MASTEROPPGAVE

Analyzing Risk and Returns of Norwegian Equity Mutual Funds

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Abstract

In this study, our research question is explicit and straightforward: "*Are the well-known Risk-Factors Capable to Predict the Returns of a Norwegian Equity Mutual Funds with a Certain Degree of Precision*?" In this paper, we focus on the causal relationship between past and future returns performance of mutual funds. We also account for other common and more recent factors to investigate causal relationships. The form and existence of these relationships have to contribute to the Norwegian financial market, both for investors and managers.

We focus on well-known risk factors, such as firm-size and book-to-market, and develop our own factor as well. The applied dataset consists of 74 Norwegian open-end equity funds with monthly observations. Data for benchmarks and funds are collected through the TITLON database. On average, we find quite low significance of all used models, compared to basic Capital Asset Pricing Model and excluding the Carhart (1997) model for the 14 funds and for Ang et al. (2006) idiosyncratic volatility model. We find that risk factors such as small-minus-big, high-minus-low, up-minus-down, liquidity, oil market risk-adjusted return, and market volatility, do not explain any significant fraction or returns variations. Prior one-year return factor results are in accordance with Gallefoss et al. (2015) and Sørensen's (2009) findings, but also show some differences. We claim that the momentum factor of Jegadeesh and Titman (1993) explains variation of returns for 14 funds with a precision of 97%. On the other hand, we show that funds with a top high idiosyncratic volatility have lower returns than other funds. Moreever, we find that funds with close to mean idiosyncratic volatility have the highest returns.

Foreword

This research is our Master's thesis in the course BE 305 E Master's Theses in Finance and Capital budgeting at Bodø Graduate School of Business (HHB) at North University in 2016.

During our Master's degree in economy and finance, we have gained curiosity about the financial market as well as understanding various investment opportunities. In our thesis we have chosen to study the Norwegian mutual fund industry and the capability for a risk factor to predict future return. This has given us a broad introduction into the mutual fund industry and its regulation. The process has been both challenging as well as informative for us, especially in the data collection process.

An opportunity to analyze all Norwegian equity mutual funds in the industry, have made this thesis both challenging and absorbing. We have acquired skills of information collection and organization; creating representative and confidential samples; and working with large arrays of data and drawing conclusions from them.

We want to thank all our professors at North University during our time here, and especially our supervisors Thomas Leirvik and Andreas Mikkelsen. They have supported us with their always-timely help and wise advice. We are also grateful to Arctic University for bringing the TITLON database. Without this straightforward and painless access to data, we hardly could do any tests.

Kirill Kholkin

Edvard Haug

Bodø, May 18, 2016

Summary

During our Master's degree in Nord University, we were introduced to scientific articles from all over the world on topics of market efficiency. Such articles are mostly based on testing and developing of models and frameworks of real financial activity. One of these articles was "On Persistence in Mutual Funds Performance" by Mark M. Carhart (1997). Among research that have tested Carhart's framework, there are some articles based on Norwegian data, like Gallefoss et al. (2013) and Sørensen (2009). However, their findings leave some of the tests undone and some of the accompanying questions unsolved.

In our study we have analyzed the Norwegian mutual funds industry. We have made a strategic selection of mutual funds, where only funds with the keywords Norge, or Norway, are included in the sample. This gave us 74 funds, which is 65% of all the Norwegian equity mutual funds. Our problem statement is as follows: "Are the well-known Risk Factors Capable to Predict the Returns of a Norwegian Equity Mutual Funds with a Certain Degree of Precision?". Our analysis is mostly based on models like Carhart (1997) and Fama and French (1993), as well as the well-known Capital Asset Pricing Model developed by Sharpe (1964) and Lintner (1965). Afterwards, we ranked funds based on standard error (deviation of regression model estimate from the true value) and tracked portfolios.

We find that Norwegian equity mutual funds on average have no exposure to the factors of Fama and French (1993) or Carhart's (1997) models. This is with accordance with later studies of the Norwegian mutual funds industry. However, we indicate that 14 funds have exposure to prior stock market returns (which is Jegadeesh and Titman's (1993) momentum). This is different from studies of the Norwegian market, but partly consistent with Carhart's (1997) findings for the US market. Carhart's model shows 97% precision with these funds. This result is better than the most efficient capital asset pricing model. We also find that the Norwegian equity mutual funds, on average, have no exposure to monthly oil market returns and market volatility (benchmark standard deviation). We also confirm the findings of Ang et al. (2006), with some corrections for the Norwegian market data. We find that lowest standard error by Fama and French (1993) model funds perform better than high standard error funds. Additionally, we point out that highest returns are performed by mean standard error funds.

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1.0 Actualization and problem statement

Mutual funds play an important role in modern financial markets. They channel a possibility to invest in diversified portfolios of assets with stable payoffs and a reduced risk. According to the literature, the share of equity mutual fund investments has grown dramatically, compared to total investments for several different markets. For example, Wahal and Wang (2011) and Hiraki et al. (2015) mention the growing role of mutual funds. Mutual funds in Norway do show a high profit that, however, comes with considerable volatility. These facts put a question upon mutual funds' performance. In other words, "skill or luck" account for abnormal profits.

1.1 Problem statement and importance

Mutual funds are well known as financial intermediaries, providing the most profitable opportunities to invest in risky assets, both for large and small investors. Mutual funds earn money similarly to the way corporations raise money. On acquired wealth, mutual funds create a portfolio according to its prospects. It can invest in real assets, equity/debt securities and even in combinations of asset claims. Mutual funds' superior performance is probably caused by professionalism of its management and superior information. Superiority, however, was argued and studied by a number of researchers.

The source of this skepticism regarding superiority is the benchmark underperformance by many mutual funds. This fact has been documented for different periods: for example, Jensen (1968), who documented the period 1945-1964 in the US., as well as Fama and French (2010), who documented the 1984-2006 period in the US. Norway is not an exception; however, compared to the US market, the Norwegian market has not been well studied. The benchmark is most often an index, where the index can be broad like MSCI or narrow like a Norwegian growth firm.

Therefore, mutual funds can be considered as a continually growing financial institution on the one hand, and on the other hand, as continually underperforming some well-known practices of investing organizations. Broad similarities in the findings of these investigations exacerbate the need for a thorough analysis of mutual funds in the other markets.

According to market efficiency hypothesis, all the relevant information regarding the price should be reflected in it. There are quite a few factors that are claimed to explain returns, e.g., small versus big firms or the market capitalization (SMB), growth versus value (HML), liquidity, etc. These factors should be relevant for the price, to explain the returns. Therefore, information about certain risk factors should be reflected in the market price. In order to check for this, we account for all available famous factors claimed to be relevant for stocks or mutual funds. Therefore, our problem statement is to check for risk factors that can forecast mutual funds returns, with a certain degree of precision.

"Are the well-known Risk-Factors Capable to Predict the Returns of a Norwegian Equity Mutual Funds with a Certain Degree of Precision?"

We therefore conduct a lens framework to look at the equity mutual funds as follows: portfolio investment strategies, as first layer; risk-factors to predict future returns, as second layer; and past returns explanatory power, as the third layer. However, it is important to state that we also focus on other risk factor patterns.

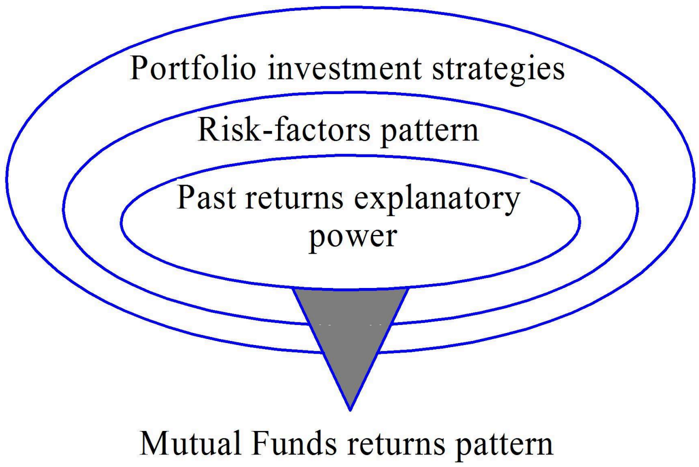

Figure 1 - Lenses of future studies

1.2 Previous studies

Academics have performed a large number of studies regarding risk factors for common stocks, such as Fama and French (1992). A number of studies have also analyzed mutual funds and risk-factors, like Grinblatt et al. (1995) and Carhart (1997). Carhart (1997) did fund that mutual fund managers are choosing stocks based on stocks' past returns, which explains a large share of mutual funds' performance.

Carhart (1997) claims that in the US market, returns of top funds are driven by momentum effect. Norwegian academics also argue about underperformance evidence and find usage of past returns risk factor. Nevertheless, Gallefoss et al. (2015), which is based on daily data, reject this statement for the Norwegian market. In our research we have augmented this argument. The other major factor we include is a version of the low-volatility anomaly derived in Ang et al. (2006). This low-volatile anomaly is the standard deviation of the residuals of a Fama and French three-factor regression.

This thesis differ from Gallefoss et al. (2015) in a way, that we have increased the time range and we have included more funds. We have also included more risk factors to check for predictability. Compared to Ang et al. (2009), we also have a wider data range. Nevertheless, in contrast to Ang et al. (2009), who looked in average international effect of idiosyncratic volatility, we checked for country-specific effect, and in this case, the Norwegian mutual fund market.

We find that Norwegian equity mutual funds on average have no exposure to the famous factors in the models by Fama and French (1993) or Carhart (1997). This is with accordance with recent studies of the Norwegian mutual funds industry. However, we indicate that 14 funds have exposure to prior stock market returns (which is momentum according to Jegadeesh and Titman (1993)). This is research is, however, different from studies done by the Norwegian market, but partly consistent with Carhart's (1997) findings for the US market. The Carhart model shows precision of 97% with these funds. This result is better than the Capital Asset Pricing Model. We also find that the Norwegian equity mutual funds, on average, have no exposure to monthly oil market returns and market volatility (benchmark standard deviation). In other words we confirm the findings of Ang et al. (2006), with some corrections for the Norwegian market data. We find that the lowest standard error on Fama and French model funds performs better than the highest standard error funds. Additionally, we point out that the highest returns are performed by mean standard error funds.

1.3 Assignment structure

Chapter 2 of this investigation starts with a background of risk factors. Thereby, chapter 2 discusses general terms such as "investment", "liquidity", and "risk". After the base is constructed we turn to the literature review and theory. Chapter 3 starts with a consistent explanation of the Market Efficiency Hypothesis, its forms and implications. It also covers development of risk factors and factor models starting with CAPM and ending up with the Carhart model. At the end of the chapter, we describe our usage of other factors, such as market volatility and idiosyncratic volatility.

Chapter 4 is devoted to the methods we use in the research. We define ontology and epistemology for the justification of our regression models. We present all models for which data are later being tested. Chapter 5 is devoted to data sample description. In addition to the reasons and characteristics of samples, we perform summary descriptive statistics. Chapter 6 performs the results for all models and factors we have tested. We conclude, critique our work and put forth ideas for further studies in chapter 7.

2.0 Investments vehicles

This chapter is devoted to a literature study of the theoretical framework that the thesis builds upon. Natural questions of this chapter include "what is an investment?" and "what is a mutual fund?" Accounting for basic definitions of an investment pattern, we move on to the classification of mutual funds, ending up with actual investigations of investment performance in the mutual funds sphere.

2.1 Investment objects and risk

The term "asset" can easily be found in the balance statement of a firm. Possible variations of it are cash, real property, equipment and others. In other words, an asset is anything that can generate cash inflows or reduce cash outflows. From basic financial accounting courses, we know that assets are divided into two main groups: liquid and illiquid assets. The liquidity of an asset shows the speed at which the asset can be converted into cash. For example, cash is liquid, while real estate generally is not. The same definition of liquidity is used in financial markets, but the asset classification is set differently, divided into real and financial. Real assets can be liquid or illiquid, but the core concept is that they produce income directly. For example, equipment is used to produce goods, and hence, income, or it can be sold for the same purpose. Financial assets are different. They are often instruments to manage real assets.

As Bodie et al. (2011: 30) note, financial assets are "means by which individuals hold their claims on real assets… or on generated by real assets income". Thereby, individuals can improve their future wealth by buying financial assets. On the other hand, corporations can use such assets for saving their funds. For example, for banks in the developed world it is required by the central bank to keep reserves in the form of highly rated assets. Insurance companies are restricted by their activity to keep funds in case of unexpected payments. Therefore, a certain organization is obligated to keep these funds. It is more than logical to keep these funds in highly rated and relatively liquid financial assets.

Financial assets can be separated into three main groups: equity, debt securities, and derivatives. Issuing equity and debt, or stocks and bonds, is a common way for firms to raise capital. Stocks are claims on income and assets, while equity is the value of ownership that is invested in a firm. Thereby, all company stocks together are the equity of the firm. Debt securities or bonds, is a way governments and corporations borrow to fund activities, by issuing claims on documented streams of cash flows. Derivatives are agreements to perform some activity, such as buying or selling stocks, bonds and real assets. Real and financial assets are investment objects. Thereby, the investment objective is generally to increase future income. For example, by buying shares of Apple Inc., the owner expects to increase future wealth in the form of dividends or price accumulation. Dividends are payments from the company to its shareholders. If dividends are not paid, then this cash will probably be used for reinvestments, which is expected to create price accumulation of the shares. Price appreciation or depreciation is called return. As financial markets are not a calm lake, but a stormy sea, share prices and dividends can deviate from period to period. The size of these possible deviations is associated with the risk of the investments.

All investment returns deviate from expected values, and as Bodie et al. (2011: 37) notes, the deviations vary both within and between asset classes. While every rational investor prefers more than less, they are tempted to balance between expected returns and associated risks, in order to maximize their wealth. The case is similar for corporations. It is natural that if some investment objects have similar risk, the ones with higher returns are always preferable. Therefore, the higher the investment risks, the higher the returns should be for investors to consume it. The extra return of an investment is called risk premium. Risk premium is a return excluding nearly risk-less investment return. The idiom “Free cheese, only in a mousetrap” suits the context in risk premium in financial markets. In conclusion, earning higher returns yields taking more risks. “Free cheese” in financial markets is called arbitrage. The possibility of arbitrage is a topic of pervasive debate upon the market efficiency theory and financial market anomalies, which will be further discussed in chapter 3.

According to Damodaran (2012) investment risks can be divided into two main groups: firm-specific and market-wide risks. Firm-specific risks affect only one firm and come from that firm’s projects, rivals, products and others. Market-wide risk (also called systematic risk) is the opposite and affects numbers of firms from the industry to the world economy. Systematic risk can be attributed to overall economy health, inflation, interest rates, etc. It is possible to reduce the investment risk by combining a number of financial assets, preferably assets with correlation less than one. Such a combination of assets is called a portfolio. At the same time, the process of risks decreasing by collecting a number of assets is called diversification. Diversification is one of the fundamental ideas in finance, first rigorously developed by Markowitz (1952). However, diversification deals only with unsystematic risk, because systematic risk is common for all possible elements of the portfolio. Hence, systematic risk is not diversifiable. The ultimate case of diversification is a portfolio with an attitude only to systematic risks. This theory lies behind Sharpe's (1964) model, which shows the required rate of return for an investor with a market portfolio (attitude only to systematic risk) for specified risk level and market. Sharpe's model will be discussed further in chapter 3.

It is natural that to carry out qualitative and effective diversification by themselves, investors need some resources. Such resources can be a large initial amount of cash, information, knowledge, and last but not least, time to monitor and carry out trades in the portfolio. As it is difficult to obtain all these requirements, companies that specialize in investments will generally outperform such marginal investors. Some of these companies manage several portfolios of financial assets, called mutual funds.

2.2 Mutual funds

Households and corporations seek the opportunity to invest, pursuing the already discussed goal – wealth increase or preservation of funds. As we stated above, qualitative and effective diversification require a number of resources. Of course, diversification is not the only way to make a good investment. Other methods, however, also require either similar resources or superior skills. Choosing securities gives rise to the phenomenon of adverse selection or "lemon market" problems (market with asymmetric information). Intermediary companies in financial markets are comparable with "lemon market" dealers. Accordingly, households and corporations channel their funds through a financial intermediary. This is probably due to lack of resources or other causalities. Intermediaries offer stable payoffs and low risks. Bodie et al. (2011: 39) note that such intermediaries are banks, investment, insurance companies and others. These institutions perform an important role in the economy by channeling funds from savers to those who have the most profitable investment opportunities.

One of such as negotiators is an investment fund. Mutual funds collect capital from investors in order to invest in a range of assets. The way investment companies raise funds is similar to issuance of equity by corporations. It needs to be stated that investment funds such as mutual funds are highly regulated in what they can invest in. On the other hand there are hedge funds, which are not regulated at all. The investment objects of funds are strictly stated by the control organization. The funds can be focused on a specific type of stocks, such as growth stocks or value stocks, or asset class funds, such as equities, real estate, bonds, sector, and other asset classes. However, as Bodie et al. (2011: 121) note, mutual funds provide important functions to the investors, such as:

1. keep investors informed;
2. provide high qualitative diversification (acting as large investors);
3. provide skilled and professional fund management;
4. low costs.

To conclude, a mutual fund is a professionally managed and highly regulated investment fund, which collects wealth from investors to purchase securities and performs special and important functions.

The understanding of how mutual funds are classified is crucial for our analysis, because it creates constraints for the data sample production. Mutual funds are usually categorized by their investment field, type of management and type of funds rising. Geographically, funds can invest in one-country assets, for example, or in sets of different countries' assets (international funds). It is natural that the risk of fund investing in only Norwegian assets will differ from international fund risks because of the exposure to different risks. Hence, an investor choosing between mutual funds should understand the risks of each alternative. Fund classification by security type is regulated differently in each country. However, funds usually have a main asset type (equity, bonds, index, sector or real estate), which covers almost all fund portfolios. Nevertheless, a fund portfolio can consist of different asset classes, and such a fund is called a combination fund. However, the type and proportions are always defined in the prospectus of the fund. Most mutual funds are not allowed to keep short positions in the market. Hedge funds, however, have fewer regulations and could, for instance, place their investment in a mix of assets. Unlike traditional mutual funds, hedge funds have certain criteria of an investor's capabilities.

Based on management type, funds can perform active and passive management. In the first case, managers are actively searching for best risk-return investments, professionally collecting them into portfolios. A passively managed fund offers an opportunity to invest in portfolios strictly linked with benchmarks, such as S&P 500, FTSE, OSEBX and others. By fund raising type, funds are divided into open-end and closed-end. These funds often have very different fees, but the most common fees are management and transaction commissions. For example, compensation for buying and/or selling stocks by the fund is a transaction fee.

These payments can make investments in mutual funds expensive. This is an additional reason for investigations into mutual funds' industry importance.

An open-end mutual fund can raise an undefined amount of capital. After the initial public offering (first sale of stock, also called IPO), capital can be increased without any restrictions. Managers can also increase its net asset values by extending the number of holders. Flexible equity gives managers additional room for maneuvers, which in theory can increase payoffs to its holders. Shares of this type can be traded in both primary and secondary markets. Hence, managers need to set aside a pool of cash, in case investors would like to withdraw their part. The amount of closed-end mutual fund shares, as well as the capital, is fixed. After a stated value of capital collection, the number of shares is locked, after which the fund manager begins the investing process. Shares of this type are traded in the secondary market, as customers cannot withdraw their wealth until a specified date. Hence, managers can place all available capital into stocks. It must be stated that the first type is traded in both primary and secondary markets, while the second type is only traded in the secondary.

A combination of open-end and closed-end funds is called Exchange Traded Fund (ETF). ETFs are traded like a stock; that is, it is possible to buy and sell them during the day, whereas for a mutual fund only after the exchange has closed. Common practice for ETF´s is that they are often traded with huge blocs share, as mention in the Kahn academy lectures. Using almost exclusively big transactions, such funds have low overhead costs, which allow management fees to be smaller than in open-end funds. Even though there are some ETFs currently being traded at the Oslo Stock Exchange, the low-cost alternative to a broad mutual fund is not present.

2.2.1 Mutual funds, regulations and evidence

Norwegian mutual funds are regulated by the standards of the Norwegian Security Association (Verdipapirfondenes forening or VFF). The goal of VFF's regulations, according to its written mandate, is to categorize its members. Such categorization allows local and foreign investors to easily get necessary information and compare funds. Furthermore, Verdipapirfondenes forening obligates funds to supply specific activity information.

Specification of funds in Norway also takes place in geographical, asset, and fund raising fields. One-country investors have to create a portfolio out of at least 80% of stated country assets. Therefore, investors specializing in the Norwegian assets, or “Norske fond”, have at least 80% exposure to the Norwegian market, which means a necessity of more than 80% of Norwegian assets in a portfolio. Funds with less than the stated proportion of country exposure are categorized as global funds. The same holds true of asset types, meaning that mutual funds that invest more than 80% in equity are called equity funds, or “Aksjefond”. On the other hand, funds investing less than 80% in equity are called combination funds. There are also bonds, real estate funds, hedge funds and others. Such funds are listed as “other funds”. The classification by fund raising type is similar to the previous discussion. It is natural that Norwegian equity funds are exposed to Norwegian financial market.

Mutual funds are big investors. According to Statistics Norway, equity funds were almost 50% of all investment funds market shares in Norway by December 2015. Moreover, equity funds, as shown in Figure 2, contribute almost 65 billion NOK, which is nearly 70% of all investment funds profits. According to the VFF “Norske fond” constituted more than 12% of equity funds by December 2015. These facts together highlight the importance of “Norske fond” performance for the Norwegian investment fund industry.

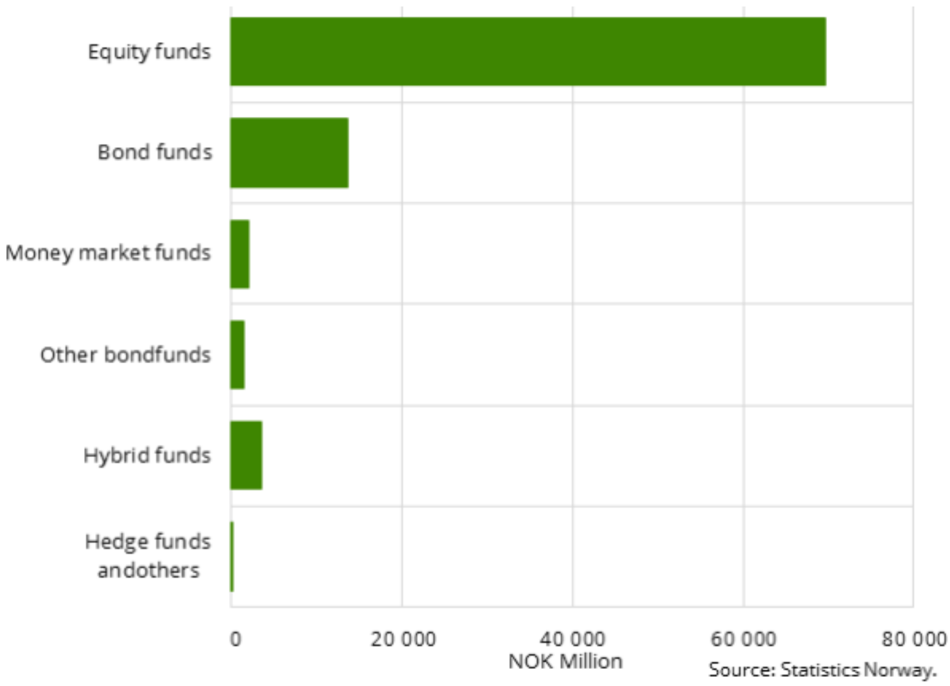

Figure 2 - Investment funds profits by December 2014

Source: Statistics Norway (www.ssb.no)

Investigating risk and return in the mutual fund industry is very important and applicable for financial market development. For example, information on real performance can show the justification of a fund’s fees. There are, however, two essential questions on mutual funds' performance: “Do mutual fund managers have superior skill or information?” and “Do mutual funds transfer economy of scale to their customers?”. These are the two main pillars to be analyzed. This is, in our opinion, because other questions are dependent on these two, such as “Is it worth investing in mutual funds?” which is instinctively connected with “Do mutual funds outperform single investors?” which refers to our first question.

As stated previously, mutual funds or financial intermediaries can be compared with “lemon market” dealers. Naturally, competition among mutual funds takes place, as well as in “lemon markets”. Mutual funds are traded almost as stocks. The conjecture is then that we can compare the mutual funds industry to the stock market. For example, in the stock market there are “winners”, persistent “winners”, “losers” and others, according to Carhart (1997). By persistence we mean a continuous position, for instance on top or in a bottom position, in terms of returns achieved by the fund or stock. By “winners” we consider funds generating abnormal (higher than average) performance. The question of performance persistence is an object of interest for financial studies. Many researchers have documented short-term persistence with different spreads between top and bottom funds. For example, Hendricks et al. (1993) found that the top funds give 6-8% higher returns than the bottom funds. Persistence is a very interesting phenomenon in light of the market efficiency theory, which will be discussed in chapter 3.

Another way to describe mutual fund performance is to compare a fund’s return to a benchmark. Studies mostly indicate underperformance of mutual funds by comparing. For example, Hendricks, Patel and Zeckhauser (1993) claimed that “academic studies since the 1960s find that mutual funds do not systematically outperform benchmark portfolios”, which is approved by many researchers, such as Jensen (1968) or Malkiel (1995). Fama and French (2010) augment this statement for short-term underperformance. However, there is always the other opinion. For example, Jensen (1968), clam that the individual funds did outperform the benchmarks in the period 1945-1964. These conclusions are based on US data. However, Norwegian mutual funds also claimed to be short-term persistent, as found by Gallefoss et al. (2015)

2.3 Summary

An asset is anything that can be converted into cash. Assets can be divided into two classes – real and financial. While liquidity shows the speed of cash convention, financial assets could often be seen as the most rapidly growing class. Financial assets such as stocks, bonds and derivatives help to hold claims on the real assets. Buying assets is investing. Investing has risks, or deviation from planned future value. Investors take more risks to achieve more returns. One way to decrease an investment's risk is to create a set of assets, called a portfolio. Such risk decreasing is called diversification. The limit of diversification is market wide risk, which is common for almost every firm, according to Bodie et al. (2011: 205). Diversification requires resources, which makes investors channel their funds to special financial intermediaries for management. One such intermediary is mutual funds. Mutual funds are strongly regulated by the field of investment, types of management and funds raising types. Equity mutual funds in Norway are obligated to invest at least 80% into Norwegian stocks. The financial literature documents two investment fund facts based on US data: short-term performance persistence according to Fama and French (2010) and continual underperformance of benchmarks according to Hendricks, Patel and Zeckhauser (1993). Norwegian mutual funds, however, are also claimed to be short persistent in terms of return by Gallefoss et al. (2015). This study is focused on Norwegian equity funds persistence and their investments risks.

3. Literature study and theory

This chapter is devoted to consistent development of a theoretical framework for further tests. Persistence and performance of any stock, including mutual funds, is strongly related to the Market Efficiency Theory. Hence, accounting for this core financial markets theory builds a base for our theoretical framework. Predictability of returns, as Fama (1991) notes, is one of the most contradictory issues in modern finance. Thereby, market anomalies perform limited evidence of a return's possible predictability. Basic ideas behind investment decisions went a long way from simple "market-risk" models like Sharpe (1964) to sophisticated multi-factor frameworks like Carhart's (1997) four-factor model. Therefore, we take a narrow walk on this road to emphasize the most important and influential points of the Carhart's model development.

3.1 Market Efficiency Theory

Market efficiency is a mature, solid theory and a topic with almost endless debate. One of the essential parts behind this theory is what kind of information is reflected in the market prices. This question is crucially important for the investors, because an answer will contribute to explaining certain investment strategies. For example, if public information, such as historical prices, would not be reflected in the price, then investors could make profits by buying undervalued or short-selling (borrowing securities which are falling in price) overvalued stocks. This means that investors, in such a case, would have a possibility to predict future fluctuations of prices. However, higher returns must only be possible with more risks. The Market Efficiency Theory stands for this statement and for the possibility of short-term predictions, only by luck. Over the last 60 years, this theory has been associated with stock prices in different sectors. The term "efficiency" has been used to define markets in currencies, oil, gold, and several of other assets.

After many time-series studies, Malkiel and Fama (1970) generalized an empirical result in the Market Efficiency Theory (MET). The result was that market equilibrium is only when prices fully reflect all available information. The Fair Game was with similar conditions, which creates a situation where higher returns are a possibility, only with a proportionally increased risk. This implies that every player has the same available information. As individuals could interpret information differently, it is fair to assume that investors can make higher than average profit. However, it is impossible to beat the market systematically and continuously by MET, just because luck cannot be systematical and continuous. Malkiel and Fama (1970) have distinguished three forms of market efficiency. These are "weak", "semi-strong" and "strong" form of efficiency, and we will now discuss each form.

The *weak* form of MET states a reflection of all historical data regarding the stock market's volume and price. This means that if there are signs for future developments, all the players have an ability to interpret them. *Semi-strong* form states reflection of all public data in a market value. By public information we consider historical values of earnings, dividends, operating cash flows and other available values, as mention by Bodie et al. (2011: 357). The *strong* form of MET states a reflection of all relevant information in a market value. This implies that even inside private information will not give an opportunity for systematic arbitrage.

Long-term funds persistence can be attributed to controversies of market efficiency. For example, a fund that generates abnormal returns for a continuous period can be predicted. However, MET does not state the impossibility of such a case, but the opposite only by luck. Thereby, if an investor were successfully predicting stocks for a year, it does not mean that this investor did this by skill. Nevertheless, if an investor successfully predicts the returns for a long period, say ten years, then this investor is probably outperforming the market systematically by skill. Investors choose mutual funds by their superior skills, scale advantages and resources. Fund managers normally make qualitative diversification in order to perform a stable rate of return. Bonds normally perform lower risks and lower return, compared to stocks with high risk and high-expected returns. In that case, mutual funds should perform with higher risks, which is probably impossible with the persistence in long-term rate of return. It must be stated that it also could be that long-term persistence is caused by a continuous market self-correction.

Concluding, the Market Efficiency Hypothesis states that stock prices fully reflect all available types of information. In such a case, as Grossman and Stiglitz (1980) claimed, informed agents could not earn a return on their information. In some way it means that there is no competition. Naturally, no one will pay for information if the price is already given. Thereby, two alternatives are possible. First, no agents will pay for the information after the price is given. Secondly, a small fraction of informed traders has no ability to influence the market prices. In both cases, there will be no equilibrium to determine these prices. Grossman and Stiglitz (1980) sum up that if information is inexpensive and informed agents have explicit information, then the equilibrium will reflect most of the informed agent's information. This leads to what Pedersen (2015) notes as an *efficiently inefficient* market. He concludes that the markets are probably between efficiency and inefficiency. Thereby, the market is "efficiently inefficient" which means a "… limited amount of capital can be invested with active managers who can beat the market using economically motivated styles". Certain analysis of available information should therefore make information precise and give the possibility of earning higher returns without any violation of the MET. Nevertheless, pure market efficiency states, as Damodaran (2012) mentions, that the returns are unpredictable and show an intrinsic value with random variations. This research is not in any sense violating market efficiency, but we sense that some of the returns variation could be captured by certain risk factors.

As Bodie et al. (2011: 366) notes, the debate about the Market Efficiency Hypothesis will probably never be settled, for at least three reasons: magnitude, selection bias and lucky-event issues. The magnitude issue states a possibility that large and intelligent investors can affect a price, which is evaluating securities. Selection bias discusses techniques of "public review of beating the market". This is probably not reasonable, as it will drive to no arbitrage case. Lucky-event issue speaks about the source of superior performance, which is as simple as luck.

Risk factors are explanatory variables used in econometrical models for market efficiency tests. Risk factors, like market efficiency tests, can be divided into two groups. The first group of risk factors is historical prices. The second group of risk factors account for all available public information, such as book values, market capitalization and trade frequency. These tests are aimed at finding relationships and casualties between returns and the applied risk factors. Naturally, it is not possible to predict future returns, but it could be possible to predict values in correlation with the returns. This makes forecasting systematic and scientific. This also drives the fact that information is included in risk factors and then included in a market price. This thesis is aimed at analyzing certain risk factors and their tests upon excess returns, called alpha.

Along with risk factors, there are market anomalies. They are called anomalies for their absence of knowledge about their reasons. For instance, the evidence by Keim (1986) of abnormal returns in January, is called the January Effect. Risk factors with evidence of higher than average alpha generation are also called anomalies.

3.2 Risk factors and market anomalies – weak form

If a market is not efficient at all, then it will be easy to beat it. On the other hand, if a market is efficient, it will be impossible to make persistent excess returns over the market. However, weak forms of MET tests, which are conducted in the US, per Jegadeesh and Titman (1993) or Lehmann (1990), and Europe by Asness et al. (2013), indicates a possibility to generate higher alpha than average. This by the usage of historical prices or returns causalities and patterns called trend following. Trend following is betting on future returns, based on continual past performance.

There are trend following patterns not just in financial markets. For example, by noticing any actions over a consistent amount of time, these actions will become a routine for an observer. Let's assume a mailman and his routine. He attends every morning at the exact same time, delivering newspapers. The observer will probably still expect the same mailman to appear on the very next morning, even with the knowledge that he can either be delayed or even not attempt at all. Of course, expecting a stock to continue go persistently as a routine is an ambitious parallel. Returns persistence might occur, but continuous persistence, as a rule cannot. Otherwise, markets should be inefficient. It is, however, hard to say that Norwegian or American markets are at least not weak efficient.

The Market Efficiency Hypothesis states a return similar to a random walk model. This means that there is no autocorrelation. Autocorrelation means correlation of signal with itself, as mentioned by Dunn (2014). To control for autocorrelation, the time-series regressions of future return have to be carried out against past returns. Regression checks for consistent correlations and works as a statistic measure to determine the relationship between variables. If, for example, past returns are highly correlated with some future returns, then there is a strong positive correlation between them. Wording it differently, the random walk model states that returns are uncorrelated.

The first study of the predictive power of returns was probably conducted by Levy (1967). His investigation showed that the top of the weekly ranked stocks generated abnormal profits for a period of around 26 weeks. The other side of the "returns effect" was proposed by Bondt and Thaler (1985), who showed that the bottom portfolio, conducted out of stocks ranking from high to low returns in a three year period, earned about 25% higher returns than the consistent top portfolio after thirty-six months, even remaining riskier. They also approved the January effect for stocks. The loser stocks have extremely low returns, which go high after thirty-six months, indicating high returns volatility. In these terms, highlighted riskiness looks fair and logical. Persistence and following reversals, however, make a great deal. Bondt and Thaler (1987) note that excess returns are due to market overreaction. An overreaction implies that investors are driving prices ether too high or low by buying/selling recently good / bad performing stocks.

The concept highlighted by Bondt and Thaler (1985, 1987) is often called long-term reversals. A reversal is a direct change of the returns development. Bondt and Thaler proposed that the reversals are likely to occur in three to five years of ether high or low performance. Jegadeesh (1990) found much shorter reversals, similarly, with negative monthly returns and negative correlations. At the same time Lehmann (1990) claimed the existence of weekly-return reversals-patterns. Short-term reversals complement both long-term reversals and persistence, making it possible to make higher profits than average by finding the pattern. These findings make simple trend following patterns riskier, as investors should account for reversals. Finally, Jegadeesh and Titman (1993) claim that the "*buying winners, selling losers*" strategies generate substantial positive returns over three to twelve months. The phenomenon of returns or price persistence is called momentum. Price-momentum, for example, is continual outperformance of one stock by another.

Jegadeesh and Titman (1993) proposed a strategy intended as the following algorithm: First, the investor has to borrow bad past-returns securities and then sell them short. Second, the proceeds are invested in the highest past (either three, six or nine month) returns stocks (Figure 3, first step). The investor is now betting that the low past return stocks and the high past return stocks will be short-term persistent. Thereby, both the long and short parts of the portfolio should appreciate the price. As the long position increases in value and the short position depreciates in value, it will make a positive return when the short position is then balanced (Figure 3, second step). If the plan works, the investor gets both bull market and bear market revenues. Rebalancing the portfolio should give a stable strategy. The most successful momentum strategy, as Jegadeesh and Titman (1993) note, is to select stocks based on their returns over the previous twelve months, then to hold the portfolio for three months. With this strategy investors can achieve an abnormal profit of 1.31% per month on average.

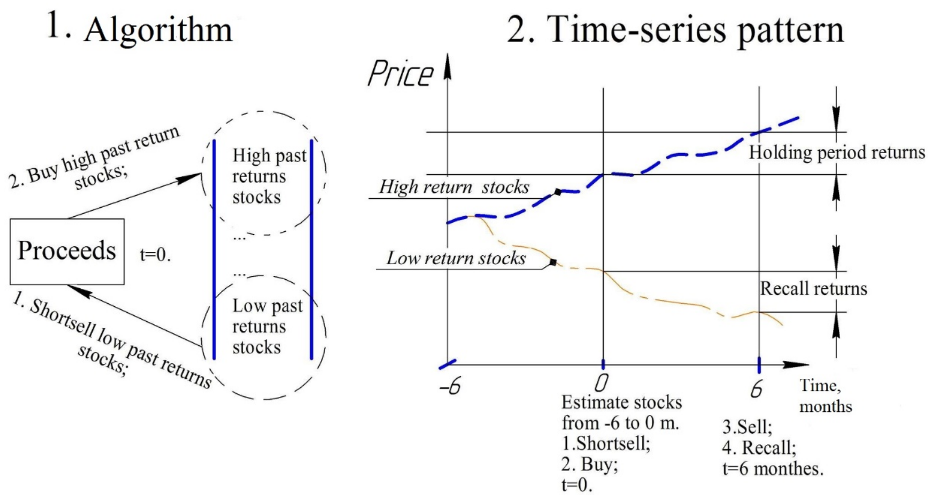

Figure 3 - 1. Algorithm of momentum Jegadeesh and Titman (1993) momentum strategy; 2. Time-series pattern of low and high past returns portfolios.

Summing up the evidence, the following patterns were documented for the US market: monthly and weekly consistent return reversals; relative persistence of returns for three to five months; three to five years' returns reversals; higher than average profitability of portfolios conducted from the top stocks, holding over a period of three to twelve months. Asness et al. (2013) document abnormal returns of the Jegadeesh and Titman (1993) strategy in Europe, including Norway. This strategy yields a possibility that the momentum strategy can be used by Norwegian mutual funds. Carhart (1997) conducted a momentum factor to track returns and their dependence upon Jegadeesh and Titman's (1993) portfolios. However, the momentum, also known as up minus down or prior one-year return (PR1YR) factor is not the only one in Carhart's four factor model. Other factors arise from semi-strong market anomalies and the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965).

Bernstein (2011) mentions that the CAPM was the first scientific model to value assets. CAPM is based on return and market-wide risk relationships. The assumption behind this causality is that all investors are holding a market portfolio, which is a diversified set of all market assets. Naturally, risk of such a portfolio is market-wide risk. In such a case, the risk of any asset can be measured as a risk added to a market portfolio.

3.3 Risk factors and market anomalies – semi-strong form

The risk of an asset in the CAPM is volatility added to the market portfolio. The market portfolio is devoted to financial indices, such as S&P 500, Dow Jones Industrial Average, FTSE 100 and OSEBX, which are diversified according to Markowitz (1952). The investments alpha is the sensitivity of an asset to a market risk, multiplied by the average market risk premium, which is called equity risk premium (ERP). ERP is also called market returns factor (MKT). MKT is a constant difference between the returns of a market portfolio and the consistent risk-free asset. CAPM was developed more than 50 years ago but remains effective and attractive for its simplicity.

$$R_i - r_f = \beta \cdot ERP + e_i \,, \tag{1}$$

Variable	Description	Variable	Description
R_t	Assets return at time t	ERP	Equity risk premium
r_f	Risk-free rate	e_i	Standard error
β	Sensitivity of an asset to market risk		

Table 1 – Equation (1) variable description (CAPM)

Empirical studies have shown that publicly available variables, do forecast future returns with a good certainty extent, as noted by Bodie et al. (2011: 374). Actually, this means that some portfolios conducted by economically motivated styles can generate higher than average returns. One such variable is market capitalization, which is also called the size or small-firm effect. Small firms tend to have higher risks and have a consistently higher growth potential. As MET postulates, higher risk implies higher returns. The small-firm effect was documented by Banz (1981), who claims that small firms tend to gain consistently higher average returns, compared to mature ones, especially in January. First, there are continuously repeated price-falls in December, and then rises in January, called the January Effect. Naturally, the fact that riskier (the smaller the riskier) firms have higher returns can be attributed to MET, while January drifts can be attributed to the January effect. Bodie et al. (2011: 371), based on Ken's French data library, claimed that average annual returns of portfolios are dependent on the size of the companies.

It is visible from Figure 2 that there are higher returns on small-firm portfolios compared to more mature companies' portfolios. Moreover, this difference is substantial, while bottom size portfolios (small) earn almost 7% higher returns than the top size (big) portfolios. As there is evidence of the possibility to generate higher returns than average, based on publicly available companies, market capitalization, size effect is attributed to market anomaly.

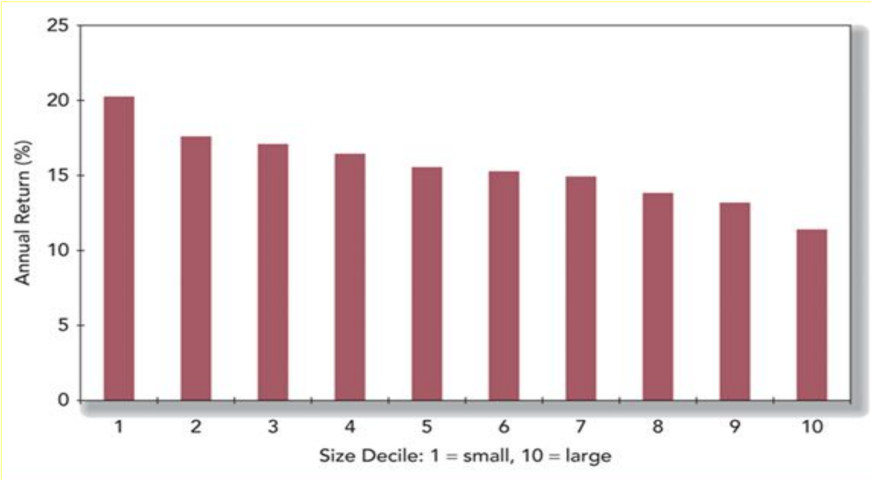

Figure 4 - Average annual returns of portfolios and size of firms included interdependence 1926-2006 (Bodie et al. (2011: 371))

The theory of small-firm effect is strongly linked to a similar study of the liquidity effect by Amihud and Mendelson (1986). The stock turnover shows the number of trades, and thereby its liquidity. Amihud and Mendelson (1986) argue that less analyzed companies are often less liquid, compared to stocks with more information and therefore more analyzed. Lower turnover and number of available estimate statements from analysts make a stock riskier, while stocks with higher turnover are more liquid and therefore less risky. Low-turnover and riskier stocks compensate for liquidity by generating higher returns. Ibbotson et al. (2013), Datar et al. (1998), Haugen and Baker (1996) and others, claim that low-turnover stocks generate higher returns than high turnover stocks. Compensation of low-turnover stocks then generates higher returns. Liquidity, however, is also attributed to market anomalies. Ibbotson et al. (2013) claim that momentum portfolio conducted out of low turnover stocks generates higher than the aggregate momentum portfolio.

Book values of earnings and equity can also be attributed to publicly available information. Basu (1977) claims that high price-earnings stocks generate returns higher than average. Fama and French (1992) argue that stocks with a high positive difference between market value and book value of equity generate higher than average profits. High P/B (price-to-book) stocks are called “high value stocks”, while low-value stocks are called “growth stocks”. Bodie et al. (2011: 373), based on Ken’s French data library, claimed that high value portfolios generate higher average annual returns than growth portfolios for the period 1926-2006. The performance of the value portfolio and growth portfolios are contributed by Bodie et al. (2011: 373), and are shown in Figure 3. It is visible that the returns of the value portfolios are substantially higher than growth portfolios returns. The difference between the strongest growth and the strongest value portfolios is up to almost at 6% monthly.

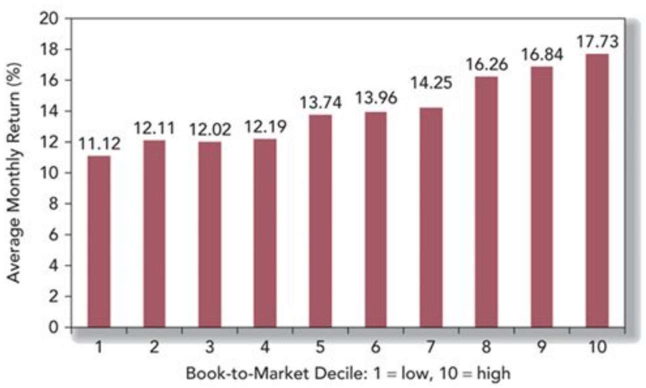

Figure 5 - Average annual returns of "value portfolio" compare to "growth portfolios" for 1926-2006 (Bodie et al. (2011: 373))

Earnings announcements are important for investors, because they are an indicator of a company's wealth. Chan et al. (1996) claim that there are abnormal price jumps after earnings announcements. In an efficient market, new information will be reflected in its prices for a short period of time. Ball and Brown (1968) argue for a sluggish response of the market prices toward to the earnings news. Bodie et al. (2011: 374), based on Ken's French data library, claim higher average annual returns of high earnings compared to low earnings surprise portfolios for the 1926-2006 period. Figure 4 shows the performance of portfolios in Bodie et al. (2011: 374). The difference between high earnings portfolio and the bottom low is up to almost 18% of average excess return in a four-month period. It is also visible that low earnings portfolios generate three-month persistent negative excess returns. Thereby, earnings can be an indicator of future returns. However, Chan et al. (1996) claim that the price momentum effect is generally stronger than the effect from earnings momentum, and that price momentum and earnings momentum are two different phenomena. This means that momentum portfolios generate higher profits; high price momentum stocks do not imply high earnings momentum. However, it does not mean that there is no possibility that high price momentum stocks cannot have high earnings momentum.

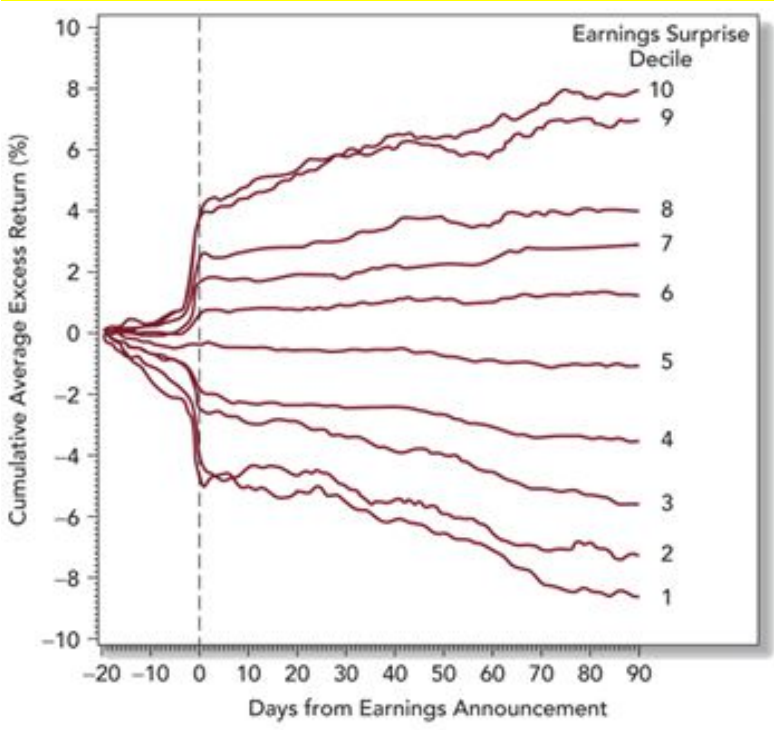

Figure 6 - Average annual returns of "value portfolio" compare to "growth portfolios" for 1926-2006 (Bodie et al. (2011: 374))

The CAPM market factor relies on sensitivity of an asset to market-wide risk. The sensitivity is measured by beta. Beta of an asset is a coefficient of alpha regression against equity risk premium. By evidence, not just market portfolio is able to track returns. Market capitalization, earnings, book value of equity, past returns and turnover also stand for investment risks. For example, low liquidity, small firm size risks are compensated by higher returns. The case with a price-to-book coefficient is a more complicated issue, as it contributes to converse effect. Nevertheless, estimates relying on that P/B can produce a good track of future returns, as the value stocks tend to have higher returns. Thereby, these market anomalies can be viewed as risk factors and it is possible to estimate exposure of an asset to certain risks. Additional model parameters should therefore imply higher precision of returns estimates. Resulting multifactor models should perform better than not only stocks, but also portfolios. This is because a portfolio can be constructed by one of the discussed investment styles. In that case, multifactor models should perform better than CAPM, in terms of return estimates for mutual funds.

3.4 Multifactor models

The marginal investor is in other words a diversified investor. That is one reason for the common risk factor in CAPM. Thereby, the risk factors as market capitalization, liquidity, size, value and past returns, are also aggregate. The first multifactor model was conducted by Fama and French (1992), who claim that along with the market factor, there are two easily measurable variables: size-to-market equity and book-to-market equity, which are able to capture different cross-section variations in a stock return. Fama and French (1992) aggregated size- and book-to-market equity, as well as done in CAPM with the equity risk premium. The size factor is attributed to a difference between the returns of the smallest and the biggest companies. Instinctively, small minus big (or SMB) portfolios perform a measure of market compensation for size risk. Thereby, exposure to size risk can be measured by a consistent regression, as done in the CAPM. On the other hand, value stocks tend to have higher returns. Thereby, the spread between value and growth portfolios shows the impact of P/B. This spread is called high-minus-low factor (HML). Fama et al. (1993) postulated the three-factor model of asset pricing, which is shown in Equation (2).

$$R_t - r_f(t) = b_m \cdot \left(R_m(t) - r_f(t)\right) + b_{SMB} \cdot SMB_t + b_{HML} \cdot HML_t + e_i \quad (2)$$

Variable	Description	Variable	Description
R_t	Assets return at time *t*	SMB_t	The difference between returns at top small and top big companies at time *t*
$r_f(t)$	Consistent treasury bill rate at time *t*	b_{HML}	Sensitivity of an asset to high minus low risk factor
b_m	Sensitivity of an asset to market risk factor	HML_t	The spread between pure value and growth portfolios returns at time *t*
$R_m(t)$	Market portfolio return at time *t*	e_i	Standard error
b_{SMB}	Sensitivity of an asset to size risk factor		

Table 2 - Equation (2) variable description (Three factor model)

Sørensen (2009) postulated a small evidence of the three-factor Fama and French (1992, 1993) model, which is significance for the Norwegian mutual fund returns estimation. However, he posits that betas of such factors as SMB and HML should probably be calculated by the fund managers for their customers. The fact that size, value and growth portfolios are equally weighted is very important. For us it is natural to think that such portfolios should be diversified, at least for MET tests for mutual funds. As mutual funds have resources for qualitative diversification, it should at least have an importance. It can be the case that bringing diversification into the game can make SMB and HML factors smaller. However, if one is conducting a portfolio based on one of the mentioned strategies, why not diversify? In addition, could the diversified portfolios change the factors' predictive power? However, it is almost impossible to get a co-variation of assets in terms of firm-specific risk. In that case, the funds are also forced to use equally weighted portfolios.

The momentum strategy is claimed by Jegadeesh and Titman (1993) and Chan et al. (1996) to generate higher return than average. As high past returns can be persistent for a certain time, it is possible to use them as a risk factor. Carhart (1997) claimed that returns of the top US mutual funds could be captured by this risk factor. The difference between high past returns and low past returns portfolios is called *winners minus losers* or *up minus down* (WML or UMD). Carhart's (1997) model uses not monthly, but prior one-year returns, as seen in Equation (3).

$$R_t - r_f(t) = b_m \cdot \left(R_m(t) - r_f(t)\right) + b_{SMB} \cdot SMB_t + b_{HML} \cdot HML_t + b_{PR1YR} \cdot PR1YR_t + e_i \quad (3)$$

Variable	Description	Variable	Description
R_t	Assets return at time *t*	b_{HML}	Sensitivity of an asset to high minus low risk factor
$r_f(t)$	Consistent treasury bill rate at time *t*	HML_t	Spread between pure value and growth portfolios returns at time *t*
b_m	Sensitivity of an asset to market risk factor	b_{PR1YR}	Sensitivity of an asset to a momentum risk factor
$R_m(t)$	Market portfolio return at time *t*	$PR1YR_t$	Returns difference between high and low past returns portfolios at time *t*
b_{SMB}	Sensitivity of an asset to size risk factor	e_i	Standard error.
SMB_t	Difference between returns of top small and top big companies at time *t*		

Table 3 - Equation (3) variable description (Carhart (1997) model)

Gallefoss et al. (2015) claim that Carhart's (1997) model certainly captures the returns of Norwegian mutual funds. However, only a small part of the returns variation is captured by the PR1YR risk factor. The fact that mutual funds returns and PR1YR are correlated is crucially important. First, it is possible to incorporate the strategy mutual funds use. Second, it is possible to separate the luck from skill question by checking for persistence and accounting for reversals. Gallefoss et al. (2015), nevertheless, claim that the returns of top and bottom funds are not driven by luck.

Gallefoss et al. (2015), Carhart (1997) and Avramov and Chordia (2006) documented a good Carhart (1997) model-performance. Avramov and Chordia (2006) claimed that a predictive multi-period model captures the effect of factors like SMB and HML. This means that the betas are allowed to vary a bit from period to period. The predictive model means that is no look-ahead bias, which is the usage of previous period variables to explain future returns variations. Nevertheless, this model will not capture effects of risk factors such as WML or PR1YR. However, Avramov and Chordia (2006) stated a link between momentum risk factor and macroeconomic variables, such as business cycle.

3.5 Momentum pitfalls, possible returns, auto correlation and mutual funds

The strategy of "buying winners and selling losers" is today known as the "price momentum strategy". The profitability of price momentum is comparable with other well-known strategies, such as "value investing". As an example, taking the average monthly return of the highest earnings-to-price portfolio is a value-oriented strategy. Fama and French (1992) did this for the period between 1963 and 1990, giving a 1.72% profit. These values are comparable, which yields the relevance of both strategies and exacerbates the importance of a trend following strategy.

Chan, Jegadeesh and Lakonishok (1996) state that earnings momentum strategies, which is selecting securities with a high six-month earnings surprise performance, generate slightly lower returns than the price momentum strategy. A number of further studies were aimed at the momentum profitability causes and reasons. At the same time, they showed that the momentum strategies, based on past performance, are still profitable. For example, Grinblatt and Han (2005) also found monthly 1% average returns for momentum strategy in the 1962-1996 period, which is consistent with the findings from Jegadeesh and Titman (1993).

All the following information regarding the momentum strategies fully proves the profitability of equity momentum strategies and return autocorrelation in the US market. This profitability is documented for a long period, from the 1960s to the present. Momentum profitability is also documented in Norway for the 1978-1995 period by Rouwenhorst (1998). Asness et al. (2013) found stock persistence (hence, momentum) for the world's largest equity markets, in Europe, the UK, Japan and the United States. They also document momentum profitability in Norway from 1978 to the present. According to this evidence, the trend-following strategy works on almost all of the mature markets. Moreover, the evidence indicates a profitability of momentum strategies for more than 20 years after its fundamental discovery. However, the trend-following pattern does still not have a perfect explanation, which is probably why it is still profitable.

One possible consequence of this fact is autocorrelation returns patterns. Bondt and Thaler (1985, 1987), Jegadeesh (1990) and Lehman (1990) have evidence of stock returns' persistence and reversals. This evidence forces us to check for such patterns in the mutual funds industry.

Let us imagine a perfect portfolio with perfect information. Such a portfolio will not include securities with negative expected returns. If needed for diversification, a security can be sold and a new one with similar covariance and positive return could be acquired. Such a portfolio is probably impossible to find. However, in the modern financial market, the nearest assets to such bizarre portfolios are probably mutual funds and hedge funds. The capital market single-securities do not perform any diversification or strategy. At the same time, the investment fund shares are portfolios with a certain strategies and certain risk decreasing. The luck or skill question concerns whether mutual funds share characteristics. Following, we see three alternatives. Mutual funds characteristics can be similar to marketable single securities, as in position 1, Figure 6. Some of the mutual funds can also outperform the market by management or economy of scale, as in position 2. Alternatively, mutual funds could be very different in their characteristics compared to securities, as in position 3.

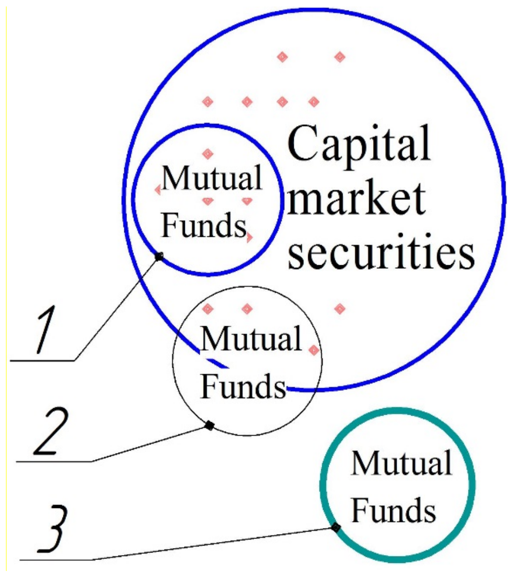

Figure 7 - Mutual funds shares characteristics

Return autocorrelations naturally deals with momentum strategies. There are two features of the momentum strategy that are important, seasonality and business cycle. This is simply because an exclusion of certain strategy conditions might destroy the sample performance, for example, as with momentum profits after 2008, as Wang and Xu (2015) mention. It was the financial crisis and a certain down economy state. This example highlighted a third important feature of momentum profits, which is market volatility. Wang and Xu (2015) posit a connection between the business cycle and market volatility, yielding high momentum profits in "down" states of the economy, and vice versa. Moreover, interpreting the mutual funds returns without these important links might lead not only to bias, but also to fundamental inference mistakes.

Seasonality of a trend-following strategy is related to higher momentum profits in certain periods. Instinctively, it is low or even negative profits in January. Abnormally high December profits and low January profits can be attributed to the January effect. Others can inhere to a momentum pattern. There is strong evidence of the January effect in the modern capital markets. Evidence of the December/January drifts for high momentum portfolios was documented by Sias (2007). However, Jegadeesh and Titman (1993) claimed analogical figures, adding April and November high profits. Sias (2007) also documents outstanding June and November profits, but not as high as Jegadeesh and Titman (1993) proved. Sias (2007) finds consistency with the hypothesis that mutual funds window-dress (impress investors) close to the last quarter's end. Hence, the trend-following strategy is not only a subject of the January effect, but also possible patterns of window-dressing and November/April outstanding payoffs.

Momentum payoffs are positive in up-market conditions, as Cooper et al. (2004) mention. Some other papers found trend-following payoffs in connection with business cycle, as mention by Bodie et al. (2011: 370-383). Therefore, analyzing a mutual fund's prices or even a stock's business cycle must be considered, especially around the year 2008. The effect of the market volatility discovered by Wang and Xu (2015) is a very strong link to the momentum strategies profitability. Hence, the market volatility pattern may also be considered, having a deeper and wider understanding. As one of the methods, periods of high market volatility can removed from the sample. Nevertheless, it can be possible to use market volatility as an explanatory variable.

3.6 Volatility anomaly and other risk factors

Ang et al. (2006) claim that aggregate (market) volatility should also be a risk factor. Thereby, market volatility is not only linked with momentum strategies, but also with an asset's expected returns. In such a case, stocks with different sensitivity to innovations in a market volatility should have different returns, according to Ang et al. (2006). Thereby, volatility of market return or the spread between high and low volatility portfolios can probably be used as a risk factor. As this paper is limited by time, we consider the usage of market (index) volatility as a risk factor. However, it probably merits further research to calculate a more comprehensive market volatility factor.

Asset pricing models such as the three-factor model by Fama and French (1993) and the four-factor model by Carhart (1997) fail to predict future returns with certainty. SMB, HML and WML (or PR1YR) capture parts of the returns variation, but the usage of prior factor values does not give any certainty. This fact accounts for the possible existence of the undeveloped risk factors. Ang et al. (2006) find that stocks with a high / low standard deviation in capital pricing models standard error tends to have a ether low / high future returns. The standard deviation of the model's standard error is called idiosyncratic volatility. Ang et al. (2009) find that stocks with low idiosyncratic volatility outperform stocks with high idiosyncratic volatility. This is in direct contradiction of the standard asset pricing models. Moreover, Jordan and Riley (2015) claim the same is true for mutual funds. As an example from Jordan and Riley (2015), they clamed that \$1 invested in a past low-return volatility mutual fund at the beginning of 2000 is worth about \$2.9 at the end of 2013. Otherwise, this same dollar could be invested in a high volatility mutual fund, giving \$1.21, while a dollar invested in the market would be worth \$1.79.

Thereby, prediction tests of the volatility in mutual funds can be used as an explanatory variable. Moreover, for idiosyncratic volatility, predictive power tests could track portfolios based on idiosyncratic volatility. Ang et al. (2009) documented effects of idiosyncratic volatility in international markets. In that way we will conduct tests of idiosyncratic volatility portfolios. For the regression tests, prior idiosyncratic volatility (from one to three months) of Fama and French's model can be used as a fifth variable in the Carhart (1997) model.

To check for mutual fund persistence and reversals in autocorrelation patterns, it is possible to use prior return. The length of this prior return has been tested in different researches like Lehmann (1990), who used three, six and nine months. Jegadeesh and Titman (1993) and Carhart (1997) used, on the other hand, twelve months' prior return. Provided that historical data is available, it is also possible to check for 36, 48 and 52-month prior return as Bondt and Thaler (1985, 1987) did.

3.7 Previous studies

As our main article concerning both mutual funds and momentum theories in the Norwegian market, Gallefoss et al. (2015) have been a huge inspiration for us. Gallefoss et al. (2015) published their article concerning performance and persistence of Norwegian mutual fund, based on daily data. Their data range is 2000–2010 and they use the Carhart (1997) model. They found short time persistence of performance up to one year for funds that were performing at the highest and for those performing at the lowest. In this research they find consistent evidence with Sørensen (2009) and very low significance of all Carhart model factors. Sørensen (2009) investigated the performance and persistence of all Norwegian equity mutual funds that have been listed on the Norwegian Stock Exchange in the period 1982 to 2008. He found no persistence in the performance of either winners or losers, using monthly data. In choosing daily data, Gallefoss et al. (2015) were able to closely evaluate performance in short-time horizons. A reasonable point is that risk exposure could change over time, and that daily data then gives a research, more or less based on the same terms of risks. Later they conclude that funds' performance either on top or bottom is too large to be explained by luck. To investigate whether mutual funds' performance is due to luck or skill, Gallefoss et al. (2015) had to distinguish whether both top and bottom funds' results are caused by managerial superior or inferior skills. This is consistent with the findings from Sørensen (2009).

Ang et al. (2009) tested the effect of idiosyncratic volatility internationally and found average significance for stocks and mutual funds. Rather than look at averages, we looked directly at the Norwegian equity mutual funds and consistently checked for the effect of idiosyncratic volatility.

3.8 Summary

The Market Efficiency Hypothesis states that prices fully reflect all available information. Malkiel and Fama (1970) distinguish between three forms of market efficiency: “weak”, “semi-strong” and “strong”. The weak form accounts for historical prices, while the semi-strong form states reflection of all public data in a market value. The strong form states reflection of all relevant information in a market value. Grossman and Stiglitz (1980) and Pedersen (2015) use the term “efficiently inefficient” market, which is a market where a “… limited amount of capital can be invested with active managers who can beat the market using economically motivated styles”. The Market Efficiency Hypothesis implies returns random walk model (absence of correlation). Asness et al. (2013), Fama and French (1992), Jegadeesh and Titman (1993) and others indicate such market anomalies as higher returns for small market capitalization (size anomaly); higher returns for high past returns stocks (momentum anomaly), higher returns for high book-to-market values (value anomaly); higher returns for low turnover (liquidity anomaly); and auto correlation patterns in stock returns. They are called small-minus-big (SMB, market capitalization), high-minus-low (HML, book-to-market), winners-minus-losers or up-minus-down (WML or UMD, past returns), prior-one-year-return (PR1YR, past returns). Factor models measure exposure to aggregate risk factors.

4. Methods

This chapter is devoted to research design, methods, regression models and defining our problem statement. A research design and selected methods should be appropriate for an investigation topic, this to provide precision and quality. The nature of reality is described by the ontology, which defines what the facts are, as described by Easterby-Smith et al. (2012: 17). On the other hand, a research epistemology describes the tools for enquiring into the ontology, as mention by Hollis (1994). Thereby, the definitions of ontology and epistemology set up a direction of a topic development. After we have accounted for the philosophical issues, we will discuss our used regression models and characteristics.

Problem statement:

"Are the well-known Risk-Factors Capable to Predict the Returns of a Norwegian Equity Mutual Funds with a Certain Degree of Precision?"

We will use regressions models to check for the predictability in the Norwegian mutual funds industry. This will give us indicators of the variation of exposure of the time-series returns, to well known risk factors. Our considered risk factors are HML, SMB, WML, PR1YR, MKT, market volatility and asset returns volatility, as well as asset return for the prior three, six, nine, twelve months. We will also augment the Fama and French (1992) and Carhart (1997) models for some of the factors. This will give us new regression models for past returns and volatility. We will also check for persistence in the Norwegian mutual funds industry, in order to make a first derivative of the skill or luck question. We will conduct a portfolio based on normal and idiosyncratic volatility in order to check their ability to predict higher returns.

4.1 Research design

A research design is all about taking strategic choices in a beginning of a research period. Incidentally, with strategic choices meaning that we use the most effective ways of data collection, processing and analyzing. The returns of mutual funds are probably either predictable or not. On the contrary, development of this topic is almost impossible in a direct way. Consistently, factors such as SMB, HML, WML and others, will indirectly answer to possible predictability methods. Returns are determined by all available and precise information as the Market Efficiency Hypothesis states. In that case, if it is impossible to predict returns, then it can be possible to predict less complicated factors, which are correlated with returns. Granted that, internal realism are defined as a philosophical view, where the truth exists, but is obscure and cannot be accessed directly, as mention in Easterby-Smith et al. (2012: 19). We conclude that the most suitable method for us is to use internal realism as ontology in this research.

"...epistemology is about different ways of inquiring into the nature of the physical and social worlds." (Easterby-Smith et al. (2012: 21)).

To understand both the physical and the social world, epistemology is divided into two contradictory perspectives. These are social constructionism and positivism. Social constructionism states that the real world is subjective and internal, as mention by Easterby-Smith et al. (2012: 24). On the other hand, positivism defines the world as external, which support a set of objective methods for the research in contrast to subjective reflection and intuition. As positivism construe independence of the observer, social constructionism is seen as most appropriate for the market efficiency tests. This is because prices and returns are defined by market equilibrium and are driven by informed agents. Hereby, the point of view form the observer is important, as it possible to drive efficient markets. The investors are interested in efficient markets to have certain risk-return casualty. At least, the marginal investors should be. Therefore, the human interests can be seen as science drivers, which is common in the social constructionism. Nevertheless, there are two reasons for chosing positivism. First, it is almost impossible for us to enquire the observer's viewpoint in our analyses. Second, internal realism is more linked to positivism epistemology, as mention by Easterby-Smith et al. (2012: 25). Finally, this whole situation is too complex to be included, and then positivism seems to be the most appropriate epistemology for our study.

A research without strong theoretical base will easily be limited to just describing single phenomenon. On the other hand, theories without empirics will easily be seen as just speculations. In other words, "*theory is grey, but the tree of life is forever green*" as Goethe (1808) concluded in Faust. Thereby, a strong relationship with a theory base and empirics is crucially important for creating this study. Therefore, the inductive method is seen as most appropriate method for this research.

Qualitative studies seek answers like "why, how, in what reason" and quantitative studies account for the influence of factors. Consequently, almost all studies regarding return predictability from a risks prospective, is then quantitative, as it seems to be the most appropriate method. Given that internal realism are linked with positivism, the observer have to be seen as independent. Secondly, the research progresses have to be done through hypothesis. Our null hypothesis is as followed: *The Norwegian mutual funds returns are unpredictable out of risk factors, such as SMB, WML, HML, volatility, idiosyncratic volatility and past returns*. It means that the mutual funds returns are unpredictable with the most known risk factors. Hypothesis 1 is then contrary, states that *The Norwegian mutual funds returns are predictable out of risk factors, such as SMB, WML, HML, volatility, idiosyncratic volatility and past returns*. The deductions are followed by persistence (like the skill or luck - question), risk factors and returns link, and the possibility to generate higher returns based on idiosyncratic volatility. Our analysis is done through empirical analysis tools, like correlation and regressions.

4.2 Models

The models that we have tested are basic CAPM (Equation 1), Fama and French (1992) three factor (Equation 2) and Carhart (1997) (equation 3) models. Carhart (1997) model is augmented for oil price market return (Equation 4) and market volatility (Equation 5). Carhart model augmented for UMD and LIQ (equations 6 and 7). Finally, we have also used an autocorrelation returns model (Equations 6 and 7). Idiosyncratic volatility is measured upon the basic Fama and French (1993) model.

4.2.1 Carhart model augmented for oil market monthly return

The idea for augmentation for oil market return is that the petroleum market is significantly important for the Norwegian economy. Thereby, probably a lot of the funds could have substantial part of their investments into this market. Hence, we will look for a correlation between the funds returns and the oil market returns. The model is viewed in Equation (4).

$$R_t - r_f(t) = b_m \cdot MKT_t + b_{SMB} \cdot SMB_t + b_{HML} \cdot HML_t \cdot b_{PR1YR} \cdot PR1YR_t + b_{OMR} \cdot OMR_t + e_i \quad (4)$$

Variable	Description	Variable	Description
R_t	Assets return at time t	HML_t	Value of HML at time *t*
$r_f(t)$	Consistent treasury bill rate at time *t*	b_{PR1YR}	Sensitivity of an asset to a momentum risk factor
b_m	Sensitivity of an asset to market risk factor	$PR1YR_t$	Returns difference between high and low past returns portfolios at time *t*
MKT_t	Market factor value at time *t*	b_{OMR}	Sensitivity to oil six - month prior returns
b_{SMB}	Sensitivity of an asset to size risk factor	OMR_t	Value of six - month oil market prior returns at time *t*
SMB_t	Value of SMB at time *t*	e_i	Standard error (idiosyncratic volatility in Fama and French model).
b_{HML}	Sensitivity of an asset to HML risk factor		

Table 4 - Equation (4) variable description (Carhart model augmented for oil market monthly return)

4.2.2 Carhart model augmented for oil market volatility

Researches like Avramov and Chordia (2006) and Wang and Xu (2015), confirms the existence of the momentum effect, but only during up economical stages. This explains the importance for prior twelve-market volatility in the Carhart (1997) model. This model is shown in Equitation (5).

$$R_t - r_f(t) = b_m \cdot MKT_t + b_{SMB} \cdot SMB_t + b_{HML} \cdot HML_t + b_{PR1YR} \cdot PR1YR_t + b_{MVOL} \cdot MVOL_t + e_i \qquad (5)$$

Variable	Description	Variable	Description
R_t	Assets return at time t	HML_t	Value of HML at time *t*
$r_f(t)$	Consistent treasury bill rate at time *t*	b_{PR1YR}	Sensitivity of an asset to a momentum risk factor
b_m	Sensitivity of an asset to market risk factor	$PR1YR_t$	Returns difference between high and low past returns portfolios at time *t*
MKT_t	Market factor value at time *t*	b_{MVOL}	Sensitivity to market volatility
b_{SMB}	Sensitivity of an asset to size risk factor	$MVOL_t$	Value of market volatility at time *t*
SMB_t	Value of SMB at time *t*	e_i	Standard error (idiosyncratic volatility in Fama and French model).
b_{HML}	Sensitivity of an asset to HML risk factor		

Table 5 - Equation (5) variable description (Carhart model augmented for oil market volatility)

4.2.3 Carhart model augmented liquidity

As we understand, liquidity should be significant for the funds. High liquidity will increase the value of shares, which indicate that they have a good structured business, in terms of debt payouts. Therefore we wanted to check for liquidity effects. This model is shown in Equation (6).

$$R_t - r_f(t) = b_m \cdot MKT_t + b_{SMB} \cdot SMB_t + b_{HML} \cdot HML_t + b_{PR1YR} \cdot PR1YR_t + b_{LIQ} \cdot LIQ_t + e_i \qquad (6)$$

Variable	Description	Variable	Description
R_t	Assets return at time t	HML_t	Value of HML at time *t*
$r_f(t)$	Consistent treasury bill rate at time *t*	b_{PR1YR}	Sensitivity of an asset to a momentum risk factor
b_m	Sensitivity of an asset to market risk factor	$PR1YR_t$	Returns difference between high and low past returns portfolios at time *t*
MKT_t	Market factor value at time *t*	b_{LIQ}	Sensitivity assets to liquidity
b_{SMB}	Sensitivity of an asset to size risk factor	LIQ_t	Value of liquidity at time *t*
SMB_t	Value of SMB at time *t*	e_i	Standard error (idiosyncratic volatility in Fama and French model).
b_{HML}	Sensitivity of an asset to HML risk factor		

Table 6 - Equation (6) variable description (Carhart model augmented for liquidity)

4.2.4 Carhart model augmented for up-minus-down

The factor Up-minus-down is a variation of the momentum factor effect PR1YR. Monthly return can also be significant, and is why we test the augmenting Carhart (1997) model for UMD. This model is shown in Equation (7).

$$R_t - r_f\,(t) = b_m \cdot MKT_t + b_{SMB} SMB_t + b_{HML} HML_t + b_{PR1YR} PR1YR_t + b_{UMD} UMD_t + e_i \qquad (7)$$

Variable	Description	Variable	Description
R_t	Assets return at time t	HML_t	Value of HML at time *t*
$r_f(t)$	Consistent treasury bill rate at time *t*	b_{PR1YR}	Sensitivity of an asset to a momentum risk factor
b_m	Sensitivity of an asset to market risk factor	$PR1YR_t$	Returns difference between high and low past returns portfolios at time *t*
MKT_t	Market factor value at time *t*	b_{UMD}	Sensitivity assets to up-minus-down factor
b_{SMB}	Sensitivity of an asset to size risk factor	UMD_t	Value of UMD at time *t*
SMB_t	Value of SMB at time *t*	e_i	Standard error (idiosyncratic volatility in Fama and French model).
b_{HML}	Sensitivity of an asset to HML risk factor		

Table 7 - Equation (7) variable description (Carhart model augmented for up-minus-down)

4.2.5 Autocorrelation models

We have tested two autocorrelation models. The factors in these models are MKT, prior returns and the volatility of the funds. We used twelve-month prior volatility of funds as the volatility risk factor. We also use funds prior one, three, six, nine and twelve-month returns, as the prior returns risk factor. These models are seeking to identify momentum trends. This is accordance to the researchers who have found autocorrelation patterns like Bondt and Thaler (1985, 1987) and Jegadeesh (1990). These models are shown in Equations (8) and (9).

$$R_t - r_f(t) = b_m \cdot MKT_t + b_6 \cdot P6MR_t + b_9 \cdot P9MR_t + b_{VOL12} P12MR_t \cdot e_i \quad (8)$$

$$R_t - r_f(t) = b_m \cdot MKT_t + b_1 \cdot P1MR_t + b_3 \cdot P3MR_t + b_{VOL12} \cdot VOL_{12} + e_i \quad (9)$$

Variable	Description	Variable	Description
R_t	Assets return at time t	$PiMR_t$	Prior returns *i* month asset returns at time *t*
$r_f(t)$	Consistent treasury bill rate at time *t*	$b_{VOL\,t}$	Sensitivity assets volatility in period *t*
b_m	Sensitivity of an asset to market risk factor	VOL12	Assets volatility in prior 12 months
MKT_t	Market factor value at time *t*	e_i	Standard error (idiosyncratic volatility in Fama and French model).
b_i	Sensitivity *i* month asset prior returns		

Table 8 - Equation (8) and (9) variable description (Autocorrelation)

4.3 Regression models and terms

These regression models checks whether the explanatory variables are capturing any variation of the dependent variable. These regression models determine constant coefficients for the explanatory variables. The coefficient of determination (R-squared or R^2) of the regression model shows how much of the dependent variable variation is captured by the used variables, as mention by Hocking (2013: 28). R-squared vary from 1 (100%) to 0 (0%) certainty. Linear regression uses least-squares estimator, which is conducted out of the residuals (explanatory variables) to capture the variation of the dependent variable. Standard deviation of the least squares estimator called standard error (SE), as mention by Ruppert (2011: 224). SE shows the forecasts of the volatility.

Our chosen models are using returns as the dependent variable and risk factors as the explanatory variables. Almost all of our models use more than one explanatory variable. Thereby, it is important to estimate the significance level of each variable. Therefore, the significance of each variable is measured by p-value. The p-value, as Ruppert (2011: 225) mention, shows the probability of the residual coefficient being equal to zero. If the residual coefficient is equal to zero, than the null hypothesis holds and there are no linear relationships between the dependent and the explanatory variable. Contrary, if this coefficient is not equal to zero for the least squares estimator, yields a rejection of the null hypothesis for the definite residual. Thereby, as lower the p-value for a variable, gives a higher possibility of linear relationships with the existence of the dependent variable. In other words, the lower p-value, gives a higher significance level of a variable. The volatility of the least squares estimator is linked with the definite variable, and is shown by each variables standard error.

Summing up, R-squared of the regression measure the variance that are captured by the model. This variation changes from 0 to 1, where 1 means 100% captured. Standard error of the model is the volatility of the model estimates. P-value shows the probability of existing linear relationships for each variable, where lower p-value stands for a higher probability.

4.4 Summary

Our research question is about the predictability in the Norwegian equity mutual funds market. By using analysis tools like regressions, gives us an indicator of the variations of an exposure of the time-series returns to the well-known risk factors, which we are using. Our considered risk factors are HML, SMB, WML, PR1YR, MKT, market volatility, asset returns volatility and prior three, six, nine, twelve-month asset returns. Therefore, we have chosen to augment models like Fama and French (1992) and Carhart (1997) for market volatility and oil market returns. Our new regression models gives a past returns and volatility exposure to prior volatility and past returns. The persistence in the Norwegian mutual funds industry makes the first derivative of the *skill or luck* question. The portfolios are based on normal and idiosyncratic volatility, and checks for cross-section of the returns.

As ontology and epistemology, we have chosen internal realism and positivism, respectively. Our used models are basic CAPM (Equation. 1), Fama and French (1992) three factor model (Equation 2) and Carhart (1997) model (Equation 3). Fama and French (1992) and Carhart (1997) models are augmented for oil price momentum (Equations 4 and 5) and market volatility (Equations 6 and 7). We have also used two different autocorrelation models (Equations 6, and 7). We have measured idiosyncratic volatility upon both Fama and French (1992) and Carhart (1997) basic models. The regression terms that we have used are R-squared (variance captured by the model), standard error and P-value.

5. Data

This chapter is devoted to data sample. Selection of funds, benchmarks, data sample construction and basic statistics is covered in this chapter.

5.1 Mutual funds database

This study is limited to only include Norwegian equity investing mutual funds. The definition of a Norwegian mutual fund is described in chapter 2. This data sample covers the period from 2000 to 2015 and is survivorship bias free. Survivor bias free means that the database include funds that are liquated or closed for period, according to Brown et al. (1992). Funds can be closed for merges, bankruptcy, due date and other reasons. The inclusion of "dead" funds is important, because the contrary way can lead to biased sample as well as biased results. Our database contains net asset values (NAVs) for 74 Norwegian equity funds. NAV are excluded the fees of buying funds. The values are adjusted for dividends, but not for the funds fees. The return on mutual funds are calculated according to Equation 10:

$$r_t = ln\left(\frac{NAV_t}{NAV_{t-1}}\right), \tag{10}$$

Variable	Description
r_t	Return of an underlying fund *t*
NAV_t	Net asset value at period $_t$

Table 9 - Equation (10) variable description (NAVs)

Needs to be stated that the share of domestic equity funds in Norway are slightly falling. In 2015, VFF claimed that 20 % of the shares consist of domestic funds in market, where a major part is global funds. However, as domestic funds might be sensitive to domestic risk factors, our investigation is limited only to the domestic funds. To set it straight, we have exclude international funds (funds investing more than 20% in foreign equity), combination funds (funds with less than 80% in domestic equity) and the category of others. These 74 funds equals 70% of the domestic equity funds market in Norway. Our sample is, howerver, restricted to 65%, because the category "other funds" was not included in the TITLON database. Our data is collected from the annual statements at the database in the VFFs website. Furthermore, the data of daily NAVs is collected from the TITLON database.

We have also chosen to excluded index funds which are passively managed, this by erasing funds with “Index” or “Indeks” in their name. We also excluded funds with an observation period less than two years. Needs to be stated, that TITLON database perform biased data for some of the mutual funds. The problem is that some funds seem to be listed twice on the TITLON database. These funds are not a duplicate, but a proportion of a main data, just taken with a different ticker. This was taken into account while we collection data, otherwise, our data sample could be significantly biased.

Gallefoss et al. (2015) conducted a analysis based on daily data. Thereby, we wanted make tests in a monthly dataset. Granted that, we changed a daily format to monthly, by taking the last day of the month in the calculation of NAVs. Our equally weighted portfolios consist of 74 funds and performing a very high annual return, up to 53%. The descriptive statistics of our funds database and annual returns of our equally weighted portfolio are shown in Table 1. The funds that are included in our database are reported in Appendix 1.

Table 1 reports the number of funds at the end of a year, born, liquidated and its return of the whole equally weighted portfolio. Column one reports number of existed funds at the end of the year. Column two represents number of funds born during the year and the next one present the number of funds being liquidated. The last column represents the annual return of the equally weighted portfolio of funds for the accounting year.

Year	**Number of funds**			**Return of equally weighted portfolio**
	End of year	**Born**	**Liquidated**	
2000	45	6	0	4.34%
2001	50	2	0	-21.09%
2002	52	8	0	**-42.28%**
2003	60	1	0	**46.11%**
2004	61	1	0	20.78%
2005	58	5	4	33.90%
2006	57	1	6	21.19%
2007	57	0	1	7.69%
2008	57	0	0	**-55.71%**
2009	56	0	1	**53.60%**
2010	56	3	1	19.94%
2011	58	3	0	-19.29%
2012	58	0	3	8.08%
2013	55	0	3	15.99%
2014	46	0	9	8.69%

Table 10 – Mutual funds database summary statistics.

Our equally weighted portfolio suffers with reversals. Like in the period 2001-2004 we saw that the return did reverse it self to its results back to the year 2000. This is strongly visible for periods like 2002-2003, 2008-2009 and 2010-2011. The positive development of return is persistent up to four years. These persistence and reversals are consistent with the evidence from Bondt and Thaler (1985, 1987).

5.2 Benchmarks and factors data

For risk-free rate we have chosen the three-month Treasury bill (ST1X). As the regressions are based on monthly data, we took the closest Treasury bill and compounded the rate for a monthly risk-free return. The ST1X are obtained from the Norwegian Central Banks website. We have observed that the NIBOR have often been used as a risk-free rate. However, we see the ST1X as the most nearest and applicable, as the normal investors experiencing the NIBOR depositing to be too costly. As benchmark for the market factor, we have chosen to use the OSEBX. In 2015, the OSEBX included 57 Norwegian equity mutual funds. We have considered this benchmark to be applicable and representable for the market return development in our population.

Our equally weighted portfolio of funds is highly correlated with the OSEBX, as it visible in Figure 8. In different time periods, our equally weighted portfolio ether slightly underperforms or outperforms the benchmark. For example, during the financial crisis (2008), the returns of our equally weighted portfolio felt slightly lower than the return in OSEBX. This was persistent for almost three years, when the OSEBX reversed its position. The annual returns reversals for our equally weighted portfolio are followed by the OSEBX reversals.

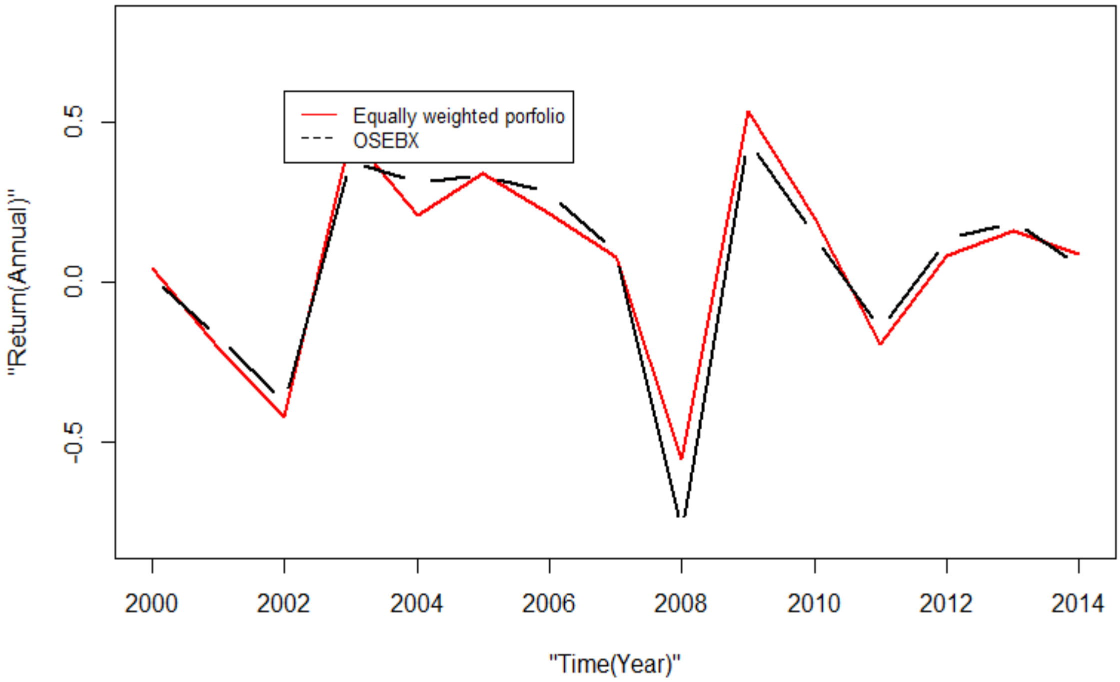

Figure 8 – Comparing the annual returns development for OSEBX and the equally weighted portfolio of mutual funds

In Figure 9, the monthly returns development for OSEBX and all funds, including dead funds, are presented. It is visible, that survived funds on average steadily underperform the benchmark on a monthly base. However, there is also periods of higher returns, compare to the benchmark. By including the dead funds shows a high correlation with the movement of OSEBX and are consistently with a lower return. During the financial crisis (2008), the survived funds did perform slightly higher than the value appreciation in the benchmark. By including dead funds into this sample, gives a weak performance after 2010, compare to the OSEBX.

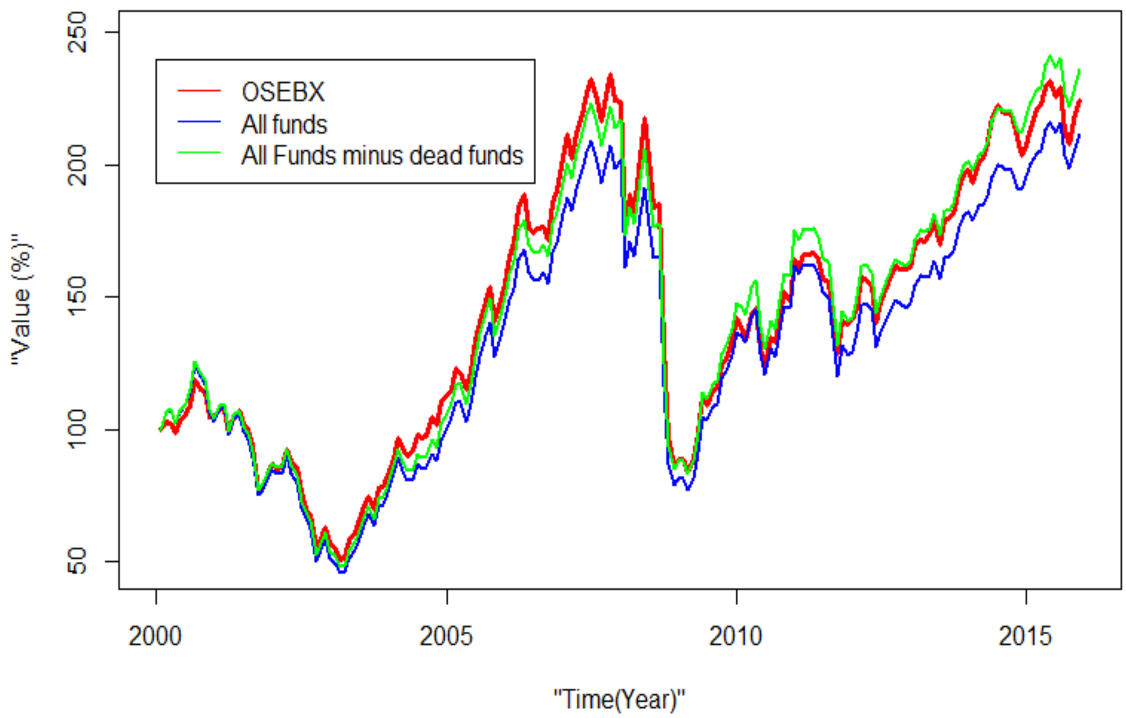

Figure 9 - Return development of OSEBX index and the equally weighted portfolio of all funds, dead funds included/excluded

As this research is mostly limited by time, we used data from Professor Bernt Arne Ødegaard webpage to calculate the three factors model by Carhart (1997). These factors are claimed to be calculate in accordance to both Jegadeesh and Titman (1993) and Fama and French (1993). Thus, factors like SMB, HML and UMD are monthly return spreads of our portfolios. PR1YR is prior one-year spread of the momentum portfolio return. These factors, is claimed to be calculated by the Norwegian equity. The data range of these factors cover period from 2000 to 2011. Other factors such as MKT, volatility and autocorrelation return factors are estimated from the funds, and the benchmarks database, and are cover from the period from 2000 to 2015.

5.3 Descriptive statistics

As our database consists of 74 mutual funds, it is illogical to perform statistical measures for each fund. Thereby, we report data of ether the best or worst performing funds for the entire period and for each five-year period. We have also report the highest and lowest Sharpe ratio funds. These descriptive statistics are showed in Table 12. The Sharpe ratio are calculated in accordance to Equation (11):

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

Variable	Description
r_p	Fund return
r_f	Risk-free rate
σ_p	Portfolio volatility

Table 11 - Equation (10) variable description (Sharpe model)

Table 12 reports the mean of monthly return, mean standard deviation and the highest / lowest performance by funds for some specified periods. The funds are compared using Sharpe ratio.

Data range	2000 - 2015	2000 - 2005	2006 - 2010	2011 - 2015
Mean monthly return	0.68 %	1.11 %	0.55 %	0.42 %
Mean standard deviation of monthly returns	6.56 %	6.90 %	6.18 %	4.17 %
Maximum monthly return	22.12 %	22.12 %	19.96 %	14.23 %
Minimum monthly return	-35.76 %	-28.68 %	-35.76 %	-15.58 %
Mean monthly Sharpe	6.58 %	11.91 %	5.07 %	7.69 %
Maximum monthly Sharpe	23.85	65.40	41.29	22.53
Minimum monthly Sharpe	-4.00	-5.58	-11.42	-14.01
Best Sharpe fund	Storebrand Norge A	Eika Norge	RF Aksjefond	Omega Investment Fund A
Worst Sharpe fund	Postbanken Aksjevekst	Postbanken Aksjevekst	WarrenWicklund Alpha	Nordea SMB

Table 12 – Mutual funds database descriptive statistics.

The mean of monthly return of all funds is highly volatile. The period from 2000 to 2005 perform the highest mean return of all. After the financial crisis, the mean return falls with 0.5 %. However, the volatility of mean returns after the finance crisis is then lower. Certain months perform with ether very high or low returns. Nevertheless, the maximum monthly returns after 2010 did decrease with 5% to 14%. The minimum return had a quite similar situation, growing from 35% to almost -15%. Both the trend from minimum and maximum returns is consistent with the volatility decreasing. As it visible from Figure 10, certain funds drive our equally weighted portfolio higher than the OSEBX.

The best Sharpe ratio funds with its return development are compared to the OSEBX, as reported in Figure 10. This pattern shows all types of funds. The first one, Eika Norge is consistently and abnormally outperforming the benchmark. Second, Storebrand Norge A, are during its existence, outperforming the benchmark consistently with 5% to 10%. Third, RF Aksjefond and Omega Investment Fund A, are very close to the OSEBX. However, RF Aksjefond and Storebrand Norge A are dead funds, while Omega Investment Fund A is started to slightly outperform the benchmark after 2013.

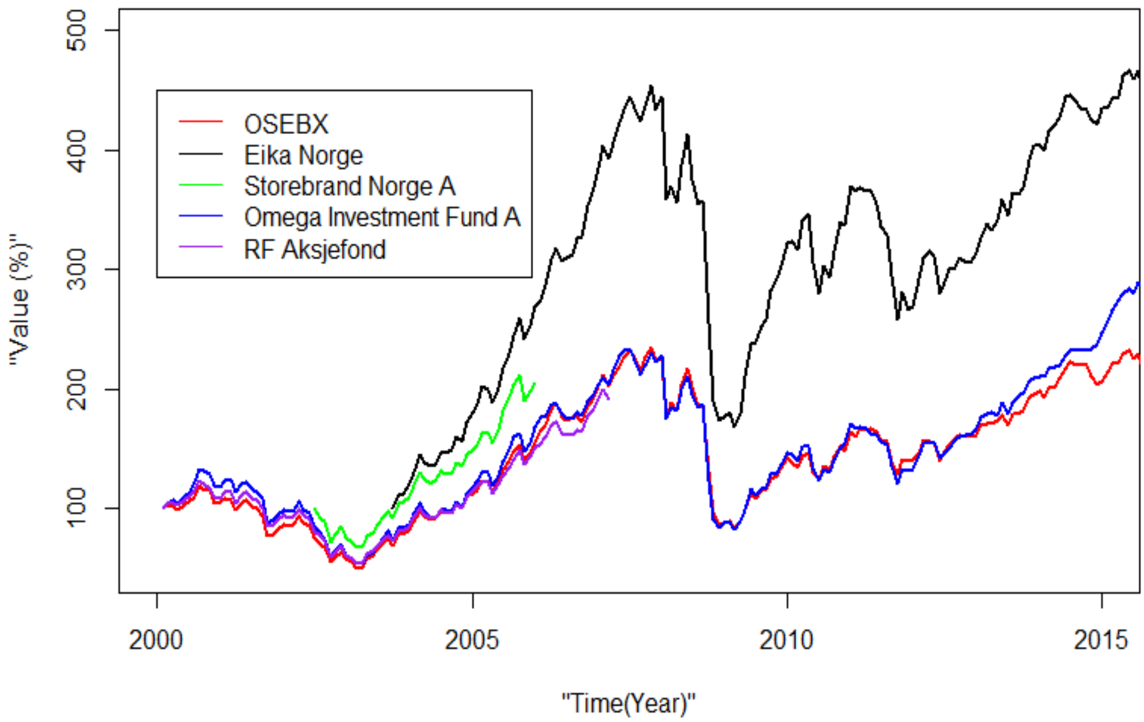

Figure 10 - Return development of OSEBX index and four best Sharpe ratio funds

During the period 2000–2015 there was 43 funds out of 74 funds, which have a higher mean monthly return than the OSEBX. In this group, there are only five funds that beat the OSEBX with more than 0.05%. On the other side, around 40% of the funds in our database underperform the market, based on mean monthly return. The other 50% percent shows a mean monthly return, which are not higher than 0.05 % plus mean monthly OSEBX return. Giving a 10% percent of the funds left, which outperform the benchmark.

The monthly return development of the worst Sharpe ratio funds, are reported in Figure 11. The only fund in existence from the “bottom four Sharp-ratio”, is Nordea SMB. It is visible, that Nordea SMB is consistently underperforming the OSEBX. This underperformance did increase after 2010, compare to previous periods. Postbanken Aksjevekst also consistently underperforms the benchmark until the liquidation. WarrenWicklund Alpha, however, did consistently outperforming the OSEBX before the financial crisis. It seems that WarrenWicklund Alpha had a potential to outperform the benchmark, but was closed down. To conclude, there are funds with a potential to outperform the benchmark. For example, WarrenWicklund Alpha. There are also funds such as Eika Norge, which consistently outperform the OSEBX. However, around 50% of all funds in our database do underperform the benchmark, based on mean monthly return.

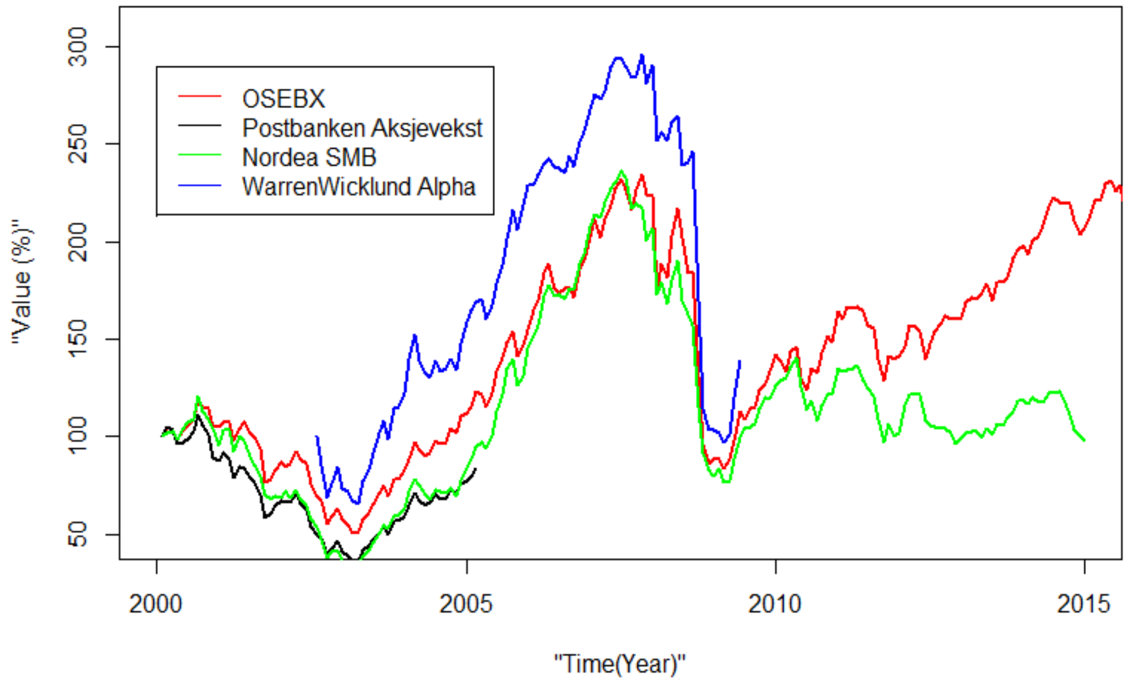

Figure 11 – Return development of OSEBX index and three worst Sharpe ratio funds

5.4 Summary

The Norwegian equity funds are determined by chapter 2, which are in accordance to the standards in the Norwegian Security Association (VFF). This data sample covers the period from 2000 to 2015 and is survivorship bias free. Our database contains of net asset values (NAVs) for 74 Norwegian equity mutual funds. These values are adjusted for dividends, but not for the funds fees. Our equally weighted portfolio suffers with reversal and therefore slightly underperforms the OSEBX. The distribution is around 50 % each of funds that underperform or outperform the OSEBX by monthly mean returns. However, there are a few funds that outperform the benchmark with more than 0.05%.

6. Empirical analysis

This chapter is devoted to our empirical results. We start out with the results from the analysis from our models, like the Capital Asset Pricing Model, Fama and French three-factor model and Carhart four-factor model. Afterword's, we augment our used models for a wider range of stocks and oil market factors. As next, we report the results for the autocorrelation models. And finally, we will discuss the performance of funds with ether high or low idiosyncratic volatility. After all, we discuss all of our findings, their linkages with previous studies and then summing up the inference.

6.1 Results from CAPM; Fama and French; Carhart models

As Carhart (1997) mention influence of momentum effect on the returns of US mutual funds, we account for the same model in the Norwegian market. To point the other models productivity, we use CAPM and Fama and French models as well. These models are using four factors: risk adjusted return of market portfolio; small minus big; high minus low and prior one-year return. There is no strong correlation between these factors, as it visible from Table 3. The highest correlation is between risk-adjusted markets return and the size factor, which is equal to 0.29. MKT have a very weak positive relation with the factors HML and PR1YR. On the other hand, SMB have a weak positive correlation with the factors HML and PR1YR. PR1YR and HML have negative weak correlation. However, all relationships between the variables are very low. Relative independence of variables put a point for impossibility of inference mistakes. In that case, there is no possibility that factors can systematically cancel each other out.

Table 13 reports correlations among MKT, SMB, HML and PR1YR.

	MKT	SMB	HML	PR1YR
MKT	1			
SMB	0.29	1		
HML	0.06	0.16	1	
PR1YR	0.08	0.01	-0.10	1

Table 13 – Correlations of Carhart model factors.

Granted that, we can report with a certain validity that Fama and French (1993) and Carhart (1997) models, on average, do not perform significantly better than CAPM in Norwegian market. These causes are low average estimates of factor loadings and nearly the same R-squared coefficient. The summary statistics for the models are performed in Table 14. CAPM on average has a R-squared equal to 0.91. At the same time, the Fama and French model, as well as the Carhart model, have a R-squared equal to 0.92. This is consistent with the fact that the MKT is the most significant factor in all of the models. The average load of the MKT is also the least volatile, giving a 0.03 standard deviation. The average load of MKT is 1, showing that the funds return move closely together with the MKT factor. The maximum and minimum loadings are 1,25 and 0,26 respectively, which indicate a weak relation between the market factor and certain funds. The P-value of MKT in all three models is close to zero.

Table 14 reports the average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

CAPM					
Factor	**Average load**	**Maximum load**	**Minimum load**	**Standard deviation**	**P-value**
MKT	0.99	1.25	0.26	0.03	0.00
R-squared	0.91				
St. Error	0.0191				
Fama and French model					
MKT	1.00	1.31	0.27	0.03	0.00
SMB	0.01	0.40	-0.69	0.10	0.31
HML	-0.03	0.76	-1.07	0.11	0.35
R-squared	0.92				
St. Error	0.0189				
Carhart model					
MKT	1.00	1.27	0.27	0.03	0.00
SMB	0.00	0.39	-0.78	0.10	0.30
HML	-0.03	0.68	-1.03	0.11	0.37
PR1YR	-0.05	0.92	-0.55	0.10	0.31
R-squared	0.92				
St. Error	0.0189				

Table 14 – Results from CAPM; Fama and French model; Carhart model.

The other two factors in the Fama and French (1993) model and three factors in Carhart (1997) model has an average loading close to zero. This means that the factors SMB, HML and PR1YR, on average, only capture a very small portion (or even zero) of the returns variation. Nevertheless, average loading of PR1YR is -0,05, and is both the highest and the least volatile above these factors. Average p-values of SMB and HML are 0.31 and 0.35 respectively, which shows a low significance. Average standard deviation of these factors is higher than the average estimates of the factor loadings, which stands for an insignificance of the Carhart factors (excluding MKT). However, these are average estimates.

It is visible, that the factor loadings have wide range regarding minimum and maximum estimates. The SMB estimates vary from 0.39 to -0.78, while HML vary from 0.68 to -1.03. At the same time, the momentum effects of the regression coefficient estimate vary from 0.92 to -0.55. The p-values also vary for Carhart factors. Granted that, it is possible to conclude that the returns of certain funds are driven by these factors. To check for this fact, as well as to be able to answer our problem statement, we use a limit for the coefficient and p-value estimates. To state "*a certain degree of precision*", as related to our problem statement, these limits are 0.2 as an upper limit for the coefficient, and -0.2, as lower limit. Thereby, if the coefficient estimate appears in this range, we assume the factor to be significant. For p-value we have chosen an upper limit at 0.15. Therefore, if a factors p-value is lower than 0.15, then we assume the factor to be significant. If the regression model parameters follow both conditions, then we assume that the factors is significant.

From this prospective, we find the SMB factor to be significant for 12 funds. The HML factor is significant for 23 funds, while the PR1YR factor have significance for 14 funds. Around 50% of the significant SMB factor funds, outperform the OSEBX. Two of these funds are liquidated during this period, which leaving five funds in existence, and outperforming the benchmark with a high exposure to SMB.

For the HML factor, there are four significant funds that outperform OSEBX. One of them is liquidated, while the others are in existence. There are three funds with a high significance to PR1YR factor, which outperform the benchmark. They are all in existence. In total, there are nine funds outperforming the benchmark with exposure to the Carhart model factors. The list of these funds is reported in Appendix 2. Table 15 reports a summary of the regression models with an exposure to the Carhart model factors.

Table 15 reports the average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values. N shows the number of funds in a set.

	SMB significant funds N = 12		HML significant funds N = 23		PR1YR significant funds N = 14	
	Average loading	**P-value**	**Average loading**	**P-value**	**Average loading**	**P-value**
MKT	1,02	0,00	1,01	0,00	1,00	0,00
SMB	**-0,24**	0,07	-0,15	0,34	-0,09	0,31
HML	-0,18	0,31	**-0,20**	0,08	-0,02	0,52
PR1YR	-0,07	0,41	-0,07	0,47	**-0,11**	0,06
R-squared	0,91		0,88		**0,97**	
Standard error	0,02		0,03		0,01	

Table 15 – Results from Carhart model for sets of funds with maximal exposure to factors

It is visible from Table 15, that the regression models for the factors with a high significance to factors like SMB and HML, do not perform much better than average regression model for all funds, in terms of R-squared. This means that the precision of the Carhart model for these funds is nearly the same as the precision of the CAPM for all funds, on average. By comparing the CAPM model parameters for the same funds sets, gives nearly the same estimates as in Table 15. Explicitly, R-squared of the CAPM for funds high significance to SMB and HML, gives a R-squared equal to 0.89, on average, for both sets. This means that the Carhart model factors (excluding MKT) for these set, only capture 2% of the returns variation. Nevertheless, there are a quite few funds in these sets with a higher precision to the Carhart (1997) model. Thereby, we state for this period, that funds with an exposure to SMB and HML in the Carhart (1997) model, do not perform significantly better than the CAPM.

However, the set of funds with a certain exposure to the momentum effect, gives a slightly higher R-squared coefficient. This means that the precision of the Carhart (1997) model for these funds is slightly higher than the precision of the CAPM for all funds, on average. Nevertheless, this is also driven by the fact that the CAPM, for these certain funds, gives a higher R-squared (94%) than for previous sets. In that case, the Carhart (1997) model factors (excluding MKT) for set of funds with an exposure to the momentum effect do capture 3% of the returns variation. This gives the Carhart (1997) model for the momentum effect exposure, a set of very high R-squared, which is equal to 97%. It was hard to compare these performances to the OSEBX, this because it considers some variable measure tools, which is beyond our thesis time-limitations.

We have compared certain funds based on the return development, with the benchmark. Hence, the funds with a value higher than the OSEBX, in terms of consistently persistence, were considered as outperformers. For the exposure sets for the SMB and HML factors, it was easier to judge. This is because these funds values were consistently up or down, with no crossing benchmark line. On the other hand, funds with the momentum effect exposure did perform with certain volatility and reversals. Therefore, we ranged the funds with "consistent outperformers", "consistent underperformers" and "hard-to-judge funds". By this, the readers can make their own judgment about these funds performances. Their return developments are shown in Figure 12. This judgment is very important, because for the US market, Carhart (1997) mentioned that the returns of the majority of top and bottom funds are driven by momentum effect. The Norwegian mutual funds market is significantly smaller than the US market, and should probably therefore be lower in terms of top and bottom funds. The other "hard-to-judge" reason is that the NAVs are not adjusted for the funds fees. Certain funds, which slightly outperform the benchmark, can do so because of the fees. While, the data of fees is beyond our research range, we leave this for further studies.

Figure 12 are showing returns development for funds, compared to the OSEBX.

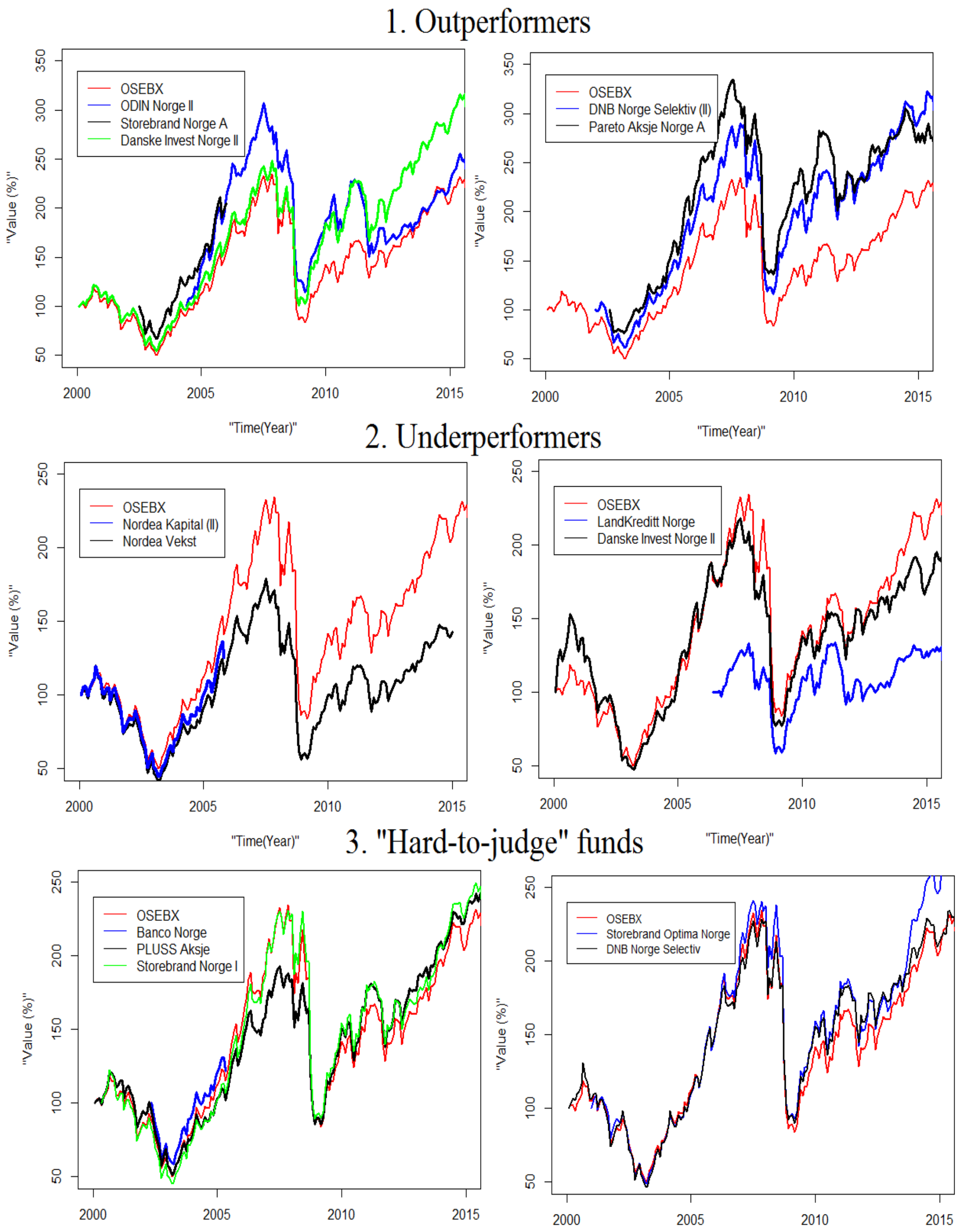

Figure 12 – Performance of funds with high exposure to momentum effect

Granted the results, we conclude that, on average, the Norwegian equity mutual funds have low exposures to ether Fama and French (1993) or Carhart (1997) factors. However, around 30% of the funds have relatively significant exposure to SMB, HML and PR1YR factors. Where SMB and HML are significant, Carhart model does not perform significantly better that the CAPM. On the other hand, where PR1YR is significant, Carhart model works with a precision of 97% on average. This estimate is very high for a regression model. These 14 funds returns can be predicted with a precision of 97%, if an investor is able to predict the factors such as MKT and PR1YR.

6.2 Results from augmented Carhart model

We augmented the Carhart (1997) model for prior twelve-month market volatility, liquidity factor, up minus down factor and oil market return. We use the market volatility, as it should help to capture more funds with the momentum effect exposure. The factors liquidity and UMD are chosen for brief tests, as there is a lack of such test in the Norwegian mutual fund market. A substantial part of the Norwegian economy is based on oil, thereby; we found it reasonable to accounting for oil market risk-adjusted returns.

On average, no augmented model performs better than CAPM. All models have an average R-squared equal to 93%. While, the average p-values of all factors (excluding MKT) are consisted lower than 0.35. This indicates an average insignificance for the Carhart model factors as well as the factors in the augmented model. A summary statistics for the augmented regression models are reported in Table 16, 17, 18 and 19.

Table 16 reports average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

Carhart model augmented for prior twelve – month market volatility					
Factors	**Average load**	**Maximum load**	**Minimum load**	**St. Deviation**	**P-Value**
MKT	0,99	1.33	0.24	0.03	0.00
SMB	-0.11	0.51	-1.29	0.16	0.40
HML	-0.01	0.64	-1.08	0.19	0.48
PR1YR	0.00	0.79	-0.28	0.19	0.45
Prior 12 month market volatility	0.08	0.82	-0.08	0.09	0.43
R-squared	0.93				
St. Error	0.02				

Table 16 – Results from Carhart model augmented for prior twelve-month market volatility

It is visible that, the range of variability for the factor loadings became slightly wider for the factors SMB and HML. On the other hand, by accounting for the market volatility gives a narrower range of the PR1YR factor loadings. The average loading of PR1YR will then be zero. We are following the same conditions for factor significance as in previously sub-chapter, for checking for a funds exposure to certain risk factors. By adding the market volatility as the explanatory variables, will not substantially change the exposure sets. Moreover, it gives a R-squared equally to 89%, even in all three sets. The market volatility factor was only significant for 10 funds. Nevertheless, the R-squared of the Carhart (1997) model, augmented for twelve-month prior market volatility for these 10 funds is the same as the CAPM R-squared. Thereby, it is possible to say that accounting for prior 12-month market volatility is not significant for the Carhart model. It might be a case to account for compounding volatility or different time range, but we leave as an idea for further studies.

Table 17 reports average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

Carhart model augmented for monthly risk-adjusted return of oil market					
Factors	**Average load**	**Maximum load**	**Minimum load**	**St. Deviation**	**P - Value**
MKT	1.00	1.31	0.30	0.03	0.00
SMB	-0.11	0.37	-1.29	0.16	0.38
HML	0.01	0.59	-1.07	0.18	0.47
PR1YR	0.00	0.50	-0.27	0.19	0.49
Oil market risk-adjusted return	-0.03	0.05	-0.14	0.02	0.26
R-squared	0.93				
St. Error	0.02				

Table 17 – Results from Carhart model augmented for monthly risk-adjusted oil market return.

It is visible from Table 17, that the oil market return is even less significant for the Norwegian mutual funds market. Average p-value of oil the market return is 0.26, which is better than the average p-values of the other factors (excluding MKT). On the other hand, monthly oil market risk-adjusted return explains, on average, 3% of the funds return variation. The range of variability of the market volatility factor loading is quite narrow. Moreover, there are no funds, which have significant exposure to the monthly oil market risk-adjusted return, based on our previously conditions for significance exposure. The fund sets with an exposure to factors like SMB, HML and PR1YR, do not substantially change. Therefore, we conclude that the oil market monthly return does not make the performance of the Carhart (1997) model any more significant.

Table 18 reports average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

Carhart model augmented for liquidity factor					
Factors	**Average load**	**Maximum load**	**Minimum load**	**St. Deviation**	**P -Value**
MKT	0.98	1.26	0.23	0.03	0.00
SMB	0.00	0.88	-0.67	0.25	0.55
HML	0.02	0.69	-1.00	0.19	0.47
PR1YR	-0.03	0.43	-0.31	0.19	0.45
Liquidity	-0.18	0.40	-1.11	0.24	0.37
R-squared	0.93				
St. Error	0.02				

Table 18 – Results from Carhart model augmented for liquidity factor.

The Carhart model augmented for the liquidity factor, on average, make all other factors less significant (excluding MKT). It does, however, increase the average p-values and make the range of variability narrower. These sets of funds with an exposure to factors like SMB, HML and PR1YR, are decreasing. There are 18 funds with a significant exposure to the liquidity factor. However, the regression on these funds performs lower on 6% R-squared, compare to the CAPM. Thereby, we can conclude that the augmentation of Carhart model for the liquidity factor is not relevant for our hypotheses.

Table 19 reports average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

Carhart model augmented for UMD					
Factors	**Average load**	**Maximum load**	**Minimum load**	**St. Deviation**	**P -Value**
MKT	0.99	1.31	0.24	0.03	0.00
SMB	-0.12	0.44	-1.26	0.16	0.36
HML	-0.01	0.62	-1.17	0.19	0.47
PR1YR	-0.01	0.54	-0.60	0.24	0.51
UMD	-0.05	0.71	-0.60	0.21	0.52
R-squared	0.93				
St. Error	0.02				

Table 19 – Results from Carhart model augmented for UMD factor

The case with liquidity insignificance almost repeats itself with the Carhart model augmented for UMD risk factor. The only difference is that in augmented for UMD model is that the ranges of variability for factor loadings are not being narrower. On the other hand, it does decrease the number of funds with an exposure to the factors, such as SMB, HML and PR1YR. The UMD factor itself is significant for only eight funds. The model, however, do not perform any better than the CAPM, in terms of R-squared.

Therefore, it is possible to conclude with a certain degree of validity that, twelve-month market volatility, monthly risk-adjusted oil market return, liquidity and up minus down factors are not significant for the mutual funds industry. Even for a certain funds, these factors do not perform any better than CAPM. Moreover, the augmentation for these factors make the other factors less significant. This means that the factors, which a model was augmented for, are not linked with the factors in the Carhart model. Alternatively, these relationships are very weak and hold only for individual funds.

6.3 Results from autocorrelation models

We have tested two autocorrelation models. The factors in these models are MKT, prior returns and volatility of funds. We use twelve-month prior volatility of the funds as the volatility risk factor. We also use funds prior one, three, six, nine and twelve-month return as the prior returns risk factor. These models are actually seeking for momentum trends.

The first model uses MKT, prior one/three month funds returns and twelve-month prior funds volatility. Summary statistics for this regression model is reported in Table 19. It is visible that, based on monthly data, prior one and three month returns do not explain the returns variation. Their p-values are equal to 0.5 on average. We also find that the average factor loadings for prior return are close to zero. The range of variability for the prior return factor loadings is very narrow. Thereby, prior one and three-month fund returns do explain a close to zero part of the returns variation, even for individual funds as well. This means there is no systematical autocorrelation of the mutual funds returns with an one/three month prior returns, based only monthly data.

The funds volatility has admittedly more significance. The range of variability for the funds volatility is close to 0.6. This implies that for individual funds, a large part of the returns variation can be explained by their prior twelve-month volatility. However, this is not the case, as the CAPM perform significantly better for the six funds with an exposure to the prior twelve-month volatility. Granted that, prior twelve-month fund volatility is not significant for forecasting future returns.

Table 20 reports average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

First autocorrelation model					
Factors	**Average loading**	**Maximum loading**	**Minimum loading**	**Standard deviation**	**P - value**
MKT	0.98	1.29	0.26	0.03	0.00
Prior 1 month return	0.01	0.15	-0.18	0.04	0.56
Prior 3 month return	-0.01	0.08	-0.12	0.03	0.51
Prior 12 month volatility	0.04	0.44	-0.21	0.08	0.40
R - squared	0.91				
St. Error	0.02				

Table 20 – Results from first autocorrelation model

The second autocorrelation model uses MKT and prior six/nine/twelve month returns. This model does also not perform any better than the CAPM. All factors (excluding MKT) are insignificant, with very small ranges of variability. The p-values are close to 0.5. Thereby, prior six, nine, twelve-month fund returns explain a close to zero part of the returns variation, even for individual funds. This means that there is no systematical autocorrelation of the mutual funds returns with a six/nine/twelve month prior return, based only monthly data. This is visible in Table 21.

Table 21 reports average, maximum and minimum factor loadings, standard deviation of the loadings and their p-values.

Second autocorrelation model					
Factors	**Average loading**	**Maximum loading**	**Minimum loading**	**Standard deviation**	**P - value**
MKT	0.98	1.28	0.26	0.03	0.00
Prior 6 month return	0.00	0.09	-0.06	0.02	0.44
Prior 9 month return	0.00	0.05	-0.08	0.02	0.52
Prior 12 month returns	-0.01	0.06	-0.09	0.01	0.48
R - Squared	0.91				
St. Error	0.02				

Table 21 – Results from second autocorrelation model.

Granted the results, it is possible to conclude that using monthly data gives no autocorrelation momentum patterns in the mutual fund returns. This is explicitly true for prior one/three/six/nine/twelve month returns. It can be the case that the momentum patterns are impossible to capture by such a simple tool, like a regression model. It can be also the case that, while using monthly data, we cannot include momentum patterns, as it is possible by using daily data.

6.4 Tests for idiosyncratic volatility

To account for idiosyncratic volatility effect, we measure standard deviation of the residuals of the Fama and French model. We run the Fama and French model on all funds using the period from 2000 to 2008 in our data sample. We choose this time period, because it allows us to estimate standard deviation with a certain degree of validity. Moreover, in that case we can look at the returns for funds after 2008 without any look-ahead bias. 68 funds are included in this particular test. After the idiosyncratic volatility measurement, we sort out funds from the lowest to the highest standard error and divide all of them into four different portfolios. Thereby, each portfolio consist of 17 funds, where the first portfolio stands for the lowest idiosyncratic volatility, and the forth portfolio stands for the highest. For example, "Portfolio 3" is the portfolio with the second highest idiosyncratic volatility.

Our findings from these tests are in the same time quite interesting and relatively ambiguous. We find that one NOK invested in the portfolio with the lowest idiosyncratic volatility in the year of 2000, would be equal to 2.09 NOK in 2015. Nevertheless, one NOK invested in the portfolio of with lowest idiosyncratic volatility in the year of 2009, would be equal to 2.47 NOK in 2015. This shows that the return of the portfolio for seven years, is generate higher returns compare to the portfolio in 15 years. In the end of 2008, the returns of almost all equity mutual funds were going down. Then, after the market was being corrected, the returns could grow explicitly. However, it is quite clear that most of this portfolio returns occur after 2008. This is visible in Figure 13, where the performance of the first portfolio with the lowest idiosyncratic volatility is compared toward the OSEBX.

It is visible that, "Portfolio 1" does not perform with any higher returns than the OSEBX, during all time horizons. One NOK invested in OSEBX in 2000, would be equal to 2.24 NOK in 2015. One NOK invested in OSEBX in 2009, would be equal to 2.52 NOK. It is possible to conclude that the returns of "Portfolio 1" are very close to the OSEBX returns.

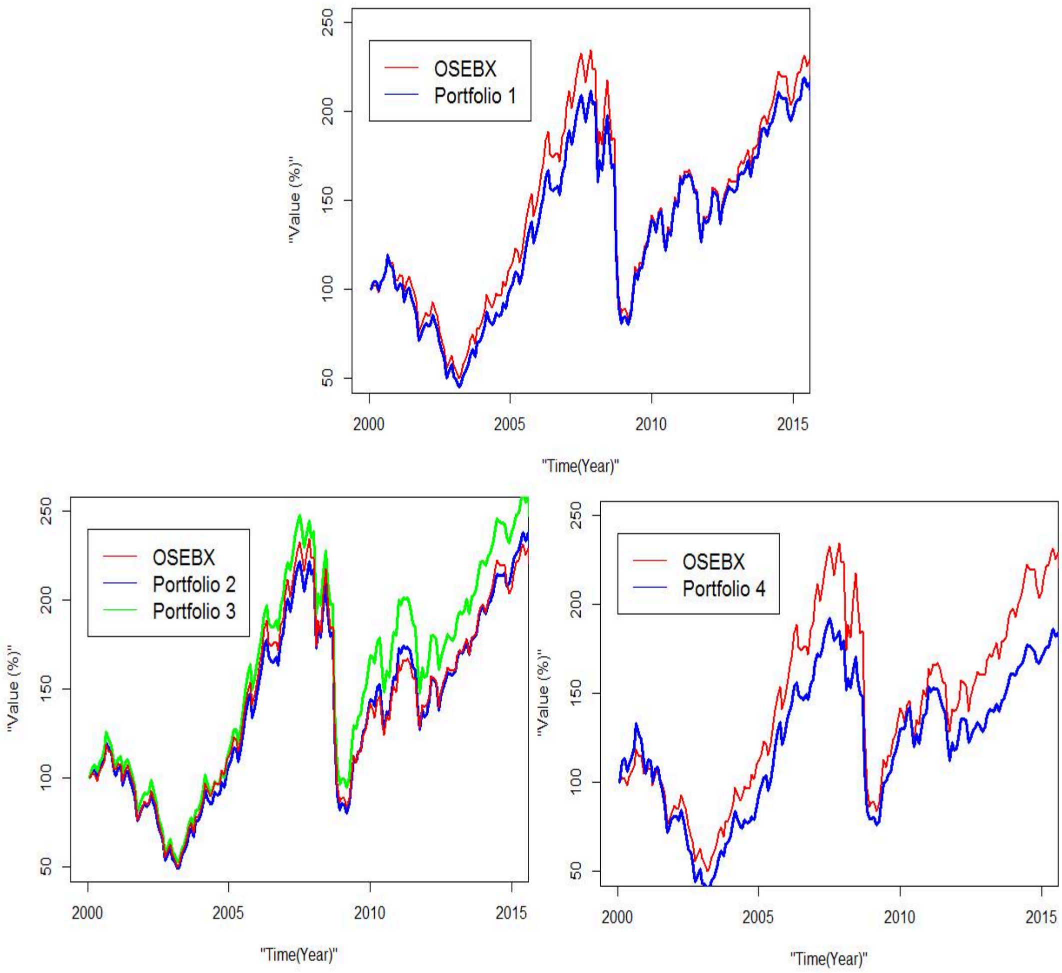

Figure 13 - Idiosyncratic volatility portfolios compared to OSEBX

The performance of "Portfolio 4" is also worse than the OSEBX in terms of returns. This is visible in Figure 13. However, the spread between the OSEBX and "Portfolio 4" is a greater, compare to the spread between OSEBX and "Portfolio 1". One NOK invested in "Portfolio 4" (highest idiosyncratic volatility) in 2000, would be equal to 1.80 NOK in 2015. This is compared to 2.24 NOK in the OSEBX and 2.09 in "Portfolio 1". On the other hand, one NOK invested in "Portfolio 4" in 2009, would be equal to 2.20 NOK in 2015. This is compared to 2.52 NOK in the OSEBX and 2.47 in "Portfolio 1". It is quite clear that the return of funds with a low idiosyncratic volatility is higher, compared to the returns of the funds with a high idiosyncratic volatility. Nevertheless, their returns on average are lower than the OSEBX returns. But this judgment is made upon quite extreme portfolios. Anyways, this fact is very important because "Portfolios 2" and "Portfolio 3" can make a substantial amendment to this judgment. Therefore, we later account for the characteristics of "Portfolio 2" and "Portfolio 3" to conclude by either they are comparable.

"Portfolio 2" and "Portfolio 3" perform the opposite to the first and the forth portfolios. One NOK invested in "Portfolio 2" in 2000, would be equal to 2.34 kroner in 2015. On the other hand, one NOK invested in "Portfolio 3" in 2000, would be equal to 2.52 NOK in 2015. The performance of "Portfolio 2" and "Portfolio 3" compared to the OSEBX, are showed in Figure 13. It is visible, that "Portfolio 3" is the only portfolio outperforming the benchmark. At the same time, "Portfolio 2" gives almost the same returns as the OSEBX.

Granted that, it is impossible to make any precise conclusions before the characteristics of a portfolio are introduced. These idiosyncratic volatility values for "Portfolio 1" and "Portfolio 2" are very close to each other. They are equal to 0.0081 and 0.0135, respectively. The average standard error for "Portfolio 3" is greater, but much more closer to the first and second portfolio values. "Portfolio 3" is equal to 0.0196 and accurse nearly in the middle between the standard errors at the first and the forth portfolios. The idiosyncratic volatility of "Portfolio 4" is equal to 0.032. This implies that the first and second portfolios both represents a quite low standard error.

Moreover, the first, second and third portfolios represent funds that are relatively to "Portfolio 4" with substantially lower estimates of the idiosyncratic volatility. The parameters of the portfolios are performed in Table 22. It is also visible, that "Portfolio 4" has a lower average monthly return both for all period and after 2008. At the same time, "Portfolio 4" perform quite similar for all period to the others standard deviation of the returns. This is even a bit lower that the first and the second portfolios. However, for the period after 2008, "Portfolio 4" shows a lower standard deviation of the returns compare to the other portfolios. Moreover, "Portfolio 4" has a lower value of return development as it was shown previously.

Parameters	***Portfolios***				***OSEBX***
	1	**2**	**3**	**4**	
Average standard error	0.0081	0.0135	0.0196	**0.032**	
Mean monthly return, all period	0.61 %	0.67 %	0.70 %	**0.53 %**	0.64 %
Mean monthly volatility, all period	6.46 %	6.51 %	6.33 %	6.44 %	6.41 %
Mean monthly return, after 2008	1.22 %	1.34 %	1.24 %	**1.09 %**	1.24 %
Mean monthly volatility, after 2008	4.78 %	4.90 %	4.78%	4.43 %	4.70 %
Value of NOK 1,- invested in 2000	2.09	2.34	2.52	**1.8**	2.24
Value of NOK 1,- invested in 2009	2.47	2.74	2.53	**2.2**	2.52

Table 22 – Summary statistics for portfolios ranked by idiosyncratic volatility.

By the means of the normal volatility, the lower returns of "Portfolio 4" after 2008 are quite logical. However, this case does not hold for a complete period of standard deviation. Granted the results, we can state that the funds with a top high idiosyncratic volatility tend to have lower return compare to the OSEBX and as well as the other funds returns. Alternatively, the bottom idiosyncratic volatility funds tend to have higher return compare to the top high idiosyncratic volatility returns. However, the funds lying in the middle by the idiosyncratic volatility distribution have the highest returns among all, and even slightly outperform the benchmark.

To conclude, the idiosyncratic volatility has a certain predictability power. The top and bottom standard error funds, on average, are relatively persistent. The effect of idiosyncratic volatility prolong at least for seven years. The distribution of the funds return within the idiosyncratic volatility between top and bottom standard error funds, is unclear. It seems that the idiosyncratic volatility effect works only on the tails of the standard error distribution. While the closer the fund is to the mean, the higher the returns are in the future.

7. Conclusion

Mutual funds in the financial markets channel an ability to invest in diversified portfolios of assets, with stable payoffs. According to the literature, the share of equity mutual fund investments has grown dramatically for different markets. For example, Wahal and Wang (2011) and Hiraki et al. (2015) mention the growing role of mutual funds. Nevertheless, it has been documented by a number of researchers, like Carhart (1997) and Hendricks et al. (1993), that mutual funds consistently underperform the benchmarks. On the other hand, portfolio construction with resources, which mutual funds have, should lead to higher than average market returns. Mutual funds in Norway do show a high profit, which, however, comes with considerable volatility. The performance of mutual funds is linked to different risk factors. If funds have an exposure to a certain factor, then this information should be reflected in the price. This reflection occurs by the actions of agents and is in accordance with the Market Efficiency Hypothesis. Therefore, we have tested different risk factors in order to check for this information. This study consists of testing 74 funds in the period 2000-2015.

We have chosen three main regression models in this research: Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965); Fama and French's (1993) three-factor model; and Carhart's (1997) four-factor model. We have also augmented the Carhart (1997) model for factors such as liquidity, market volatility, monthly oil market risk-adjusted return and up-minus-down. We have also checked individual funds' exposure to these factors as well as for the Carhart (1997) model factors. We have also tested autocorrelation models, which account for past funds returns and volatility. Thereafter, we checked for idiosyncratic volatility, using the model from Ang et al. (2006).

We find that CAPM are the most efficient models on average, and that neither Fama and French's model, nor Carhart's model perform significantly better. However, we find 14 funds, which have an R-squared equal to 97% and a low p-value for momentum factor from Jegadeesh and Titman (1993). Thereby, the performance of these funds is driven by factors such as market return and momentum effect. Neither Gallefoss et al. (2015), whose work is based on daily data, or Sørensen (2009) captured these 14 funds. Carhart (1997) states that the returns of top funds are driven by the momentum effect. From these 14 funds, only five funds consistently outperform the benchamrk. The other funds' returns have fluctuate and it was therefore hard for us to evaluate their perfomance.

We find that factors like monthly oil market returns, market volatility, liquidity and up-minus-down of the agumented Carhart (1997) model do not make the model any more precise. Some individual funds have a strong exposure to the liquidity factor and market volatility. However, the inclusion of these factors drives the R-squared of the Carhart (1997) model low, and this is the case where CAPM performs significantly better. The autocorrelation models showed that there is no systematic relationship between factors like monthly returns and funds' prior twelve-month volatility or prior one, three, six, nine, and twelve month return. The factor loadings for these factors are almost constantly very low, and the p-value is high.

With tracking portfolios ranked by the Fama and French model's standard error (idiosyncratic volatility), we found that funds with the highest idiosyncratic volatility have consistently lower returns compared to other funds and to the OSEBX. This is consistent with the findings in Ang et al. (2006). Nevertheless, the opposite is not always the case. Funds with the lowest idiosyncratic volatility had higher returns compared to funds with the highest idiosyncratic volatility, but still lower than the mean. Therefore, we find that funds with idiosyncratic volatility close to the mean have achieved higher returns. And as an essential finding in this research, only funds with an idiosyncratic volatility close to the mean slightly outperform the benchmark. However, with these conclusions it is still impossible to make a judgment regarding the "skill or luck" question.

7.1 Criticism to thesis

By ending this study, we have different ideas on how to improve this research. To begin with, we want to explain our ideas involving the variables we have chosen. In our empirical results, we have calculated a number of different time series for different factor values. As we had 74 funds, it was nearly impossible to track each fund with an exposure to certain risk factors. This is mostly about factors such as SMB, HML and PR1YR. An allowance for a deeper analysis could give a more certain conclusion regarding this, for example, funds with an exposure to PR1YR.

While estimating regression models we decided to take medium values as limits for the significance. To answer "*a certain degree of precision*" as stated in our main hypotheses, we chose a p-value lower than 0.15 and factor loading higher or lower than 0.2 and -0.2 as the significance range. But if we could rearrange our limit values as, for example, Carhart (1997) did, the conclusions would be more certain and explicit. As a last one, our analysis of the oil market sensitivity is performed only by monthly return. To draw wider conclusions about the oil market exposure, we certainly need to include more factors, such as prior returns and prior volatility for an oil market, in different periods.

7.2 For further studies

By conducting this Master's thesis, we have increased our understanding of the topic of mutual funds. With the knowledge that this research has given us, we certainly feel an increasing curiosity regarding what areas this study can be expanded into. When we began this research, we knew that our thesis was mostly limited by time. Therefore, we will present our ideas in this sub-chapter for further directions.

First of all, we feel that it has been interesting to do our own calculation of the UMD and LIQ factors in the Carhart (1997) model. By this, we have had the chance to include a wider data range. In addition we wanted the possibility to include other variations of the momentum effect factor, as it turns out to be one of the most significant factors. For example, prior three years return from Bondt and Thaler (1985, 1987).

Another interesting topic would be to include a performance evaluation for each of the funds in our database. By having these estimates, we might have had a chance to further investigate these funds with an exposure to different risk factors, especially those with exposure to the momentum factor. Regarding idiosyncratic volatility, we see two further directions. The first is to create a wider ranking and then to calculate the return periodically in this rebalancing portfolio. A second way is to include more data to check for length of idiosyncratic volatility effects. Regarding the number of funds, it should be interesting to include more. For some reason TITLON didn't have the data for some of the funds we found at the website for the Verdipapirfondenes forening.

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Professor Bernt Arne Ødegaard (Professor at the university of Stavanger) :

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Appendix

Appendix 1 – Funds in the database

Appendix 2 – Funds with exposure to SMB

Appendix 3 – Funds with exposure to HML

Appendix 4 – Funds with exposure to PR1YR

Appendix 1 – Funds in the database

CODE	NAME
BF-NORG	Banco Norge
VI-GAMBA	Gambak
CA-AKSJE	Carnegie Aksje Norge
GN-NOAK2	DnB NOR Norge Selektiv (III)
PV-VEKST	Postbanken Aksjevekst
FO-AKSJE	PLUSS Aksje (Fondsforval)
FO-INDX	PLUSS Markedsverdi (Fondsforv)
HF-NORGE	Handelsbanken Norge
HO-NORGE	Holberg Norge
KL-AKSNO	KLP AksjeNorge
KF-AVKAS	Nordea Avkastning
KF-KAP	Nordea Kapital
KF-KAPIT	Nordea Kapital II
KF-KAIII	Nordea Kapital III
KF-SMB	Nordea SMB
KF-VEKST	Nordea Vekst
SG-NORGE	ODIN Norge
OD-NORII	ODIN Norge II
OR-FIN30	Orkla Finans 30
PO-AKTIV	Pareto Aksje Norge - andelsklasse I
SB-DENOR	Delphi Norge
DF-VEKST	Delphi Vekst
SP-INNLA	Storebrand Aksje Innland
SB-NORGE	Storebrand Norge
SP-NORGA	Storebrand Norge A
SP-NORGI	Storebrand Norge I
SP-OPTIM	Storebrand Optima Norge
SP-VEKST	Storebrand Vekst
SB-VERDI	Storebrand Verdi
TF-NORGE	Terra Norge
SU-AKTIV	Globus Aktiv
SU-GLNO	Globus Norge
SU-NORGE	Globus Norge II
NF-RFAKS	RF Aksjefond
WW-ALPHA	WarrenWicklund Alpha
HF-OBX	XACT OBX
KF-NOEQM	Nordea Norway eq Mark Fond
SP-NORGH	Storebrand Norge H
IS-NORGE	Landkreditt Norge
KF-AKPEN	Nordea Norge Verdi
VI-PRTOV	Pareto Verdi
AI-AKTIV	Alfred Berg Aktiv

GA-KAPIT	Alfred Berg Aktiv II
GA-GAMB	Alfred Berg Gambak
VL-AKNOR	ABN AMRO Aksje Norge
AI-NORGS	Alfred Berg Norge +_gml
DA-FIUNI	Danske Invest Aktiv Formuesforvalt
FF-NORGE	Danske Invest Norge I
FF-NORII	Danske Invest Norge II
FF-VEKST	Danske Invest Norge Vekst
BF-HUMAN	Alfred Berg Humanfond
BF-NORGE	Alfred Berg Norge Etisk
NR-NORGE	Atlas Norge
SP-NOINS	SP-NOINS
DK-PBNOR	DNB Norge
DK-NORGE	DNB Norge (Avanse I)
DK-NORII	DNB Norge (Avanse II)
DI-RINV	DNB Norge (I)
DK-NORG3	DNB Norge (III)
DK-NORIV	DNB Norge (IV)
VI-NSEL1	DnB NOR Norge Selektiv (I)
DK-NSEL2	DNB Norge Selektiv (II)
DK-NSEL3	DNB Norge Selektiv (III)
DK-OBX	DnB NOR OBX
KF-NOPLS	Nordea Norge Pluss
OR-INVF	Pareto Investment Fund A
NF-PLUSS	Eika SMB
FV-NORGE	FORTE Norge
EK-NORGE	Eika Norge
FT-GNRTR	Swedbank Generator
DK-NSEL1	DNB Norge Selektiv
FK-SPAR	Fondsfinans Norge
PO-AKTNY	Pareto Aksje Norge - andelsklasse A
PO-VERDI	Pareto Aksje Norge - andelsklasse B

Appendix 2 – Funds with exposure to SMB

CODE	NAME
BF-NORG	Banco Norge
GN-NOAK2	DnB NOR Norge Selektiv (III)
HO-NORGE	Holberg Norge
SP-NORGA	Storebrand Norge A
SB-VERDI	Storebrand Verdi
SU-AKTIV	Globus Aktiv
SU-GLNO	Globus Norge
SU-NORGE	Globus Norge II
EK-NORGE	Eika Norge
FK-SPAR	Fondsfinans Norge
PO-VERDI	Pareto Aksje Norge - andelsklasse B

Appendix 3 – Funds with exposure to HML

CODE	NAME
VI-GAMBA	Gambak
PV-VEKST	Postbanken Aksjevekst
KF-KAPIT	Nordea Kapital II
KF-KAIII	Nordea Kapital III
SG-NORGE	ODIN Norge
OD-NORII	ODIN Norge II
PO-AKTIV	Pareto Aksje Norge - andelsklasse I
SB-DENOR	Delphi Norge
DF-VEKST	Delphi Vekst
SP-NORGA	Storebrand Norge A
SP-VEKST	Storebrand Vekst
SB-VERDI	Storebrand Verdi
SU-AKTIV	Globus Aktiv
SU-GLNO	Globus Norge
SU-NORGE	Globus Norge II
GA-KAPIT	Alfred Berg Aktiv II
GA-GAMB	Alfred Berg Gambak
VL-AKNOR	ABN AMRO Aksje Norge
BF-NORGE	Alfred Berg Norge Etisk
DK-PBNOR	DNB Norge
DK-NSEL1	DNB Norge Selektiv
PO-VERDI	Pareto Aksje Norge - andelsklasse B

Appendix 4 – Funds with exposure to PR1YR

CODE	NAME
BF-NORG	Banco Norge
FO-AKSJE	PLUSS Aksje (Fondsforval)
KF-KAPIT	Nordea Kapital II
KF-VEKST	Nordea Vekst
OD-NORII	ODIN Norge II
SP-NORGA	Storebrand Norge A
SP-NORGI	Storebrand Norge I
SP-OPTIM	Storebrand Optima Norge
IS-NORGE	Landkreditt Norge
FF-NORII	Danske Invest Norge II
FF-VEKST	Danske Invest Norge Vekst
DK-NSEL2	DNB Norge Selektiv (II)
DK-NSEL1	DNB Norge Selektiv
PO-AKTNY	Pareto Aksje Norge - andelsklasse A