2.09 %
Alfred Berg Norge Inst	May 2014	Dec 2017	14.90 %	0.71 %	1742.00	0.62 %
Arctic Norwegian Equities	Oct 2012	Dec 2017	14.80 %	1.51 %	2108.80	1.44 %
C WorldWide Norge	Jan 2006	Dec 2017	11.52 %	1.21 %	461.50	1.44 %
Danske Invest Norge II	Jan 2006	Dec 2017	12.97 %	1.26 %	557.00	1.41 %
Danske Invest Norge Vekst	Feb 2006	Dec 2017	11.06 %	1.76 %	420.30	3.27 %
Danske Invest Norske Aksjer Inst I	Jan 2006	Dec 2017	13.03 %	0.91 %	1925.40	1.46 %
Delphi Norge	Jan 2006	Dec 2017	12.90 %	2.02 %	713.00	4.58 %
Delphi Vekst	Jan 2006	Sept 2013	9.08 %	2.70 %	122.70	7.75 %
DNB SMB	Jan 2006	Dec 2016	11.08 %	1.98 %	988.90	6.01 %
Eika Norge	Dec 2007	Dec 2017	12.72 %	2.05 %	688.80	3.10 %
Eika SMB	Dec 2007	Sept 2013	7.40 %	2.05 %	38.82	10.37 %
FIRST Generator	June 2013	Dec 2017	20.03 %	1.61 %	797.50	7.58 %
Fondsfinans Norge	Jan 2006	Dec 2017	14.02 %	1.01 %	1055.60	3.92 %
FORTE Norge	Sept 2011	Dec 2017	15.36 %	2.03 %	52.03	7.67 %
FORTE Trønder	Feb 2013	Dec 2017	18.70 %	2.03 %	100.40	7.57 %
Handelsbanken Norge	Jan 2006	Dec 2017	14.20 %	2.03 %	1724.70	21.68 %
Holberg Norge	Jan 2006	Dec 2017	8.66 %	1.51 %	1197.70	5.40 %
KLP AksjeNorge	Jan 2006	Dec 2017	11.38 %	0.90 %	3658.70	1.01 %
Landkreditt Norge	June 2010	May 2016	7.91 %	1.76 %	106.60	5.46 %
Landkreditt Utbytte A	Mars 2013	Dec 2017	17.68 %	1.52 %	364.10	15.28 %
NB Aksjefond	Jan 2006	Sept 2013	9.04 %	2.05 %	120.90	3.39 %
Nordea 1 - Norwegian Equity	Jan 2006	Dec 2017	10.15 %	2.32 %	427.60	1.42 %
Nordea Avkastning	Jan 2006	Dec 2017	12.30 %	1.90 %	2107.20	0.89 %
Nordea Kapital	Jan 2006	Dec 2017	11.98 %	1.01 %	2161.70	0.83 %
Nordea Norge Pluss	May 2011	Dec 2017	13.21 %	1.01 %	505.90	1.40 %
Nordea Norge Verdi	Jan 2006	Dec 2017	12.41 %	1.51 %	1498.90	9.19 %
Nordea SMB	Jan 2006	Jan 2015	2.11 %	2.00 %	324.60	8.64 %
Nordea Vekst	Jan 2006	Jan 2015	9.34 %	2.02 %	928.20	1.28 %
ODIN Norge	Jan 2006	Dec 2017	8.03 %	1.19 %	4938.50	9.77 %
ODIN Norge II	Jan 2006	Oct 2015	6.14 %	0.91 %	245.40	11.64 %
Pareto Aksje Norge	Jan 2006	Dec 2017	9.31 %	1.55 %	7135.20	4.67 %
Pareto Equity Edge	Jul 2010	Aug 2015	9.67 %	0.83 %	314.90	5.65 %
Pareto Investment Fund	Jan 2006	Dec 2017	13.21 %	1.80 %	677.10	3.35 %
PLUSS Aksje	Jan 2006	Dec 2017	11.59 %	1.21 %	120.80	1.98 %
PLUSS Markedsverdi	Jan 2006	Dec 2017	11.51 %	0.91 %	109.20	1.24 %
Storebrand Aksje Innland	Jan 2006	Dec 2017	11.06 %	0.61 %	1232.70	1.69 %
Storebrand Norge	Jan 2006	Dec 2017	11.94 %	1.51 %	331.00	1.65 %
Storebrand Norge H	Dec 2010	May 2014	12.42 %	0.35 %	446.90	2.10 %
Storebrand Norge I	Jan 2006	Dec 2017	11.45 %	0.28 %	2170.30	1.80 %
Storebrand Norge Institusjon	Jan 2011	Jan 2014	6.50 %	0.21 %	1139.00	1.24 %
Storebrand Optima Norge	Jan 2006	Dec 2017	11.90 %	1.01 %	270.20	2.79 %
Storebrand Vekst	Jan 2006	Dec 2017	13.90 %	2.03 %	384.20	12.85 %
Storebrand Verdi A	Jan 2006	Dec 2017	11.84 %	2.02 %	1174.60	3.92 %
Terra Norge	Jan 2006	Sept 2013	6.68 %	2.04 %	426.60	2.72 %

C: Industry composition

Table C.1 Global Industry Classification Standard

This table summarizes information about the GICS hierachy per December 2017. The 11 sectors, 24 Industry groups and 69 industries are reported.

Sector		Industry Group		Industry	
10	Energy	1010	Energy	101010	Energy Equipment & Services
				101020	Oil, Gas & Consumable Fuels
15	Materials	1510	Materials	151010	Chemicals
				151020	Construction Materials
				151030	Containers & Packaging
				151040	Metals & Mining
				151050	Paper & Forest Products
20	Industrials	2010	Capital Goods	201010	Aerospace & Defense
				201020	Building Products
				201030	Construction & Engineering
				201040	Electrical Equipment
				201050	Industrial Conglomerates
				201060	Machinery
				201070	Trading Companies & Distributors
		2020	Commercial & Professional Services	202010	Commercial Services & Supplies
				202020	Professional Services
		2030	Transportation	203010	Air Freight & Logistics
				203020	Airlines
				203030	Marine
				203040	Road & Rail
				203050	Transportation Infrastructure
25	Consumer Discretionary	2510	Automobiles & Components	251010	Auto Components
				251020	Automobiles
		2520	Consumer Durables & Apparel	252010	Household Durables
				252020	Leisure Products
				252030	Textiles, Apparel & Luxury Goods
		2530	Consumer Services	253010	Hotels, Restaurants & Leisure
				253020	Diversified Consumer Services
		2550	Retailing	255010	Distributors
				255020	Internet & Direct Marketing Retail
				255030	Multiline Retail
				255040	Specialty Retail
30	Consumer Staples	3010	Food & Staples Retailing	301010	Food & Staples Retailing
		3020	Food, Beverage & Tobacco	302010	Beverages
				302020	Food Products
				302030	Tobacco
		3030	Household & Personal Products	303010	Household Products
				303020	Personal Products
35	Health Care	3510	Health Care Equipment & Services	351010	Health Care Equipment & Supplies
				351020	Health Care Providers & Services
				351030	Health Care Technology
		3520	Pharmaceuticals, Biotechnology & Life Sciences	352010	Biotechnology
				352020	Pharmaceuticals
				352030	Life Sciences Tools & Services
40	Financials	4010	Banks	401010	Banks
				401020	Thrifts & Mortgage Finance
		4020	Diversified Financials	402010	Diversified Financial Services
				402020	Consumer Finance
				402030	Capital Markets
				402040	Mortgage Real Estate Investment Trusts (REITs)
		4030	Insurance	403010	Insurance
45	Information Technology	4510	Software & Services	451020	IT Services
				451030	Software
		4520	Technology Hardware & Equipment	452010	Communications Equipment
				452020	Technology Hardware, Storage & Peripherals
				452030	Electronic Equipment, Instruments & Components
		4530	Semiconductors & Semiconductor Equipment	453010	Semiconductors & Semiconductor Equipment
50	Communication Services	5010	Telecommunication Services	501010	Diversified Telecommunication Services
				501020	Wireless Telecommunication Services
		5020	Media & Entertainment	502010	Media
				502020	Entertainment
				502030	Interactive Media & Services
55	Utilities	5510	Utilities	551010	Electric Utilities
				551020	Gas Utilities
				551030	Multi-Utilities
				551040	Water Utilities
				551050	Independent Power and Renewable Electricity Producers
60	Real Estate	6010	Real Estate	601010	Equity Real Estate Investment Trusts
				601020	Real Estate Management & Development

D: T-test

A t-test is a type of inferential statistic used to determine if there is a significant difference between the means of two groups, which may be related in certain features. The t-statistics from the difference between the average in group 1 and group 2 are given by:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^{\frac{1}{2}}} \tag{D.1}$$

where,

$\bar{x}_1$ and $\bar{x}_2$ = average values of each of the groups

s_1^2 and s_2^2= variance of each of the groups

n_1 and n_2= number of observations in each of the groups

If the difference in average between group 1 and 2 is large, one will reject the null hypothesis.

E: Results from robustness checks

E.1 Active return (using ICI2)

Table E.1 Active return (using ICI2)

This table summarizes active return, before and after expenses, for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI2, which is given by $ICI2_{i,t} = \sum_{j=1}^{11}\left(\left(\frac{w_{j,t}}{t_{uc,t}}\right) - \overline{w}_{j,t}\right)^2$, where $ICI2$ for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $\left(\frac{w_{j,t}}{t_{uc,t}}\right)$, relative to the sector weights of the OSEFX, $\overline{w}_{j,t}$. Where $t_{uc,t}$ is the sum of the fund's total holdings without unclassified stocks and cash at time *t*. The active returns and expenses are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. T statistics are shown in parentheses.

	Before expenses	Expense ratio	After expenses
Panel A: 2006 to 2017			
All Funds	0.188**	0.127	0.061
	(2.152)	-	(0.697)
Decile 1	0.203***	0.105	0.098
	(3.247)	-	(1.563)
Decile 2	0.214***	0.118	0.096
	(2.683)	-	(1.199)
Decile 3	0.190**	0.136	0.054
	(2.002)	-	(0.568)
Decile 4	0.155	0.149	0.007
	(1.010)	-	(0.042)
Decile 4 – Decile 1	-0.048	0.044	-0.091
	(-0.286)	-	(-0.550)
Panel B: 2010 to 2017			
All Funds	0.149	0.122	0.027
	(1.602)	-	(0.292)
Decile 1	0.171***	0.098	0.074
	(3.070)	-	(1.318)
Decile 2	0.194**	0.114	0.081
	(2.394)	-	(0.995)
Decile 3	0.139	0.135	0.003
	(1.352)	-	(0.031)
Decile 4	0.155	0.141	0.014
	(0.893)	-	(0.080)
Decile 4 – Decile 1	-0.016	0.044	-0.060
	(-0.089)	-	(-0.328)

E.2 Regression results from the CAPM (using ICI2)

Table E.2 CAPM (using ICI2)

This table summarizes alphas, before and after expenses, using the CAPM, for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI2, which is given by $ICI2_{i,t} = \sum_{j=1}^{11}\left(\left(\frac{w_{j,t}}{t_{uc,t}}\right) - \overline{w}_{j,t}\right)^2$, where $ICI2$ for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $\left(\frac{w_{j,t}}{t_{uc,t}}\right)$, relative to the industry weights of the OSEFX, $\overline{w}_{j,t}$. Where $t_{uc,t}$ is the sum of the fund's total holdings without unclassified stocks and cash at time *t*. The alphas are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. Standard errors of the regressions are given in parentheses.

	Before expenses	After expenses
Panel A: 2006 to 2017		
All Funds	0.237***	0.111
	(0.073)	(0.073)
Decile 1	0.235***	0.131**
	(0.054)	(0.054)
Decile 2	0.249***	0.131*
	(0.073)	(0.073)
Decile 3	0.241***	0.010
	(0.082)	(0.008)
Decile 4	0.238*	0.009
	(0.132)	(0.013)
Decile 4 – Decile 1	0.003	-0.041
	(0.143)	(0.143)
Panel B: 2010 to 2017		
All Funds	0.204**	0.083
	(0.088)	(0.088)
Decile 1	0.196***	0.100*
	(0.055)	(0.055)
Decile 2	0.239***	0.126
	(0.078)	(0.077)
Decile 3	0.193*	0.006
	(0.099)	(0.009)
Decile 4	0.253	0.010
	(0.166)	(0.015)
Decile 4 – Decile 1	0.057	0.013
	(0.174)	(0.174)

E.3 Regression results from risk factors (using ICI2)

Table E.3 Factor estimates for the four-factor model (using ICI2)

This table summarizes the factor loadings using the Carhart (1997) four-factor model for different portfolios of funds for both the period of 2006 to 2017 and 2010 to 2017. The samples are divided into deciles based on the lagged ICI2, which is given by $ICI2_{i,t} = \sum_{j=1}^{11}\left(\left(\frac{w_{j,t}}{t_{uc,t}}\right) - \overline{w}_{j,t}\right)^2$, where $ICI2$ for fund *i* at time *t* is defined as the sum of the squared deviations of the value weights for each of the 11 different sectors held by the fund, $\left(\frac{w_{j,t}}{t_{uc,t}}\right)$, relative to the sector weights of the OSEFX, $\overline{w}_{j,t}$. Where $t_{uc,t}$ is the sum of the fund's total holdings without unclassified stocks and cash at time *t*. The first column reports the four-factor alphas, and the remaining four columns report the factor loadings using returns before expenses. Alphas are expressed at a monthly frequency, in percent, and the portfolios are rebalanced monthly. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. The standard errors of the regressions are given in parentheses.

	Alpha	Market beta	Size beta	Value beta	Momentum beta
Panel A: 2006 to 2017					
All funds	0.172**	0.960***	0.122***	0.021	-0.002
	(0.073)	(0.016)	(0.024)	(0.019)	(0.018)
Decile 1	0.193***	0.954***	0.029	0.009	0.019
	(0.058)	(0.013)	(0.019)	(0.016)	(0.014)
Decile 2	0.175**	0.977***	0.091***	-0.011	0.020
	(0.076)	(0.017)	(0.025)	(0.020)	(0.018)
Decile 3	0.171**	0.959***	0.122***	0.027	0.006
	(0.082)	(0.018)	(0.027)	(0.022)	(0.020)
Decile 4	0.176	0.950***	0.260***	0.036	-0.058*
	(0.123)	(0.027)	(0.040)	(0.033)	(0.030)
Decile 4 – Decile 1	-0.018	-0.004	0.231***	0.028	-0.076**
	(0.137)	(0.030)	(0.045)	(0.037)	(0.033)
Panel B: 2010 to 2017					
All funds	0.114	0.984***	0.138***	0.019	0.016
	(0.092)	(0.024)	(0.031)	(0.024)	(0.024)
Decile 1	0.151**	0.986***	0.044**	0.009	0.017
	(0.061)	(0.016)	(0.021)	(0.016)	(0.016)
Decile 2	0.151*	0.975***	0.077***	-0.005	0.029
	(0.086)	(0.023)	(0.029)	(0.023)	(0.022)
Decile 3	0.081	0.991***	0.149***	0.034	0.030
	(0.103)	(0.027)	(0.035)	(0.027)	(0.027)
Decile 4	0.122	0.985***	0.286***	0.036	-0.006
	(0.168)	(0.044)	(0.057)	(0.044)	(0.044)
Decile 4 – Decile 1	-0.029	-0.001	0.243***	0.027	-0.024
	(0.179)	(0.047)	(0.061)	(0.047)	(0.047)