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Active vs Passive Portfolio Management in Norway - a study of persistence and market timing

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Abstract

This paper investigates whether money managers in Norway outperform their respective benchmarks and create value for their investors. To get a better understanding of this, an aggregated portfolio of Norwegian mutual funds is examined for persistence in their returns using the Fama-French five-factor model. Further is the Henriksson-Merton market timing factor added to the model to observe if the mutual funds are able to predict good and bad market conditions. When accounting for the five-factor model, the abnormal return drops from 0.47% to 0.14 % p.a. compared to a simple model only controlling for the market factor, not considering fees. The results are rarely significant and do not show any conclusive evidence of positive persistent returns among the top performing funds, nor negative persistent returns among the worst performing funds. In general, the sample exhibit negative but insignificant market timing ability.

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1.0 Introduction/motivation

In January 2017 the Financial Times published an article asking the question; *"are we coming to the end of active management?"*. With actively managed funds charging high fees and struggling to beat cheaper passively managed index portfolios, this is a valid question to ask. If this is truly the case, then why would any investor be interested in placing capital under these conditions?

Historically, actively managed mutual funds have been the alternative with the most assets under management. However, since 2007 the US actively managed mutual fund industry has seen a steady outflow of capital. Currently, 28.5 % of assets under management in the US are held in some passive alternative (Moody's Investor Service, 2017), and according to Moody's projections, passive alternatives will overtake the active market share somewhere between 2021-2024. Even the "oracle of Omaha", Mr. Warren Buffet, is sceptical of active management. In 2007, he wagered US$ 500,000 that a selection of hedge funds would not over an extended period, match the performance of an unmanaged SP500 index fund. The results were overwhelming; Buffet's index fund had an average annual return of 7.1 %, while the respective hedge funds only had an average return of 2.2 % (Berkshire Hathaway Inc, 2016).

There are very few papers looking into the role of active management in Norway. A recent study by the Norwegian Consumer Council shows that active Norwegian funds with a global geographical focus lose 0.89 percent compared to its benchmark, while active Norwegian funds with a focus in Norway beat their benchmark with 0.86 percent (both numbers calculated per year after fees) (Forbrukerrådet, 2018). The study also reflects around the small amount of research available on active management in Norway, especially considering the fiduciary duty active fund managers are subjected to. This becomes even more interesting considering the trading platform Nordnet, which offers an index fund tracking OBX without any cost. However, the Norwegian Consumer Council study only considers raw unadjusted returns and does not take into account the amount of risk undertaken by the mutual funds. These facts serve as motivational backdrop for conducting our study on the Norwegian mutual fund market.

From the mid-20th century, the Efficient Market Hypothesis (*EMH*) has been the prominent economic theory. Developed by Nobel laureate Eugene F. Fama

(1970), the hypothesis implies that it is *"impossible to beat the market"*. A key paper by William Sharpe (1991, p. 7) claims that *"before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar"*. For this reason, active management will yield lower returns due to higher fees, after costs. However, this also means that there exist superior money managers that are able to beat the market, equally offset by inferior managers not able to do the same. In contrast to the Efficient Market Hypothesis, the Grossman-Stiglitz paradox states that market prices will never be perfectly efficient, since money managers would lack the incentive to do the work necessary to make prices efficient (Grossman & Stiglitz, 1980). Furthermore, Malkiel (2003) claims that there will always exist irrational behaviour in the market and mistakes will be made. This would lead to pricing irregularities, implying that inefficiencies exist along with opportunities for abnormal return.

However, all actors in the actively managed investment world use, to some extent, the same publicly available information, at the same time. They all have talented teams of financial experts with a drive to outperform one another and their respective benchmarks. This competition acts as a price setting mechanism and a reasonable inference is that with more competition comes fewer opportunities of beating the market. This is supported by the general consensus among economical researchers. Among them are Malkiel (1995) who showed that the aggregate actively managed fund underperforms the market both before and after fees are accounted for. Carhart (1997) further showed that the only significant persistence in performance is underperformance by the worst performing funds. While Sun, Wang, and Zheng (2009) finds that active management adds value by providing higher returns during down markets, taking their fees into account, active management underperforms in normal times. Despite the economic research, actively managed mutual funds continue to be the alternative with the most assets under management. However, with the economic theory in mind it seems that it is difficult, if not impossible, to create abnormal returns on an aggregate level for active managed portfolios. So, is there still a place for active management in today's market? Can the two vehicles coexist or is active management a thing of the past?

In this paper we examine actively managed Norwegian mutual funds, primarily investing in Norwegian equities, in the period 2000 to 2017. The Fama-French five-factor model is utilized to test if the actively managed funds yield greater risk-adjusted returns than the market before considering their fees. Our sample contains 55 open-ended Norwegian mutual funds and their respective *Net Asset Value* (*NAV*), gathered from the TRD database. The data sample is clear of survivorship bias, as the database used includes all funds active at any point in the sample period. Actively managed funds are compared to a Norwegian market proxy on an aggregate level and tested for evidence of persistent abnormal returns. Further is their ability to predict conjunctures in the market tested. By studying this, possible characteristics in the actively managed funds that warrant a continued place in investors' portfolios will be identified.

Our research is structured as follows: Firstly, an equally weighted portfolio is created of all sample funds active at some point during the sample period. Secondly, the mutual funds are sorted in quartile portfolios at the start of every holding period. The top quartile (*Q1*) consists of the top performing funds the prior year, with respective holding periods of either twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consists of the worst performing funds. Quartile 2 (Q2) and quartile 3 (Q3) are also constructed, in addition to one "*top minus bottom*" portfolio (long *Q1* and short *Q4*). Lastly, the portfolios are regressed on the Fama-French Five-factor model to create risk adjusted returns in the period January 2001 to June 2017. From these regressions, the alpha is obtained to see if the mutual funds are able to generate abnormal returns over the market on an aggregated level. Persistence in the returns is identified if previous winners or losers show significant abnormal returns in the holding period following the tracking period. If any of the quartiles show significant positive alpha, then it is possible that a trading strategy exists where an investor could beat the market over time. Hence, the efficient market hypothesis would fail to hold. The alphas obtained from the quartiles also show if there are persistence in the returns, both among the best and worst performing funds. Further is the Henriksson-Merton (1981) market timing ability factor added to the five-factor model to identify if the mutual funds are able to predict good and bad market conditions. If the beta from the market timing factor is positive, then an investor could benefit from the market timing skills found in the actively managed mutual funds.

After running our model, we do not find any conclusive evidence that active Norwegian mutual funds are able to create persistent positive risk adjusted returns. When adding the remaining four Fama-French styled factors to a simple model, only controlling for the market factor, the abnormal return of an equally weighted portfolio of all funds in the sample drops from 0.0389 % to 0.0115 % in monthly terms. Correspondingly, the alpha from this portfolio is not significant. The sensitivity of our results is scrutinized and subjected to different changes in underlying assumptions throughout the analysis. One test of robustness is conducted by dividing the sample into four sets of sub periods. Our results are generally unaffected by the variations in time periods and other assumption changes, although with some small inconsistencies. Only one of the sub periods (*2013-01 to 2017-06*) produce statistically significant results indicating abnormal returns greater than zero. Furthermore, there is not found any conclusive evidence of positive persistent returns among the top performing funds nor negative persistent returns among the worst performing funds. Thus, we conclude that actively managed mutual funds in Norway, focusing on Norwegian equities, are not able to beat the market or generate positive risk adjusted returns on a persistent basis.

Our test for market timing abilities in the mutual funds finds little evidence of significant positive coefficient estimates for the market timing factor. The only period which consistently shows significant coefficients for the market timing factor is the second sub period (*2005-01 to 2008-12*), in which they all are consistently negative. We therefore conclude that investors are not able to benefit from market timing skills found in the actively managed mutual funds in our sample.

The Fama-French five-factor model has not seen vigorous testing in the Norwegian market. This study finds that utilizing the Fama-French five-factor model, compared to the simple regression of excess return on the market factor, does not seem to add any explanatory power when looking at returns in the Norwegian mutual fund market. It is further confirmed when adding the different Fama-French factors individually to the simple regression. However, all strategies show significant and positive exposure to the market factor (*Mkt*) and the size factor (*SMB*). Leading us to believe that there might exist a tradeable strategy focusing on size within the Norwegian mutual funds market.

There is no public library containing all the five Fama-French styled factors for the Norwegian market. Therefore, have we chosen to use the value factor (*HML*) and the size factor (*SMB*) provided by Bernt Arne Ødegaard's data library and to calculate the profitability factor (*RMW*) and the investment factor (*CMA*) ourselves. We are aware that factors created from different databases can be based on different underlying assumptions and that this can bias the results. However, we choose to go forward with our strategy as the creation of the factors is somewhat outside the scope of our paper. The accounting data and the security data used to create the two factors are collected from the Centre for Corporate Governance Research (CCGR) at Handelshøyskolen BI and from the TRD database respectively. These datasets provide enough data points to create the two factors for the period 2001-01 to 2017-06 and are based on data from an average of 153 companies. The two factors are constructed by double sorting a set of portfolios on size-operating profitability and size-investment behaviour. In order not to risk bias in the result due to factor correlation, ideally, the effects of all the three other factors would simultaneously be controlled for to get full isolation of the specific factor. Nevertheless, this would be extremely time consuming and we therefore chose to focus on the size effect as Fama and French (2015).

The two factors created in this thesis are not statistically significant at a five percent level in any period. Among the four Fama-French factors is the size factor the most statistically significant throughout the different time periods, being statistically significant at a ten percent level in all periods, except sub period 3. For the full sample period, none of the factors are statistically significantly at a five percent level, further implying that the Fama-French four factors do not adequately describe return variation for companies in the Norwegian market.

2.0 Literature review

In 1992, Fama and French published their first scientific article introducing the three-factor model. By doing this they disregarded the assumptions long held in the financial scientific community, that the average stock returns are only positively correlated to the market "beta". This simple prediction was introduced by the work of Sharpe (1964), Lintner (1965) and Black (1972), in which their combined research shaped the well-known Capital Asset Pricing Model (*CAPM*), a model describing the theoretical required rate of return for a given asset. The essence of the CAPM is based on the market portfolio being mean-variance efficient as explained by Markowitz (1952).

The CAPM was further extended by Jensen (1968) when he introduced Jensen's alpha, a measure of the abnormal return of a portfolio. The model tries to evaluate if a fund manager is able to "*beat the market*" and gain excess risk adjusted return, over its theoretical expected return. Although criticized by many, the measure has been used by several scholars in the decades following the publication. The article by Jensen concludes that active management does not consistently outperform their respective benchmarks.

Kraus and Litzenberger (1976) reviewed the assumptions of inconsistency in the CAPM. Prior to this, scholars argued that the intercept in the model was too high, in addition to the slope of the CAPM predicted to be too steep. Using a three-moment valuation model, incorporating the effect of systematic skewness to the model, they concluded that the initial criticism of the CAPM were not justifiable.

Grinblatt and Titman (1989) suggested a new model to test for the existence of abnormal performance. Using the Jensen measure and accounting for survivorship bias, they concluded that abnormal return in fact do exist, particularly among growth funds and funds categorized as small asset value funds. However, the consistency and skill seemed to deteriorate with fees and expenses. They published a new article in 1992, suggesting somewhat positive persistence in mutual funds' performance, meaning that past performance to some extent could be used when evaluating performance (Grinblatt & Titman, 1992).

Gruber (1996) investigates the reasons why investors continue to place capital in actively managed portfolios, given the negative abnormal return historically seen compared to their appropriate benchmarks. The research highlights customer services, low transaction costs, diversification and professional management as explanatory factors. However, Gruber admits that the three first, respectively, are provided by passive investments as well. Furthermore, he argues that future fund performance to some extent could be predicted by using past performance. Seemingly, some investors have realized that it is possible to benefit from this, as the flow of new capital into funds follows the predictions of the funds future performance.

Malkiel (1995) found that funds consistently were able to outperform the market, however, his findings were conflicting after taking survivorship bias into account. He then concluded that an investor would be better off investing in an index fund, as the actively managed portfolios tended to underperform.

Carhart (1997) confirmed the conclusions of Malkiel (1995) and built further on the Fama-French three-factor model and the research of Jegadeesh and Titman (1993). By adding the momentum factor to the three-factor model, it became a central model for future studies. Testing for persistence in the funds' returns made it possible to check whether previous winners were able to proceed with high returns and losers continue to underperform. Wermers (1997) showed to some extent that investment strategies based on momentum could affect the persistence in performance among funds. Accounting for survivorship bias, the author showed that the funds with superior performance one year, also had good performance among their peers the following year, not unlike the momentum effect in stocks introduced in Jegadeesh and Titman's article. Wermers also implied that fund managers demonstrated stock picking abilities in bull markets, and timing abilities in bear markets.

Berk and Green (2004) concludes that active portfolio management does not have superior performance over passive benchmarks and makes a prediction that all active managers have zero abnormal return (α) net of all costs. Their model concludes that the funds expected returns to investors are competitive and assumes that the funds are in a decreasing return to scale environment. Their conclusion entails that new capital will flow to funds, because rational investors will seek information about past performance, although this new flow of capital would act as a disadvantage, rather than an improvement for the funds following years' performance. The authors disregard the effect of persistence, however will not conclude that the gathering of information about performance or chasing performance is wasteful, as they find the distribution of skill among portfolio managers to show a significant skill level. Based on the concept of *equilibrium accounting*, Fama and French (2010) goes further than Berk and Green, and states that the aggregate investors have α close to zero, and in fact, a negative α after expenses.

Sun, Wang, and Zheng (2009) take a different approach when testing for abnormal return among funds. Instead of categorizing all active managed funds in one homogeneous group, they differentiate active funds by degrees of activity. In down markets, the most active funds have superior performance compared to the least active funds after adjusting for risk. However, this *counter-cyclical* performance is not found in bull markets. When concluding that the most active funds also charge higher fees, offsetting the superior abnormal return, Sun et al suggests that investors are willing to pay a premium to hedge against a possible future downturn in the economy.

When reviewing their own three-factor model, Fama and French (2015) came up with a new and improved five-factor model. A recent paper by Sheng, Simutin, and Zhang (2017) has shown that when controlling for the exposure to Fama and French's two added factors, high-fee funds significantly outperform low-fee funds before expenses and perform equally well after considering fees. The implication of this contradicts the recommendation of Malkiel (2016) for individual investors; to not invest in active funds with expense ratios above 50 basis points. Malkiel's advice is in line with the general consensus that investors in high-fee funds earn significantly worse factor-adjusted returns than investors in low-fee funds net of fees (e.g. Fama and French (2010)). Sheng et al (2017) suggest that funds charging 1% higher fee delivers 1% higher alpha before deducting fees. This supports the theory of Berk and Green (2004) that funds charging higher fees generate higher alfa before considering fees.

2.1 Fama-French Factor Models

Despite of its popularity, the CAPM has received severe criticism for not holding due to anomalies in asset pricing. Fama and French (2004) argued that the model fails to explain the full risk-return relationship. Based on criticism of the CAPM, Fama and French published their paper on the three-factor model. Here they study several contradictions and effects of anomalies in asset pricing on the CAPM. Most notably they researched the size effect found by Banz (1981) and the findings of

Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) who found that returns on U.S. stocks are positively related to the ratio of a firm's book value to its market value. By including these two factors, the model should better explain the anomalies that create variation in the cross-sectional returns that differ from the CAPM equilibrium. Fama and French confirmed their hypothesis and showed that the *"size and book-to-market equity capture the cross-sectional variation in average stock returns"* (Fama & French, 1992, p. 450). To capture the return created by the two factors not explained by the CAPM, Fama and French added the components SMB and HML to the CAPM, capturing the size-effect and book-to-market-effect respectively.

The three-factor model is defined as:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{F,t}\right) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Even though the three-factor model is widely regarded as one of the most important economic models, it has received criticism. Most notable is the criticism for failing to capture much of the variation in average returns related to profitability and investment as shown by Novy-Marx (2013) and Titman, Wei, and Xie (2004). This prompted Fama and French to enhance their model into a five-factor model which includes the two factors profitability (RMW) and investment (CMA). Their test of the model shows that it explains between 71 % and 94 % of the cross-section variance of expected returns for the size, book-to-market, profitability and investments in the portfolios they examined (Fama & French, 2015).

The five-factor model is defined as:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{F,t}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t e_{i,t}$$

In 2010, Fama and French included the widely used momentum factor, by Carhart (1997), to their previous three-factor model. However, when later presenting their five-factor model, they tested the model with both the momentum factor and the liquidity factor of Pástor and Stambaugh (2003) and showed that including these factors only gave minimal increase in model performance (Fama & French, 2015). They also found that adding the profitability and investment factors make the value factor redundant when you are interested in describing abnormal returns, *"a four-factor model that drops HML performs as well as a five-factor model"* (Fama & French, 2015, p. 19). The five-factor model is still young and has not been subject to substantial testing. Nevertheless, the authors themselves have accentuated a recurring problem from the three-factor model. They argue that the model has problems with capturing low returns on small stocks whose returns perform similar to firms that have high investments despite low profitability.

After Fama and French published the five-factor model, some concerns have been raised on the model. Blitz, Hanauer, Vidojevic, and van Vliet (2016) discusses five concerns they have with the five-factor approach. Among the concerns are points on the momentum factor and the robustness of the new factors. They especially criticize the fact that Fama and French omits the widely acknowledged momentum factor which has been documented by several other studies. Regarding robustness, even though Fama and French themselves have stated that asset growth anomalies is less robust, in the new model they have defined the investment factor as an asset growth anomaly (Fama & French, 2008). Here Blitz et al (2016) find evidence for using net share issuance instead. This would also fit better with the dividend discount model that Fama and French use to explain the reasoning behind their five-factor model. Despite their concerns, Blitz et al (2016) admits that the model has significantly improved explanatory power, which is in line with the findings of Chiah, Chai, Zhong, and Li (2016). They find that in Australian equities, the model is superior to other models and the value factor keeps its explanatory power when describing abnormal returns.

When they introduced their two new factors, Fama and French found that including the new factors lead to enhanced model performance in the US stock market. However, they also admit that a global version of the model does not explain international stock returns (Fama & French, 2016). In turn, this raises the question of whether the Fama-French five-factor model is the best model to use when analysing the Norwegian market.

As financial markets become more globally integrated, fundamental findings are likely to become more similar across the world. This will make models that are derived from one market applicable for global use. On the other hand, research has shown that models based on the US market leads to inconsistencies when applying them globally. Ferson and Harvey (1993) and Dumas and Solnik (1995) present several discrepancies in using country specific models to explain international stock returns. When testing the Fama-French global three-factor model, Griffin (2002, p. 798) found that "*Fama-French-style models are best done* *on a within-country basis*". Fama and French has later found that local models perform better than global models (Fama & French (2012, 2016)). There is not much country specific work in Norway on the Fama-French factors. Findings show that there is an observed risk compensation for size while the value effect does not give significant risk compensation in Norway (Næs, Skjeltorp, & Ødegaard, 2009). This is in line with an early study by Heston, Rouwenhorst, and Wessels (1995), who found size effects in twelve European countries, including Norway in the period 1978 to 1990.

2.2 Market timing

To find whether fund managers are able to predict changes in the market, Treynor and Mazuy (1966) conducted the study *Can Mutual Funds Outguess the Market*. They analysed 57 mutual funds in the period 1953-1962 and only found one fund which possessed significant market timing ability. They also discovered that a mutual fund's return is completely dependent on the general market fluctuations. Henriksson (1984) used the market timing model of Henriksson and Merton (1981) and found that only three out of 116 funds in their sample possessed significant positive market timing abilities. Furthermore, only one fund had significant estimates in both sub periods when the sample was split in two. Daniel, Grinblatt, Titman, and Wermers (1997) used characteristics as the performance measure and believed that this gave more precise estimates of expected returns than factor sensitivities are able to. Despite recognizing that their model is aligned with covariance-based pricing models that have shortcomings, they claim that their framework better reveals if a manager has stock picking and market timing ability. They find no evidence that funds possess market timing abilities.

Bollen and Busse (2001) followed Goetzmann, Ingersoll, and Ivković (2000) and argued that earlier research might have failed due to the use of monthly data, claiming that the decision to change market exposure is done more frequently than monthly. They used both monthly and daily data and found that daily data gave more accurate results, showing that a substantial number of funds in their sample showed market timing ability.

3.0 Theory

Considering the literature review presented in this paper, the vast majority of scholars find that active management on an aggregate level does not beat the passive alternative. This is in line with the view of William Sharp's central article on active management *The Arithmetic of Active Management*, where he claims that "*before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar*" (Sharpe, 1991, p. 7). Consequentially, active management will yield lower returns due to higher fees. This entails that active management is a *zero-sum game*, or in fact a *negative-sum game* as claimed by Fama and French (2010). This will hold for any time period and is the standard argument for passive management. However, if the claim is that the average active manager will deliver return equal to the market, then there must exist managers that are able to outperform as well as underperform the market portfolio. Furthermore, Sharpe's claims are based on strict definitions of passive and active management, where a passive investor holds every asset represented in the market. For his claims to be correct, a passive investor is not able to conduct any trades in the current time period. Additionally, there cannot be any trading between the two segments. These restrictions do not hold in the real world. Index funds have restrictions on their investments and consequently do not hold all possible assets in the market. According to Sharpe's theory, this implies that index funds are not truly passive investments. Hence, there are opportunities to create abnormal returns for active funds that trade with index funds. Additionally, index funds must conduct trades to rebalance their portfolios, which in turn will create possibilities for active management to conduct "smart" trades for their investors. In such trades, money managers might be able to take advantage of inefficiencies in the market and the subsequent pricing irregularities.

The foundation of the CAPM was built on the Modern Portfolio Management theories (*MPT*), first introduced by Markowitz (1952). The theory assumes that all investors are risk averse, aiming to minimize portfolio return variance in combination with maximizing expected return. By doing this, an investor could achieve a portfolio considered mean-variance efficient, a portfolio found on the efficient frontier. This portfolio contains a set of assets that would yield the highest possible return subject to a given level of risk acceptance. It is important to realize that there is no superior point on the efficient frontier, only different levels of risk aversion. Points found below the efficient frontier are sub-optimal and do not yield sufficient return, as one could find a portfolio yielding a greater return for the same amount of risk. Choosing one of these points would be irrational investment behaviour. Even though Malkiel supports the efficient market hypothesis, he notes that there will always exist irrational behaviour and that mistakes will be made, which in turn will lead to pricing irregularities (Malkiel, 2003). The Efficient Market Hypothesis (*EMH*) was developed by Eugene Fama in 1970. Fama claims that asset prices fully reflect all available information, which implies that it is impossible to beat the market since only new information changes the asset prices (Fama, 1970). He introduced three stages of market efficiency; weak form, semi-strong form and strong form, distinguished by the amount and type of information available in the market. Of the three forms it seems more likely that it is the semi-strong form of efficiency that describes the real-world conditions in the best way, although elements from all three probably are present. In the semi-strong form, new information spreads instantaneously and becomes integrated in the prices immediately. Therefore, pricing irregularities are quickly found and corrected. This implies neither studying past prices to predict future prices nor looking for undervalued stocks would help to create abnormal returns. The validity of the EMH has been tested by authors like Henriksson and Merton. In their paper, they test whether managers are able to create value for their investors by predicting future events rather than solely following the market (Henriksson & Merton, 1981). For instance, a passively managed index covering the American market would have been heavily invested in technology stocks before the "*dot-com*" bubble and in American banks before the financial crisis in 2008. Evidence of market timing would disregard the validity of the EMH.

The Grossman-Stiglitz paradox states that market prices cannot be perfectly efficient, since investors would lack an incentive to do the work necessary to make prices efficient (Grossman & Stiglitz, 1980). Prices in the market only partially reflect the information of informed investors, so those who conduct additional research and possess additional information does in fact receive compensation for their effort. Their view contradicts the efficient market hypothesis by Fama; however, it is supported by Malkiel. He notes that the dominance of EMH has lost much of its power among economic theory with the entry of research fields like behavioural economics (Malkiel, 2003). With this view in mind, psychological elements will affect asset prices and money managers might take advantage of hypothesis like the existences of seasonal anomalies such as the *January effect*, first observed by Wachtel (1942).

In light of the economic theories discussed in this paper, we examine the validity of these theories in the Norwegian fund industry. More specifically, if the theories hold in terms of persistence in returns, predictability and market timing skills among the fund managers. Three main hypotheses are identified, which are to be tested on actively managed Norwegian mutual funds with a geographical focus in Norway.

1. Actively managed mutual funds are not able to generate risk-adjusted returns greater than passive management.

2. Actively managed mutual funds are not able to deliver positive risk adjusted returns persistently over time.

3. Actively managed mutual funds do not have market timing abilities.

4.0 Methodology

When testing for persistence in performance among the Norwegian mutual funds, we follow to some extent the framework of Carhart (1997). While Carhart formed 10 synthetic decile portfolios, we create 4 synthetic quartile portfolios ranked from best to worst based on a one-year tracking period. This is due to the smaller sample size obtained from the Norwegian mutual fund market. Additionally, a separate portfolio is constructed by subtracting the bottom quartile portfolio from the top quartile portfolio. The strategy in this "*top minus bottom*" portfolio entails going long on the top quartile (*Q1*) and short on the bottom quartile (*Q4*). Lastly, we construct an equally weighted portfolio of all sample funds (*EW all*) active at some point during the sample period is constructed. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. Equal weighting is assumed to be the optimal choice when measuring mutual funds' performance.

In line with Carhart (1997), the tracking period of the funds' performance is set to 12 months, as a shorter tracking period could show autocorrelation especially when using monthly data. The portfolios are then tested for persistence over both a 3-month and 12-month holding period. Persistence is deemed plausible if previous winners or losers show significant abnormal returns also in the period following the tracking period. Another method of detecting persistence is to check for consistent rankings among the funds. The returns are risk-adjusted using the Fama-French five-factor model and the managers market timing ability is tested with the market timing model by Henriksson and Merton (1981).

4.1 Fama-French Five-Factor Model

The lack of research on the five-factor model in Norway serves as motivation for us to use it in our research. While it has been shown that the model is not perfect, it seems to be the best suited model for us to measure performance of active management. Fama and French (2015) argue that their new model outperforms their previous three-factor model in capturing the size, value, profitability and investment patterns in average stock returns. Further it is evident that factors based on the Norwegian market data should be used to get the best fitting model.

The five-factor model is defined as:

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t e_{i,t}$$

where,

$R_{i,t}$	is the return of portfolio *i* at time *t*
$R_{F,t}$	is the risk-free rate at time *t*
$R_{m,t}$	is the return of the value-weighted market proxy at time *t*
SMB_t	is the return on a diversified portfolio of small minus big stocks at time *t*
HML_t	is the difference between the returns on diversified portfolios of high and low B/M stocks at time *t*
RMW_t	is the difference between the returns on diversified portfolios of stocks with robust and weak profitability at time *t*
CMA_t	is the difference between the returns on diversified portfolios of stocks of low and high investment firms at time *t*
$e_{i,t}$	is the zero mean residual at time *t*

When testing for abnormal return, Jensen's alpha is applied to the model. This method is originally based on the CAPM, but it has also been used together with other models like the three and five-factor model. The framework measures the difference between actual and predicted returns. A positive alpha means that the equity in question creates return beyond the benchmark.

4.2 Henriksson-Merton Market Timing Model

Measuring the level of skill of is very difficult since the decision behind the timing to enter or exit a security could be due to luck rather than skilled marked timing abilities. To test this, we have chosen to use the market timing model created by Henriksson and Merton (1981):

$$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + y_i(R_{M,t} - R_{F,t})D + e_{i,t}$$

where,

D is a dummy variable that equals 1 when $R_{m,t} > R_{F,t}$ and zero otherwise.

y_i is the market timing ability

The simple concept behind the model is that a "*market timer*" attempts to predict when stocks will outperform bonds, $R_{M,t} > R_{F,t}$, and otherwise, $R_{M,t} < R_{F,t}$. This suggests that one should take on risk (*high beta*) when stocks are cheap and reduce risk (*low beta*) when stocks are expensive. Meaning that a successful "*market timer*" will invest in the market when risk premiums are high and exits the market when the risk premium is low. While the model presented above is based on the CAPM, our model is modified to incorporate the explanatory variables with the Fama-French five factors. Although the model does not originally assume the CAPM framework, it can be adopted to multifactor pricing models (Henriksson and Merton, 1981). It is worth to mention that mutual fund managers' ability to shift asset allocation might be restricted by the funds' objectives and their structural constraints. Since hedge fund managers are not imposed the same restrictions, one might expect more evidence of market timing abilities in hedge fund managers, as indicated by Fung and Hsieh (1997).

5.0 Fama-French Factor construction

5.1 Fama-French factors – Operating Profitability and Investment

There is no public library containing all the five Fama-French styled factors for the Norwegian market. While the public library of Bern Arne Ødegaard provides data for the Fama-French three-factor model, he does not have data for the last two factors. To solve this problem, we have chosen to use the size factor (*HML*) and the book-to-market factor (*SMB*) provided by Ødegaard and to construct the operating profitability factor (*CMA*) and investment factor (*RMW*) ourselves. Brückner, Lehmann, Schmidt, and Stehle (2015) argued that the underlying assumptions vary considerably from one database to another, so the choice of database can impact the factor construction. We recognize that using factors based on different databases might create biases, however we choose to go forward with our strategy as the creation of the factors is somewhat outside the scope of our paper and it would be very time consuming.

5.1.1 Sample construction

The accounting data used to create the two factors has been collected from the Centre for Corporate Governance Research (*CCGR*) at BI Norwegian Business School. After adjusting the data, 324 companies have sufficient data points to create the factors for at least one year. The sample consists of yearly data in the period 1998-01 to 2015-12. The security data has been collected from the TRD database and holds monthly data from 2000-01 to 2017-12. After adjustments are made it includes data on 306 companies. When the two adjusted data sets are merged, an average of 153 companies per year have both accounting and security data. This lets us create the two factors for the period 2001-01 to 2017-06.

Given the small sample size, there is a trade-off between keeping data and excluding companies with incomplete data for the entire one-year holding period. This is among other things affected by companies that are delisted during a year, which can lead to survivorship bias. We have chosen to remove companies with less than six observations in total from the dataset from TRD, this is seen as inadequate. Our portfolio returns are weighted with the observations that are actually available, and this is considered as sufficient to get the correct accumulated portfolio returns. Our data set does not contain any companies with negative book equity or book value of assets which could distort the measuring of the two factors.

Table 1: Accounting Variables

Profitability factor	*Item number in CCGR-list*	
Total revenue	Consolidated	Non-consolidated
Total operating revenue	item_15011	item_11
Other interest income	item_15024	item_24
Other financial income	item_15025	item_25
Total operating expenses		
Acquisition cost of goods sold	item_15013	item_13
Payroll expense	item_15014	item_14
Other operating expenses	item_15018	item_18
Interest expenses		
Other interest expenses	item_15030	item_30
Other financial expenses (such as brokerage fee)	item_15031	item_31
Interests expense paid to companies in the same group	item_15029	item_29
Book equity		
Shareholder equity		
Assets		
Total fixed assets	item_15063	item_63
Total current assets	item_15078	item_78
Liabilities		
Total provisions	item_15091	item_91
Total other long-term liabilities	item_15098	item_98
Total current liabilities	item_15109	item_109
Deferred tax and investment tax credit		
Deferred tax asset	item_15045	item_45
Deferred tax	item_15089	item_89
Investment factor	*Item number in CCGR-list*	
Total assets	Consolidated	Non-consolidated
Total fixed assets	item_15063	item_63
Total current assets	item_15078	item_78

Table description:

The table displays accounting variables obtained from the Centre for Corporate Governance Research (CCGR) at Handelshøyskolen BI used to create the Fama and French-style factors profitability (RMW) and investment (CMW). The data consist of both consolidated and unconsolidated data in the period 1999-01 to 2015-12.

5.1.2 Variables

i) **Size** is defined as share price multiplied with shares outstanding:

$$market\ cap_{\tau} = share\ price_{\tau} \times shares\ outstanding_{\tau-1}$$

The market capitalization is calculated in June, based on outstanding stocks at 31.12 in year *t-1* and the stock price in June in year *t* with data from TRD. Thomas Reuters reports outstanding shares at year-end and is defined as the difference between issued shares and treasury shares. If the company has more than one type of common share, the number is adjusted to reflect the par value per share.

(ii) **Operating profitability** is defined as operating profit less interest expenses relative to book equity, all measured at the end of fiscal year $\tau - 1$:

$$OP_{\tau} = \frac{total\ revenue_{\tau-1} - \ total\ operating\ expenses_{\tau-1} - interest\ expenses_{\tau-1}}{book\ equity_{\tau-1}}$$

where,

$$book\ equity_t = shareholder\ equity_t + deferred\ tax_t + investment\ tax\ credit_t$$

When calculating the book equity value, Fama and French (2015) used the sum of costs of goods sold and selling, general and administrative expenses. This study uses acquisition of cost of goods sold, payroll expense and other operating expenses to find the corresponding sum in the CCGR data.

(iii) **Investment behaviour** is defined as book asset growth from year $\tau - 2$ to year $\tau - 1$:

$$Inv_{\tau} = \frac{total\ assets_{\tau-1} - total\ assets_{\tau-2}}{total\ assets_{\tau-2}}$$

all measured at fiscal year-ends. Investment is calculated as the growth in total assets from the fiscal year ending in year *t-2* to the fiscal year ending in year *t-1*.

5.2 Portfolio construction

5.2.1 Sorting

Our factor mimicking portfolios for the operating profitability factor and the investment factor are constructed using a double sorting technique. The double sorting technique involves first sorting all the stocks by one firm characteristic and then sorting them by another characteristic. This forms portfolios which groups together stocks with similar characteristics and aims to isolate the effect from the factor in question from the other factors. Since the Fama-French five-factor model assumes the presence of four firm-specific effects, ideally, the effects of all the three other factors would simultaneously be controlled for to get full isolation of the specific factor. By not getting full isolation the results might be biased due to factor correlation. However, sorting by all four factors simultaneously is beyond the possibilities considering the data available for this thesis as it would entail creating 128 portfolios for the two factors. We will therefore go forward with the double sorting technique, keeping in mind the possibility of bias. The double sorting is done at the end of June to be sure that the companies' accounting process is complete, and the information is publicly available. The monthly excess return is then observed between July and the following June.

5.2.2 Factor mimicking portfolio construction

Our sample stocks are first sorted by size and then sorted by the respective sorting variable. The size breakpoint is the sample median market capitalization and the stocks are divided into two size groups, i.e. big and small. All the stocks are then sorted into three groups; robust/neutral/weak for operating profitability and conservative/neutral/aggressive for investment. The operating profitability and investment breakpoints are the 30th and 70th percentiles. This gives us factor mimicking portfolios consisting of between 20-27 stocks. This sorting gives right-hand-side (*RHS*) variables built on factor mimicking portfolios with a 2 x 3 sorting. Fama and French (2015) found that sorting the variables by 2 x 2 or 2 x 2 x 2 x 2 sort is not significantly better than the 2 x 3 original sort from the three-factor model and therefore we base our factor portfolio construction on this. Like Fama and French, our portfolios are first sorted on size, accounting for the size effect. This is in line with earlier mentioned Norwegian research (Næs, Skjeltorp, and Ødegaard, 2009) and produces two sets of portfolios for each factor. The operating profitability and investment factors are calculated as the difference between the average return between the two robust and weak operating profitability portfolios, and the conservative and aggressive investment portfolios respectively. The two factors are called RMW (robust minus weak), and CMA (conservative minus aggressive). The market factor is further explained in section 6.3.

Table 2: Construction of the profitability and investment factors.

Panel A: Size - OP			
	Weak	Neutral	Robust
Small	SW	SN	SR
Big	BW	BN	BR
Panel B: Size- Inv			
	Conservative	Neutral	Aggresive
Small	SC	SN	SR
Big	BW	BN	BR

Panel C

Breakpoints	Factor Construction
30th and 70th OP sample percentiles	RMW = (SR + BR)/2 - (SW + BW)/2
30th and 70th Inv sample percentiles	CMA = (SC + BC)/2 - (SA + BA)/2

Table description:

The stocks are sorted into two size groups, small and big, using the sample median. Then the two groups are further split into three operating profitability (OP), and investment (Inv) groups using 30% and 70% quantile breakpoints. The operating profitability and investment groups are divided into robust/neutral/weak and conservative/neutral/aggressive for investment respectively. This forms six VW portfolios per double sort which acts as the building blocks for the factors. Panel C contains the structure of the factor mimicking portfolios RMW and CMA.

6.0 Data

6.1 Fund Selection

The final sorting of the dataset contains 55 open-ended Norwegian registered mutual funds and their respective “Net Asset Value” (*NAV*), gathered from the TRD database (see *Appendix 19*). These funds create the basis of the performance, which is tested on an aggregate level against the market proxy (described further in section *6.3*). Funds that are seemingly passive, meaning that they are tracking specific indices are excluded from the sample. The remaining funds are actively managed aiming for positive abnormal return through equity investments. Furthermore, the funds are classified with regard to their main geographical focus area, whereas only the funds focusing mainly in Norwegian equity are kept in the sample. To avoid double accounting only the main fund is kept among those listed twice or more under different asset classes, as A/B or I/II etc.

6.2 Time Period and Sub Periods

The sample period reaches from January 2001 through June 2017, giving 198 months of data to be tested. This combined with data of 55 mutual funds should more than satisfy a general statistical minimum.

The chosen period makes it possible to compare our work with previous papers and further gives an understanding of the Norwegian fund market. Additionally, four sets of sub periods of four years are constructed, allowing for analysis of shorter investment horizons. These sub periods also allow for robustness checks of the full time period. The four sub periods are as follows:

Sub period 1	=	2001-01 → 2004-12	(48 months)
Sub period 2	=	2005-01 → 2008-12	(48 months)
Sub period 3	=	2009-01 → 2012-12	(48 months)
Sub period 4	=	2013-01 → 2017-06	(54 months)

As our sample contains two large financial crashes, the distribution of the data can be particularly affected by the extreme observations measured in conjecture with these two periods. Editing the data, e.g. leaving out extreme observations, can give an artificial improvement to the dataset. However, we have chosen to include all observations even though they might skew our sample data.

We are aware that this might affect the probability of conducting type I and II errors. The sub periods allow for robustness checks for the full time period.

6.3 Market factor / Benchmark

As this paper investigates the performance of Norwegian funds on an aggregate level, a market proxy is used instead of every individual fund's chosen benchmark. As the true market portfolio is imperceptible, the best-fit market proxy in excess of the risk-free rate is chosen.

Table 3: Descriptive statistics

Portfolio	Monthly excess return	St.dev.	Min.	Median	Max.
EW all	0,005961	0,060297	-0,263484	0,013738	0,151160
Mkt	0,005775	0,061315	-0,258580	0,013893	0,156584

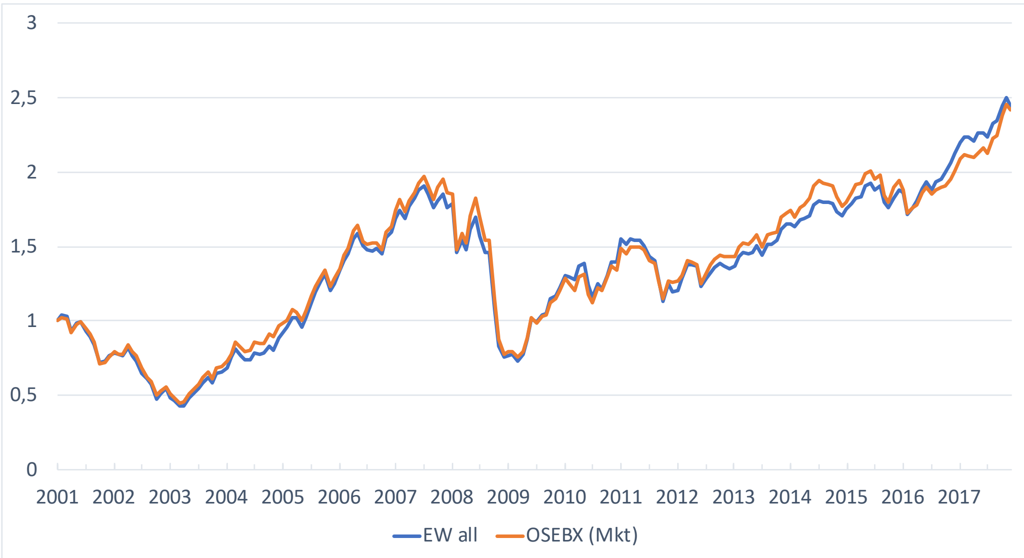

Table description:

The table displays the average, standard deviation, minimum, median and maximum monthly excess returns for the equally weighted portfolio of mutual funds (*EW all*), as well as for the market proxy (*Mkt*). The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The graph displays the cumulative excess returns of the *EW all* and *Mkt* portfolio.

The market proxy chosen for the funds focusing on investments in the Norwegian equity market, is the publicly available OSEBX index gathered from Oslo Børs. The index is constructed from the most traded shares listed on Oslo Børs. As of December 2017, the index contained 67 companies. Note that the index does not exclude the largest companies in Norway (i.e. Equinor, DNB and Telenor), which might bias the index as these companies had a combined market capitalization of 40.3 % in 2017 (Ødegaard, 2018b, p. 36).

However, descriptive statistics of the benchmark in excess of the risk-free rate compared to the equally weighted portfolio of funds indicates that the OSEBX is suitable to be used as a market universe proxy and should reflect the funds' variation in returns. A well-diversified portfolio of funds should be able to reflect the stock universe, as seen in *Table 3*.

6.4 Risk-Free Rate

The proxy for risk-free rate in Norway is gathered from the publicly available data library of Bernt Arne Ødegaard. These are forward looking one-month risk-free rates, estimated from government securities and NIBOR.

6.5 Survivorship and Incubation Bias

The dataset includes funds that are inactive today, given that they have been active for some time during the sample period. Therefore, the dataset of funds will not be subject to survivorship bias, which could have given an upward bias in the results.

Funds are usually tested with internal fund capital before they are released to the public. This time period is called the incubation period and is included in our data sample gathered from the TRD database. According to Evans (2010), incubated funds outperforms released funds on a risk adjusted level, meaning that the performance of the funds in the sample might be subject to an upward bias in their early stages. Further, only top performing funds are released to the public following their incubation period. This can create an upward bias in the results as the poor performing funds are neglected from the data sample. Keep in mind that this paper tests funds publicly available for investors, and therefore does not need to be concerned about funds not surviving the incubation period.

7.0 Results

7.1 Model Diagnostics

When testing our data, we will use the classical linear regression model framework (CLRM). To use this estimation technique, five assumptions regarding the error term accompanies the model. If these assumptions are violated, one important consequence is that hypothesis testing made on the coefficient estimates might be invalid (Brooks, 2014, p. 91). Further discussion is done on the 2nd and 5th assumption, while the other assumptions hold for our data. The results from the diagnostics test on the equally weighted portfolio is included in *Appendix 1-8*.

CLRM Assumptions:

(1) $E(u_t) = 0$
(2) $Var(u_t) = \sigma^2 < \infty$
(3) $Cov(u_i, u_j) = 0$
(4) $Cov(u_t, x_t) = 0$
(5) $u_t \sim N(0, \sigma^2)$

7.1.1 Assumption 2 – the assumption of homoscedasticity

Normally, it is assumed that the variance of the errors is constant, known as homoscedasticity. If the variance increases or decreases with time, i.e. is not constant, it is said to be heteroscedastic. White's test for heteroscedasticity, accompanied with both the F-test framework and Lagrange Multiplier (*LM*) test, is used to test for homoscedasticity in the residuals. Both tests reject the null hypothesis of homoscedasticity and we therefore find presence of heteroscedasticity in the data. Our regressions are therefore corrected with White's heteroscedasticity-consistent standard errors (*HSE*). As can be seen in *Appendix 1* and *4*, after applying White's HSE, the coefficient estimates are unchanged and only the standard errors have changed. The standard errors are larger and hence the p-values of the coefficients estimates will be larger as well. This means that the variables become less significant and type II errors are less likely to occur.

7.1.2 Assumption 5 – Normality

The fifth assumption assumes that the variables follow a normal distribution. If this assumption is violated one cannot use the standard single or joint hypothesis tests on the coefficient estimates as these tests assume a normal distribution. Non-normality in a sample, where normal distribution is assumed, might cause the coefficient estimates to be incorrect. When testing for normality, the Bera-Jarque test is applied and the null hypothesis of normally distributed residuals is rejected. The rejection of the normality assumptions is normal with financial data due to the presence of extreme observations found in the tails of the distribution. Unfortunately, there is no obvious solution to the problem. However, when the test sample is sufficiently large the distribution will be approximately normally distributed, regardless of the absence of normality in the errors. This follows from the central limit theorem and the law of large numbers. Our sample is deemed to be sufficiently large and hence we find that the standard statistical tests hold.

7.1.3 Multicollinearity

When using *OLS*, the explanatory variables should ideally not be correlated, i.e. correlation coefficient of zero. This means that adding or removing a variable from the regression will not change the coefficient estimates of the other variable. However as expected, when studying financial markets, correlation between the factors in the model is found. While a certain level of correlation between the variables is normal, problems can occur if the variables are very highly correlated with each other. Most notable consequences are less precise coefficient estimates and too large standard errors for the individual variables. The latter can lead to type II errors when looking at the explanatory power of the individual variables. What is considered large correlation is debated among scholars, but we consider correlation between 0 and +/- 0.7 to be within a reasonable range. Hence the correlation between our factors is deemed to be reasonable and multicollinearity is not a problem. Our most notable correlation coefficients, which is somewhat high, is between the market factor and *SMB*, in addition to the market factor and *RMW*. The correlations are negative 0.561 and negative 0.433 respectively (see *Table 4*). In comparison, Fama and French (2015) found a positive correlation coefficient of 0.70 between *HML* and *CMA* when testing their 2 x 3 and 2 x 2 sort of the US-market (Fama & French, 2015, *Table 4*). Concerning the strong positive relationship between HML and CMA, Chiah et al (2016) did not find these factors to be correlated in Australia, however they report that their correlation results are mostly consistent with Fama and French (2015).

Table 4: Correlation matrix

	Mkt	SMB	HML	RMW	CMA
Mkt	1,0000	-0,5610	-0,1442	-0,4329	0,1067
SMB	-0,5610	1,0000	0,0914	0,0608	-0,0676
HML	-0,1442	0,0914	1,0000	0,0287	-0,0140
RMW	-0,4329	0,0608	0,0287	1,0000	-0,0735
CMA	0,1067	-0,0676	-0,0140	-0,0735	1,0000

Table description:

The table shows the correlation between the model-factors used in the five-factor model during the sample period, as described in section 6.2. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively.

7.2 Factor mimicking portfolio descriptive statistics

Table 5 show the descriptive statistics from the factor mimicking portfolios for the full period. SMB gives the highest return during the full period of 0.47 % per month. Interestingly, in sub period 3 (2009-01 to 2012-12) following the financial crisis, SMB, HML and RMW yields negative return while CMA yields a positive return (see *Appendix 20, Panel C*). Indicating that companies with a conservative investment strategy where better able to withstand the turmoil following the crisis. This reverts in sub period 4 (2013-01 to 2017-06) where SMB, HML and RMW are positive, while CMA is negative (see *Appendix 20, Panel D*). However, only the HML factor in sub period 3 gives a statistically significant return at a five percent level.

Table 5: Factor mimicking portfolio – Descriptive statistics

	SMB	HML	RMW	CMA
Mean	0,47 %	0,10 %	0,12 %	-0,08 %
std dev	3,75 %	4,13 %	5,04 %	4,64 %
t-stat	1,77	0,34	0,32	-0,24

Table description:

Descriptive statistics of monthly factor returns for the sample period, as described in section 6.2. *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. SMB and HML is provided by Ødegaard's public library. The profitability factor and investment factor are created with a 2x3 sort, first sorted on size, then on the respective factor. The operating profitability and investment groups are divided into robust/neutral/weak and conservative/neutral/aggressive for investment respectively, using 30% and 70% quantile breakpoints. RMW and CMA are calculated as the difference between the average return between the two robust and weak operating profitability portfolios, and the conservative and aggressive investment portfolios respectively. Mean and standard deviation is in percentage.

For the full period none of the factors are statistically significantly at a five percent level. SMB, which is generally the most significant throughout the different time periods is statistically significant at a ten percent level in all periods, except sub period 3 (2009-01 to 2012-12) (see *Appendix 20, Panel C*). The two factors created in this thesis (*RMW* and *CMA*) are not statistically significant at a five (or ten) percent level in any time period in the sample. This is confirmed when viewing the descriptive statistics for the factor building blocks (see *Appendix 21*), both for the RMW and CMA are all portfolios statistically insignificant. Further, the RHS portfolios that form the basis for the factor constructions do not follow the same pattern one would expect if these factors are valid for the Norwegian market. Fama and French find that robust companies yield higher returns than weak companies and companies with a conservative investment behaviour yield higher return than aggressive companies (Fama & French, 2015, *Table A1*) This is not found in our sample, CMA even yield a slight negative return of -0.08% per month when looking at the full period. These facts lead us to believe that the Fama-French four factors do not adequately describe return variation for companies in the Norwegian market.

7.3 Fama-French Five-Factor Model results

This section reviews the performance of an equally weighted portfolio of all funds in our sample (*EW all*). Both the full time period as well as four sets of sub periods (as described in section 6.2) will be investigated. As seen in *Table 6*, the well diversified portfolio has an average excess monthly return of 0.5961 % with a standard deviation of 6.03 % per month. This is similar to the market proxy which has an average excess monthly return of 0.5775 % and a standard deviation of 6.13 % per month. In the different sets of sub periods the average excess monthly returns are quite spread, but it makes sense that the period following the financial downturn of 2008 (*sub period 3*) experiences higher returns in the recovery phase. The average returns in this sub period is 1.3475 % per month, equalling 2.3 times higher returns than in the full time period.

Table 6: Five Factor Regression (Full time period)

Portfolio	Excess monthly return	Std Dev	Five Factor Model: Adj. R-squared	Alpha	Mkt	SMB	HML	RMW	CMA	Simple Regression Model: Adj. R-squared	Alpha	Mkt
EW all	0,5961 %	0,0603	0,971	0,000115	0,961480	0,095355	-0,066738	-0,084781	-0,008867	0,962	0,000389	0,964715
				(0,8862)	(0,0000)	(0,0004)	(0,0028)	(0,0000)	(0,6275)		(0,6424)	(0,0000)
Q1 (12m)	0,6148 %	0,0619	0,963	0,000171	0,986100	0,086846	-0,052067	-0,074403	-0,012390	0,956	0,000449	0,986847
				(0,8454)	(0,0000)	(0,0040)	(0,0479)	(0,0020)	(0,5840)		(0,6269)	(0,6269)
Q2 (12m)	0,6086 %	0,0614	0,970	0,000382	0,969380	0,055934	-0,070145	-0,070217	0,010727	0,964	0,000409	0,982854
				(0,6487)	(0,0000)	(0,0411)	(0,0017)	(0,0005)	(0,5806)		(0,6213)	(0,0000)
Q3 (12m)	0,6246 %	0,0613	0,970	0,000453	0,972330	0,072861	-0,074757	-0,074669	0,007930	0,963	0,000576	0,981817
				(0,5621)	(0,0000)	(0,0041)	(0,0001)	(0,0000)	(0,6282)		(0,4944)	(0,0000)
Q4 (12m)	0,6297 %	0,0621	0,942	-0,000669	0,921970	0,169930	-0,068356	-0,119660	-0,029413	0,920	0,000016	0,910544
				(0,5478)	(0,0000)	(0,0000)	(0,0178)	(0,0000)	(0,2220)		(0,9891)	(0,0000)
Q1-Q4 (12m)	0,0874 %	0,0133	0,184	0,000274	0,986040	0,108960	-0,096277	-0,079491	-0,001156	0,119	0,000433	0,076303
				(0,7752)	(0,0000)	(0,0011)	(0,0013)	(0,0022)	(0,9641)		(0,6278)	(0,0000)
Q1 (3m)	0,5800 %	0,0621	0,958	0,000274	0,986040	0,108960	-0,096277	-0,079491	-0,001156	0,947	0,000601	0,986226
				(0,7752)	(0,0000)	(0,0011)	(0,0013)	(0,0022)	(0,9641)		(0,5562)	(0,0000)
Q2 (3m)	0,5800 %	0,0612	0,974	-0,000017	0,973440	0,069771	-0,042917	-0,077126	0,004618	0,968	0,000131	0,981493
				(0,9827)	(0,0000)	(0,0067)	(0,0396)	(0,0001)	(0,8097)		(0,8672)	(0,0000)
Q3 (3m)	0,6214 %	0,0608	0,967	0,000531	0,960540	0,057142	-0,057814	-0,073907	-0,011060	0,961	0,000601	0,971963
				(0,5543)	(0,0000)	(0,0592)	(0,0096)	(0,0001)	(0,5240)		(0,4828)	(0,0000)
Q4 (3m)	0,5132 %	0,0588	0,946	-0,000765	0,929480	0,150890	-0,069686	-0,112310	-0,018344	0,927	-0,000199	0,922987
				(0,4740)	(0,0000)	(0,0000)	(0,0122)	(0,0000)	(0,4064)		(0,8605)	(0,0000)
Q1-Q4 (3m)	0,1165 %	0,0135	0,096	0,000840	0,064130	-0,083083	0,016290	0,045262	0,017023	0,077	0,000800	0,063239
				(0,3514)	(0,0048)	(0,0032)	(0,4544)	(0,0248)	(0,3814)		(0,3896)	(0,0000)

Table description:

The table shows descriptive statistics and results gathered utilizing the Fama-French five-factor model and a simple regression model. Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consists of the worst performing funds. The "*top minus bottom*" (*Q1-Q4*) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

The simple regression of excess return on the market premium shows a risk adjusted abnormal return of 0.0389 % per month. However, when all the five Fama-French factors are accounted for, the alpha almost completely vanishes as the equally weighted portfolio has a highly insignificant abnormal return of 0.0115 % per month, or 0.1380 % in annual terms. The insignificance of the alpha shows the inability of the Norwegian funds to create abnormal returns. In addition, in most sub periods are the alphas statistically insignificant (see *Table 7*), except from sub period 4 which have a significant positive abnormal return of 0.2368 % per month. As an additional robustness test, each of the 55 individual funds in our sample are regressed on the five-factor model. These regressions show an average alpha of 0.2390 % with 23 out of the 55 alphas being significantly positive. Even though this is somewhat higher than the results from the equally weighted portfolio, we conclude that active portfolio managers are not able to create abnormal returns in Norway on an aggregate level.

Given that the equally weighted portfolio of funds is well diversified, it is expected to see the market beta close to one in both regression models, as seen in *Table 6*. The five-factor model shows that the portfolio is significant and positively exposed to the market factor (*Mkt*) and the size factor (*SMB*). Additionally, it shows significant and negative exposure to the book-to-market equity factor (*HML*) and the profitability factor (*RMW*), and insignificant negative exposure to the investment factor (*CMA*). Næs, Skjeltorp, and Ødegaard (2009) finds that there is an observed risk compensation for size while the value effect (*book-to-market equity*) does not give significant risk compensation in Norway. Further, it is found that when the additional four factors are introduced to the simple regression of excess return on the market premium, the adjusted R-squared is only marginally increased (*Table 6*) going from 96 % to 97 %. Evidence of this is found throughout all sub periods also when testing for persistence in our results. This incremental change is somewhat contradictory to Fama and French (2016) who finds that when regressing the test-portfolios return on the five-factor model, it explains approximately 90 % of the return variation in all markets tested (North-America, Europe, Japan and Pacific-Asia). These results lead us to believe that the market factor alone is able to explain most of the variation of returns in the Norwegian mutual fund universe.

To further test the explanatory power of the Fama-French factors, each individual factor is added individually to the simple regression, resulting in four different sets of two-factor models. While the *alpha* from the simple regression is expected to decrease when adding extra explanatory variables, we do not find any pattern of this in our sample. There are no significant differences in the *R-squared* nor the *adjusted R-squared* gathered from these two-factor models (see *Appendix 14*). When going from a one-factor model to the two-factor models, the measures are almost completely unchanged showing that the adjusted R-square does not seem to get penalized for the loss of degrees of freedom. These results lead us to believe that the Fama-French style factors have low explanatory power in the Norwegian market.

Table 7: Summary - Equally weighted portfolio of all funds

EW all	Full Period 2001.01-2017-06	Sub1 2001.01-2004.12	Sub2 2005.01-2008.12	Sub3 2009.01-2012.12	Sub4 2013.01-2017.06
Alpha	0,000115 (0,8862)	-0,001095 (0,5412)	0,000642 (0,5850)	-0,001077 (0,4743)	0,002368 (0,0395)
Excess monthly return	0,5961 %	0,0773 %	-0,0568 %	1,3745 %	0,9457 %
Std Dev	0,0603	0,0708	0,0759	0,0594	0,0265

*p-values in parentheses

Table description:

The table shows descriptive statistics of the *EW all* portfolio and summarizes results gathered utilizing the Fama-French five-factor model. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

7.4 Persistence

7.4.1 Holding periods of 12 months

The portfolios investigated in this section are formed on the beginning of every year and sorted on lagged one-year performance. The portfolios are then held for 12 months, then re-sorted and re-formed, resulting in a monthly time series of each quartile portfolio from January 2001 to June 2017. The portfolio weights are adjusted whenever a fund vanishes during the holding period of 12 months, but the disappearing funds are included until they are out of business. Both the full sample period as well as four sets of sub periods (as described in section 6.2) are investigated.

As seen in *Table 6*, there is not much spread in the quartiles' average excess monthly returns and standard deviations. It is difficult to see a clear trend among the performance, although the "*top minus bottom*" portfolio (*Q1-Q4*) has by far the lowest average excess monthly return for the full sample period. This indicates that a trading strategy going long on the prior years' best performing funds, and short the worst performing funds, is not valid. Even though financial theory suggests otherwise, many investors believe that good fund performance one year should indicate good performance also in the following year. If that would have been the case, the top quartile (*Q1*) should have outperformed the second quartile (*Q2*), which should have outperformed the third quartile (*Q3*), and so on. Then the "*top minus bottom*" trading strategy (*Q1-Q4*) could have shown some promise. That is not the case in our sample when looking at the average excess return. However, in sub period 4 the top quartile (*Q1*) shows an average excess return of 1.0820 % per month compared to the clustered returns of the rest of the quartiles around 0.91 % per month. This could indicate to some extent a small degree of persistence among top performers in this sub period (see *Appendix 18*).

Although not significant, the third quartile (*Q3*) marginally outperforms the other quartiles in terms of abnormal return. The portfolio yields 0.0453 % above the market premium on a monthly basis. There is some indication of persistence among bad performers in the fourth quartile (*Q4*) with an abnormal return of -0.0669 % per month. This quartile is the worst performing portfolio in the full time period regression, as well as in sub periods 1 and 2. However, none of the alphas in question are significant, and we can therefore not conclude definitively that there exists persistence among bad performers in the sample.

Table 8: Summary - Five Factor regressions

Portfolio	Alpha (Full Period)	Alpha (Sub1)	Alpha (Sub2)	Alpha (Sub3)	Alpha (Sub4)
EW all	0,000115 (0,8862)	-0,001095 (0,5412)	0,000642 (0,5850)	-0,001077 (0,4743)	0,002368 (0,0395)
Q1 (12m)	0,000171 (0,8454)	-0,001470 (0,4947)	0,000145 (0,9155)	-0,001010 (0,5102)	0,004347 (0,0059)
Q2 (12m)	0,000382 (0,6487)	-0,000634 (0,7615)	0,002399 (0,1341)	-0,001489 (0,3125)	0,001422 (0,2181)
Q3 (12m)	0,000453 (0,5621)	-0,000583 (0,7822)	0,001424 (0,2497)	-0,001107 (0,4438)	0,002170 (0,1045)
Q4 (12m)	-0,000669 (0,5478)	-0,002080 (0,4127)	-0,001276 (0,4856)	-0,001421 (0,5141)	0,001651 (0,2867)
Q1-Q4 (12m)	0,000274 (0,7752)	0,000610 (0,7346)	0,001421 (0,4404)	0,000411 (0,7465)	0,002696 (0,1208)
Q1 (3m)	0,000274 (0,7752)	-0,002226 (0,3488)	0,003290 (0,0743)	-0,000948 (0,5560)	0,002541 (0,0880)
Q2 (3m)	-0,000017 (0,9827)	-0,001373 (0,4849)	-0,000354 (0,7954)	-0,001325 (0,3308)	0,001872 (0,0850)
Q3 (3m)	0,000531 (0,5543)	-0,000013 (0,9954)	0,000682 (0,6052)	-0,000424 (0,8201)	0,001896 (0,1790)
Q4 (3m)	-0,000765 (0,4740)	-0,001244 (0,6310)	-0,000734 (0,6955)	-0,003506 (0,0967)	0,003413 (0,0296)
Q1-Q4 (3m)	0,000840 (0,3514)	-0,000982 (0,6347)	0,004024 (0,0942)	0,002558 (0,0837)	-0,000872 (0,5923)

*p-values in parentheses

Table description:

The table summarizes results gathered utilizing the Fama-French five-factor model. Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consists of the worst performing funds. The "*top minus bottom*" (*Q1-Q4*) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns in their respective period or sub period, as described in section 6.2. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

In sub period 4, the top quartile (*Q1*) has a significant positive alpha almost twice as large as the equally weighted portfolio of all funds (*EW all*), which is also significantly positive (see *Table 8*). In addition to having the highest average excess return, this portfolio also has the highest abnormal return of 0.4347 % per month. While this could indicate persistence in performance among the top performing funds in this sub period, no significant *alphas* are found in any other sub period nor in the full time period. We therefore conclude that active portfolio managers are not able to generate persistent abnormal returns in Norway when controlling for 12 months holding periods.

Similar to the equally weighted portfolio of all funds, the five-factor model shows that all quartile portfolios held for twelve months are significant and positively exposed to the market factor (*Mkt*) and the size factor (*SMB*). It also shows significant and negative exposure to the value factor (*HML*) and the profitability factor (*RMW*), and insignificant negative exposure to the investment factor (*CMA*).

7.4.2 Holding periods of 3 months

The portfolios investigated in this section are formed on the beginning of every quarter of each year and sorted on lagged one-year performance. The portfolios are then held for 3 months, then re-sorted and re-formed, resulting in a monthly time series of each quartile portfolio from January 2001 to June 2017. The portfolio weights are adjusted whenever a fund vanishes during the holding period of 3 months, but the disappearing funds are included until they are out of business. Both the full time period as well as four sets of sub periods (as described in *section 6.2*) is investigated.

As in the portfolios with a 12-month holding period, there is not much spread in the quartiles' average excess monthly returns and standard deviations (see *Table 6*). The three months holding strategy for the full time period produces the lowest average excess returns, compared to the twelve months holding strategy and the equally weighted portfolio of all funds. This pattern is not present when looking at the different sub periods. Among the portfolios with three months holding periods, the third quartile (*Q3*) also marginally outperforms the other quartiles in terms of excess return and abnormal return per month, with returns of 0.6246 % and 0.0453 % respectively. Furthermore, there is no trend in declining performance from the previous year's best performing funds to the worst performing funds. Also, here the "*top minus bottom*" portfolio (*Q1-Q4*) performs worst in average excess return terms for the full time period, although in sub period 2 the portfolio performs relatively good compared to the other portfolios. Although not significant, in abnormal risk adjusted terms the long-short strategy is the best performing (or least negative) portfolio in the full time period, as well as in sub period 2 and 3.

In sub period 4, the bottom quartile (*Q4*) shows a statistically significant positive alpha of 0.3414 % per month, almost 1.5 times higher than the equally weighted portfolio of all funds (see *Appendix 18*). This is opposite to the findings for the (earlier mentioned) twelve months holding period strategy in the same sub period. Here the top quartile (*Q1*) has a statistically significant positive alpha of 0.4347 % per month while the bottom quartile (*Q4*) is not statistically significant.

Similar to the equally weighted portfolio of all funds, and the portfolios held for 12 months, the five-factor model shows that all quartile portfolios held for three months are significant and positively exposed to the market factor (*Mkt*) and the size factor (*SMB*). It also shows significant and negative exposure to the value factor (*HML*) and the profitability factor (*RMW*), and insignificant negative exposure to the investment factor (*CMA*).

7.5 Market Timing

To test if the mutual funds possess market timing abilities the Henriksson-Merton (1981) model for market timing ability is utilized. Our findings are summarized in *Table 9*. The equally weighted portfolio of actively managed mutual funds has a negative market timing ability of -0.0248 which also holds in sub period 2,3 and 4. Only sub period 1 (*2001-01 to 2004-12*) show consistent positive market timing abilities for all quartiles as well as for the equally weighted portfolio. The top quartile (*Q1*) with three months holding period show the highest market timing ability factor among the quartiles of 0.2214, which is natural since the "best" mutual funds should be included in this quartile. Although, this in conflict with the bottom quartile (*Q4*) showing highest market timing ability and the top quartile (*Q1*) showing the lowest under the twelve-month holding strategy in the same period.

However, as with most of our findings, the beta coefficients are not statistically significant in sub period 1, except from in Q1 (*3m*). The only period where the data show signs of statistical significance is in sub period 2 (*2005-01 to 2008-12*). Here the mutual funds show consistently negative market timing ability. The "*top minus bottom*" portfolio (*Q1-Q4*) shows the best market timing ability subjected to the three-month holding portfolios. This is true for the full time period, as well as sub period 2, 3 and 4, although the results are not significant. For the twelve-month holding strategy portfolios, the portfolio is among the worst performing in timing ability terms for the full time period and in sub period 1. In contrast, the portfolio is among the best performing portfolios in sub period 2 and 3, and highly outperforms the other portfolios in sub period 4. None of the *betas* regarding the "*top minus bottom*" portfolios (*Q1-Q4*) are significant at the 5 % level, however the *beta* for sub period 1 (*12m*) is significant at the 10% level. We therefore conclude that actively managed mutual funds in Norway, focusing on Norwegian equity, does not show any sign of market timing abilities. This is in line with the findings from Henriksson and Merton (1981) and Bollen and Busse (2005) that does not find any evidence of market timing in monthly data.

Table 9: Summary - Market Timing regressions

Portfolio	ß (Full Period)	ß (Sub1)	ß (Sub2)	ß (Sub3)	ß (Sub4)
EW all	-0,024883 (0,5748)	0,158224 (0,1564)	-0,160180 (0,0078)	-0,013554 (0,8498)	-0,110802 (0,1963)
Q1 (12m)	-0,074020 (0,1320)	0,084858 (0,4171)	-0,154812 (0,0169)	-0,034876 (0,6394)	0,012384 (0,9271)
Q2 (12m)	-0,040467 (0,3372)	0,100283 (0,3911)	-0,222197 (0,0004)	-0,045811 (0,5128)	-0,148694 (0,1624)
Q3 (12m)	0,021305 (0,6026)	0,176955 (0,1319)	-0,116125 (0,0427)	0,048983 (0,4418)	-0,075879 (0,4016)
Q4 (12m)	-0,016666 (0,8046)	0,241487 (0,1088)	-0,139902 (0,2151)	-0,068033 (0,5798)	-0,182576 (0,0869)
Q1-Q4 (12m)	-0,057354 (0,2466)	-0,156629 (0,1529)	-0,014910 (0,8878)	0,033157 (0,6818)	0,194960 (0,1782)
Q1 (3m)	0,012362 (0,7812)	0,221453 (0,0207)	-0,085099 (0,2017)	0,024906 (0,6928)	0,013732 (0,9183)
Q2 (3m)	-0,040124 (0,3220)	0,131706 (0,1948)	-0,210801 (0,0004)	-0,030749 (0,6465)	-0,116748 (0,2625)
Q3 (3m)	-0,013117 (0,8177)	0,165361 (0,2588)	-0,162061 (0,0553)	-0,050313 (0,6076)	-0,120618 (0,2501)
Q4 (3m)	-0,080337 (0,1529)	0,112548 (0,4329)	-0,177738 (0,0445)	-0,123667 (0,2803)	-0,182486 (0,0882)
Q1-Q4 (3m)	0,092699 (0,0516)	0,108906 (0,2800)	0,092639 (0,3562)	0,148573 (0,1153)	0,196218 (0,1562)

*p-values in parentheses

Table description:

The table summarizes results gathered utilizing the Fama-French five-factor model and the Henriksson-Merton market timing model. Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (*Q1-Q4*) portfolio is a long Q1 and short Q4 portfolio. The table displays the regression results as the above-mentioned portfolios are regressed on the Fama-French five-factor model with the addition of the Henriksson-Merton market timing factor. *Beta* is the measure of the market timing factor which is a dummy variable that equals 1 when the market gives higher return then the risk-free rate, $R_{Mt} > R_{Ft}$, and zero otherwise, $R_{Mt} < R_{Ft}$. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

8.0 Conclusion

Based on our results, we conclude that Norwegian actively managed mutual funds are not able to persistently generate risk-adjusted returns greater than the market in Norway. Nor, do we find any evidence of market timing ability among the funds in our sample. Leading us to believe that the Efficient Market Hypothesis hold for the Norwegian mutual fund universe.

When testing the Fama-French five-factor model on the Norwegian market, it is not found to add any explanatory power compared to the simple regression of excess returns on the market premium. The change is miniscule, going from explaining 96 % to 97 % of the cross-sectional variation in the returns of the equally weighted portfolio. This is consistent through all holding periods and time periods in our sample. It is further confirmed by adding the different Fama-French factors individually to the simple regression of excess return on the market premium. The adjusted R-squared going from a one-factor model to the two-factor models are also almost completely unchanged, indicating low explanatory power of the Fama-French style factors in the Norwegian market. This pattern is also seen when evaluating the different factor returns in the factor construction section; here the individual factors do not show significant effect in explaining returns for Norwegian companies. However, within all strategies we have significant and positive exposure to the market factor (*Mkt*) and the size factor (*SMB*). Also, significant and negative exposure to the value factor (*HML*) and the profitability factor (*RMW*) is found in the sample. This leads us to believe that there might exist tradeable strategies within the Norwegian mutual funds market, most notably funds that focus on size.

1. Actively managed mutual funds are not able to generate risk-adjusted returns greater than passive management.

When accounting for all the five Fama and French factors, the abnormal return of an equally weighted portfolio decrease from 0.0389 % to 0.0115 % per month, compared to a simple regression model only controlling for the market factor. Furthermore, the alpha for this portfolio is not to statistically significant. These results are supported by several robustness checks where the results are largely unaffected by the different underlying assumptions. Only one sub period (*2013-01 to 2017-06*) exhibit statistically significant results indicating abnormal returns greater than zero. We therefore do not find any conclusive evidence of abnormal return in our equally weighted portfolio of all funds before considering fees.

2. Actively managed mutual funds are not able to generate positive risk adjusted returns persistently over time.

In the period between the years of 2013-17 (*sub period 4)* the top quartile funds (*Q1)* with twelve months holding periods (*12m*) show positive significant abnormal return. This portfolio generates an alpha almost twice as large as the significant positive alpha from the equally weighted portfolio of all funds (*EW all*). While this could indicate persistence in performance among the top performing funds in this sub period, it is contradicted by the significantly positive alpha found among the worst performing funds with three months holding strategy in the same sub period. Furthermore, there is no evidence of positive persistent returns in any other sub period nor any negative persistent returns among the bottom quartiles. Additionally, this is confirmed by the insignificant "*top minus bottom"* trading strategy in our sample. Therefore, we conclude that there is no persistence in the abnormal (negative or positive) returns among the Norwegian mutual funds focusing on Norwegian equities.

3. Actively managed mutual funds do not have market timing abilities.

The only period where the data consistently show significant coefficients of market timing ability are in sub period 2 (*2005-01 to 2008-12*), in which they all are consistently negative. In general, the sample exhibit negative but insignificant market timing ability within both holding periods and in all sub periods. We therefore conclude that the mutual funds in our sample do not show any sign of market timing abilities.

9.0 Comments and Future Research

This paper contributes to the small amount of research available on the Norwegian mutual fund market. Our findings seem to be in line with the majority of economic theory and research. When investigating the returns of actively managed mutual funds in Norway, an aggregated portfolio of these funds does not seem to be able to beat the market. This seems evident after comparing the portfolios risk-adjusted return to a market proxy. As our market proxy we have chosen to use the OSEBX index, however for a retail investor the market proxy is most realistically accessible through an index fund. Although index funds represent a low-cost alternative compared to mutual funds, they also charge some level of fee, with a typical Norwegian index fund charging between 0.20-0.30 (e.g. DNB and KLP). Hence index funds will most likely generate 0.20-0.30 % lower returns than the actual market index, and it seems likely that the results from our test might have seen a different outcome if this aspect would be included as a parameter. Therefore, an interesting extension of our research would be to investigate this topic from the practical viewpoint of a retail investor, comparing actual investable opportunities and not a market proxy. Such a study could also contain research on the diversification benefits gained when investing in an index fund versus an actively managed portfolio. When investing in a SP500 index fund, an investor gain exposure to the 500 largest companies in the US across various differentiated industries. However, when tracking the OSEBX index an investor gain much less diverse exposure as the largest companies in Norway (i.e. Equinor, DNB and Telenor) had a combined market capitalization of 40.3 % in 2017 . One might argue that the OSEBX index does not fully reflect the market portfolio and that an actively managed mutual fund might provide larger diversification benefits for an investor in the Norwegian market. If this were to be true, then this could be a characteristic that speaks in favour of investing through actively managed mutual funds in Norway. Concerning the market timing abilities of Norwegian mutual funds; here the robustness of our results should be challenged using daily data to see if the market timing abilities of Norwegian active mutual funds follow the pattern found by Bollen and Busse (2001).

When conducting our research, the returns of the aggregated portfolio of actively managed mutual funds are risk-adjust using the Fama-French five-factor model. After testing its fit on the Norwegian market, the five-factor model seems to be somewhat lacking explanatory power when looking at the variation of returns in Norwegian mutual funds. Here further research should test the validity of the model within the Norwegian market. Additionally, our decision to base our model on factors constructed from two different databases could bias the results, and this aspect should be taken into account when reviewing our results.

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Appendix

Appendix 1: Regression results of the equally weighted portfolio of all funds

	Original regression			
	Beta	SE	Tstat	P-value
Alpha	0,000115	0,000750	0,152820	0,878700
Mkt	0,961480	0,016457	58,425000	0,000000
SMB	0,095355	0,024130	3,951800	0,000109
HML	-0,066738	0,017749	-3,760100	0,000225
RMW	-0,084781	0,016499	-5,138600	0,000001
CMA	-0,008867	0,015735	-0,563520	0,573740

Table description:

The table displays the results from a regression of excess return on the Fama-French style five factors. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively.

Appendix 2: CLRM Assumption 1 – Mean of residual is zero

Test	P-value
T-test	1,0000

Table description:

The table displays the p-value from testing the mean of the residual for the equally weighted portfolio of all funds. H_0 (mean of the residual is zero) is not rejected at a 5% significance level. The first CLRM assumption

$(E[u_{CC,t}] = 0)$ is not violated.

Appendix 3: CLRM Assumption 2 – Variance of the residual is constant (homoscedastic)

Test	P-value
F-test	1,37E-06
LM-test	3,87E-06

Table description:

The table displays the p-values from the White's test for heteroscedasticity of the equally weighted portfolio of all funds for heteroscedasticity using the F-test framework and Lagrange Multiplier. H0 (homoscedasticity) is rejected at a 5% significance level. The second CLRM assumption $\left(VAR\left[u_{CC,t}\right] = \sigma^2 < \infty\right)$ is violated, and we conclude that the residuals are heteroscedastic.

Appendix 4: Regression with White heteroskedasticity-consistent standard errors

	Beta	SE	Tstat	P-value
Alpha	0,000115	0,000800	0,143333	0,886174
Mkt	0,961482	0,020694	46,461273	0,000000
SMB	0,095355	0,026542	3,592570	0,000414
HML	-0,066738	0,022071	-3,023734	0,002831
RMW	-0,084781	0,019944	-4,250893	0,000033
CMA	-0,008867	0,018241	-0,486091	0,627445

Table description:

The table displays the results from a regression of excess return on the Fama-French style five factors using White heteroskedasticity-consistent standard errors. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively.

Appendix 5: CLRM Assumption 3 – Autocorrelation in the residual

Test	P-value
F-test	0,2233
LM-test	0,2181

Table description:

The table displays the p-values from the test for autocorrelation in the residual. Both an F-test and the Breusch-Godfrey LM test with 4 lags is conducted. H_0 (covariance over residuals are zero over time) is not rejected at a 5% significance level. The third CLRM assumption $(Cov(u_{CC,i}u_{CC,j}) = 0 \; for \; i \neq j)$ is not violated.

Appendix 6: CLRM Assumption 4 – Factor correlation with the residual

1.0e-14 *	u(i,t)
Mkt	-0,141
SMB	0,094
HML	0,029
RMW	0,054
CMA	-0,020
corr(x(i,t), u(i,t))	

Table description:

The table displays the correlation between the factors and residual. There are not significant levels of correlation between the factors and the residual (all coefficients are approximately zero, 1.0e-14 *). We conclude that $Cov(u_{CC,t}, x_{i,t}) = 0 \; for \; all \; i = 2, \ldots, k$. The fourth assumption is not violated.

Appendix 7: CLRM Assumption 5 – Distribution of the residual

CLRM Assumption 5	
Test	**P-value**
Bera-Jarque	0,0185
Normality assumption	

Table description:

The table displays the p-value from the Bera-Jarque test for normal distribution in the residual. H_0 (residuals are normally distributed with mean zero and variance σ^2) is rejected at a 5% significance level. The fifth CLRM assumption ($u_{CC,t} \sim N(0, \sigma^2)$) is violated, and we conclude that the residual is not normally distributed.

Appendix 8: Histogram of residuals

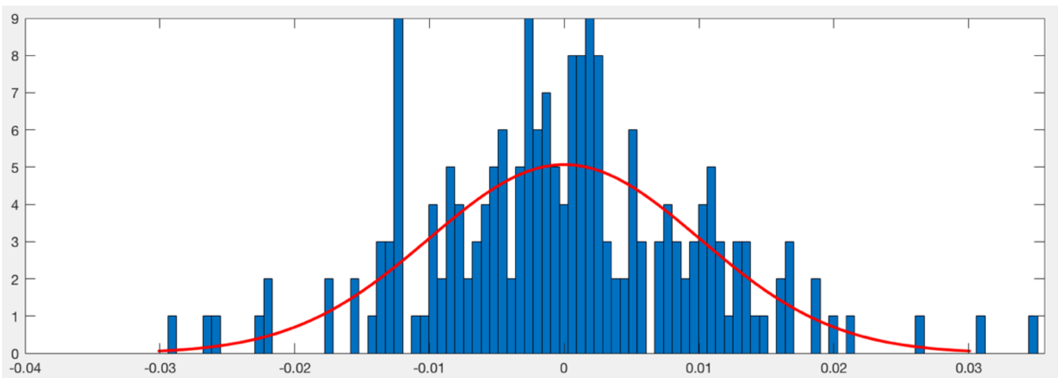

Table description:

The histogram displays the distribution of the residuals. Its shows several extreme observations found in the tails of the distribution.

Appendix 9: Simple regression (Full time period)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt
EW all	0,5961 %	0,0603	0,000389 (0,6424)	0,964715 (0,0000)
Q1 (12m)	0,6148 %	0,0619	0,000449 (0,6269)	0,986847 (0,6269)
Q2 (12m)	0,6086 %	0,0614	0,000409 (0,6213)	0,982854 (0,0000)
Q3 (12m)	0,6246 %	0,0613	0,000576 (0,4944)	0,981817 (0,0000)
Q4 (12m)	0,6297 %	0,0621	0,000016 (0,9891)	0,910544 (0,0000)
Q1-Q4 (12m)	0,0874 %	0,0133	0,000433 (0,6278)	0,076303 (0,0000)
Q1 (3m)	0,5800 %	0,0621	0,000601 (0,5562)	0,986226 (0,0000)
Q2 (3m)	0,5800 %	0,0612	0,000131 (0,8672)	0,981493 (0,0000)
Q3 (3m)	0,6214 %	0,0608	0,000601 (0,4828)	0,971963 (0,0000)
Q4 (3m)	0,5132 %	0,0588	-0,000199 (0,8605)	0,922987 (0,0000)
Q1-Q4 (3m)	0,1165 %	0,0135	0,000800 (0,3896)	0,063239 (0,0000)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 10: Simple regression (Sub period 1)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt
EW all	0,0773 %	0,0708	-0,001365 (0,4901)	0,988136 (0,0000)
Q1 (12m)	0,1015 %	0,0700	-0,001087 (0,6261)	0,971489 (0,0000)
Q2 (12m)	0,0485 %	0,0725	-0,001709 (0,3825)	1,013781 (0,0000)
Q3 (12m)	0,1056 %	0,0736	-0,001165 (0,5812)	1,026207 (0,0000)
Q4 (12m)	0,0167 %	0,0688	-0,001880 (0,4609)	0,945977 (0,0000)
Q1-Q4 (12m)	0,0848 %	0,0126	0,000792 (0,6666)	0,025512 (0,3360)
Q1 (3m)	-0,0023 %	0,0737	-0,002225 (0,3931)	1,017717 (0,0000)
Q2 (3m)	0,0493 %	0,0713	-0,001668 (0,3662)	0,998368 (0,0000)
Q3 (3m)	0,1585 %	0,0707	-0,000553 (0,7728)	0,988298 (0,0000)
Q4 (3m)	0,0494 %	0,0703	-0,001601 (0,5329)	0,968205 (0,0000)
Q1-Q4 (3m)	-0,0517 %	0,0153	-0,000624 (0,7748)	0,049512 (0,1186)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 11: Simple regression (Sub period 2)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt
EW all	-0,0568 %	0,0759	0,000371 (0,8237)	0,938478 (0,0000)
Q1 (12m)	-0,1073 %	0,0807	-0,000074 (0,9653)	0,998435 (0,0000)
Q2 (12m)	0,0714 %	0,0766	0,001660 (0,3544)	0,945687 (0,0000)
Q3 (12m)	-0,0091 %	0,0757	0,000848 (0,5532)	0,938690 (0,0000)
Q4 (12m)	-0,1729 %	0,0718	-0,000858 (0,7370)	0,871151 (0,0000)
Q1-Q4 (12m)	0,0656 %	1,6542 %	0,000784 (0,6823)	0,127284 (0,0000)
Q1 (3m)	0,1536 %	0,0782	0,002499 (0,2279)	0,961620 (0,0000)
Q2 (3m)	-0,1216 %	0,0769	-0,000264 (0,8713)	0,950800 (0,0000)
Q3 (3m)	-0,0761 %	0,0760	0,000179 (0,9142)	0,939914 (0,0000)
Q4 (3m)	-0,1615 %	0,0738	-0,000713 (0,7526)	0,901885 (0,0000)
Q1-Q4 (3m)	0,3152 %	1,5179 %	0,003212 (0,1334)	0,059735 (0,0293)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 12: Simple regression (Sub period 3)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt
EW all	1,3745 %	0,0594	-0,000352 (0,8506)	1,013268 (0,0000)
Q1 (12m)	1,3247 %	0,0602	-0,001111 (0,5201)	1,032082 (0,0000)
Q2 (12m)	1,3705 %	0,0605	-0,000736 (0,6646)	1,038054 (0,0000)
Q3 (12m)	1,4479 %	0,0607	0,000029 (0,9873)	1,038662 (0,0000)
Q4 (12m)	1,3041 %	0,0575	-0,000174 (0,9502)	0,949939 (0,0000)
Q1-Q4 (12m)	0,0206 %	0,0122	-0,000937 (0,5836)	0,082143 (0,0070)
Q1 (3m)	1,3884 %	0,0604	-0,000454 (0,8099)	1,030637 (0,0000)
Q2 (3m)	1,4054 %	0,0609	-0,000519 (0,7398)	1,047539 (0,0000)
Q3 (3m)	1,4560 %	0,0608	0,000150 (0,9406)	1,035751 (0,0000)
Q4 (3m)	1,0788 %	0,0563	-0,002146 (0,4390)	0,929657 (0,0000)
Q1-Q4 (3m)	0,3096 %	0,0129	0,001691 (0,3345)	0,100981 (0,0014)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 13: Simple regression (Sub period 4)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt
EW all	0,9457 %	0,0265	0,002867 (0,0177)	0,847530 (0,0000)
Q1 (12m)	1,0820 %	0,0274	0,004353 (0,0120)	0,831724 (0,0000)
Q2 (12m)	0,9066 %	0,0276	0,002160 (0,0592)	0,888145 (0,0000)
Q3 (12m)	0,9174 %	0,0264	0,002621 (0,0288)	0,842766 (0,0000)
Q4 (12m)	0,9138 %	0,0274	0,002626 (0,1126)	0,837436 (0,0000)
Q1-Q4 (12m)	0,1683 %	0,0118	0,001727 (0,3084)	-0,005711 (0,9179)
Q1 (3m)	0,9401 %	0,0274	0,002825 (0,0768)	0,845629 (0,0000)
Q2 (3m)	0,9415 %	0,0268	0,002712 (0,0202)	0,862019 (0,0000)
Q3 (3m)	0,9111 %	0,0274	0,002317 (0,0695)	0,873728 (0,0000)
Q4 (3m)	1,0223 %	0,0263	0,003912 (0,0121)	0,811601 (0,0000)
Q1-Q4 (3m)	-0,0822 %	0,0104	-0,001087 (0,4631)	0,034028 (0,4841)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 14: Factor Contribution

Regression	Alpha	Adj. R-squared	R-squared
Mkt	0,000389 (0,6424)	0,962	0,962
Mkt & **SMB**	-0,000445 (0,5830)	0,966	0,967
Mkt & **HML**	0,000486 (0,5541)	0,964	0,964
Mkt & **RMW**	0,000704 (0,3666)	0,968	0,968
Mkt & **CMA**	0,000380 (0,6507)	0,962	0,962

*p-values in parentheses

Table description:

The table shows the simple regression of monthly excess return on the market proxy, and four other two-factor models. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 15: Five Factor regression (Sub period 1)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt	SMB	HML	RMW	CMA
EW all	0,0773 %	0,0708	-0,001095 (0,5412)	0,974830 (0,0000)	0,130970 (0,0459)	-0,126500 (0,0007)	-0,030932 (0,3495)	-0,002971 (0,9100)
Q1 (12m)	0,1015 %	0,0700	-0,001470 (0,4947)	0,977045 (0,0000)	0,191406 (0,0021)	-0,105806 (0,0228)	-0,017975 (0,6946)	-0,001479 (0,9638)
Q2 (12m)	0,0485 %	0,0725	-0,000634 (0,7615)	0,983105 (0,0000)	0,023435 (0,6762)	-0,129856 (0,0021)	-0,031389 (0,3898)	0,011464 (0,6673)
Q3 (12m)	0,1056 %	0,0736	-0,000583 (0,7822)	1,011205 (0,0000)	0,101403 (0,0835)	-0,140120 (0,0017)	-0,021677 (0,5726)	0,019079 (0,4876)
Q4 (12m)	0,0167 %	0,0688	-0,002080 (0,4127)	0,928646 (0,0000)	0,206166 (0,0060)	-0,130337 (0,0045)	-0,054703 (0,1885)	-0,015519 (0,6213)
Q1-Q4 (12m)	0,0848 %	0,0126	0,000610 (0,7346)	0,048399 (0,2915)	-0,014760 (0,8458)	0,024531 (0,4652)	0,036727 (0,1735)	0,014040 (0,5578)
Q1 (3m)	-0,0023 %	0,0737	-0,002226 (0,3488)	1,036401 (0,0000)	0,238069 (0,0005)	-0,187182 (0,0012)	0,005000 (0,9256)	0,007955 (0,8372)
Q2 (3m)	0,0493 %	0,0713	-0,001373 (0,4849)	0,973027 (0,0000)	0,089112 (0,0791)	-0,096347 (0,0200)	-0,041832 (0,2631)	0,013656 (0,6321)
Q3 (3m)	0,1585 %	0,0707	-0,000013 (0,9954)	0,976602 (0,0000)	0,058805 (0,3317)	-0,099074 (0,0060)	-0,019598 (0,5482)	-0,020205 (0,3809)
Q4 (3m)	0,0494 %	0,0703	-0,001244 (0,6310)	0,925219 (0,0000)	0,121392 (0,1033)	-0,123787 (0,0141)	-0,072026 (0,0941)	0,011636 (0,6870)
Q1-Q4 (3m)	-0,0517 %	0,0153	-0,000982 (0,6347)	0,111182 (0,0213)	0,116677 (0,1732)	-0,063396 (0,2415)	0,077026 (0,0681)	-0,003681 (0,8980)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 16: Five Factor regression (Sub period 2)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt	SMB	HML	RMW	CMA
EW all	-0,0568 %	0,0759	0,000642 (0,5850)	0,933642 (0,0000)	0,087552 (0,0706)	-0,054115 (0,1898)	-0,207909 (0,0001)	0,054175 (0,1076)
Q1 (12m)	-0,1073 %	0,0807	0,000145 (0,9155)	0,991062 (0,0000)	0,063572 (0,2510)	-0,062312 (0,2243)	-0,147827 (0,0054)	0,050135 (0,1439)
Q2 (12m)	0,0714 %	0,0766	0,002399 (0,1341)	0,925344 (0,0000)	0,046573 (0,3761)	-0,055139 (0,1491)	-0,213507 (0,0000)	0,099972 (0,0775)
Q3 (12m)	-0,0091 %	0,0757	0,001424 (0,2497)	0,922569 (0,0000)	0,040553 (0,3075)	-0,049038 (0,0607)	-0,171278 (0,0001)	0,039162 (0,2508)
Q4 (12m)	-0,1729 %	0,0718	-0,001276 (0,4856)	0,894498 (0,0000)	0,192795 (0,0066)	-0,048676 (0,4562)	-0,290880 (0,0011)	0,021421 (0,6793)
Q1-Q4 (12m)	0,0656 %	0,0165	0,001421 (0,4404)	0,096564 (0,0001)	-0,129223 (0,0093)	-0,013636 (0,7354)	0,143053 (0,0151)	0,028714 (0,5588)
Q1 (3m)	0,1536 %	0,0782	0,003290 (0,0743)	0,936635 (0,0000)	0,047942 (0,4436)	-0,079917 (0,1141)	-0,217706 (0,0002)	0,095155 (0,0510)
Q2 (3m)	-0,1216 %	0,0769	-0,000354 (0,7954)	0,960316 (0,0000)	0,089869 (0,1014)	-0,013219 (0,6879)	-0,161197 (0,0008)	0,091596 (0,0225)
Q3 (3m)	-0,0761 %	0,0760	0,000682 (0,6052)	0,925459 (0,0000)	0,051103 (0,3357)	-0,056773 (0,2021)	-0,176734 (0,0036)	0,048181 (0,2058)
Q4 (3m)	-0,1615 %	0,0738	-0,000734 (0,6955)	0,909623 (0,0000)	0,150424 (0,0116)	-0,062806 (0,2210)	-0,273163 (0,0010)	-0,020711 (0,6265)
Q1-Q4 (3m)	0,3152 %	0,0152	0,004024 (0,0942)	0,027012 (0,3505)	-0,102482 (0,1499)	-0,017111 (0,6769)	0,055457 (0,4373)	0,115865 (0,0387)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 17: Five Factor regression (Sub period 3)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt	SMB	HML	RMW	CMA
EW all	1,3745 %	0,0594	-0,001077 (0,4743)	1,044561 (0,0000)	0,148558 (0,0017)	-0,022199 (0,5936)	-0,144090 (0,0005)	-0,006333 (0,9112)
Q1 (12m)	1,3247 %	0,0602	-0,001010 (0,5102)	1,077712 (0,0000)	0,142222 (0,0021)	0,048807 (0,2676)	-0,108441 (0,0011)	-0,039010 (0,4358)
Q2 (12m)	1,3705 %	0,0605	-0,001489 (0,3125)	1,039154 (0,0000)	0,095005 (0,0502)	-0,032950 (0,4292)	-0,133143 (0,0010)	0,014733 (0,7735)
Q3 (12m)	1,4479 %	0,0607	-0,001107 (0,4438)	1,055323 (0,0000)	0,129092 (0,0042)	-0,065143 (0,0745)	-0,135225 (0,0007)	0,032313 (0,5420)
Q4 (12m)	1,3041 %	0,0575	-0,001421 (0,5141)	1,015043 (0,0000)	0,236993 (0,0005)	-0,050491 (0,4495)	-0,203784 (0,0022)	-0,030667 (0,7307)
Q1-Q4 (12m)	0,0206 %	0,0122	0,000411 (0,7465)	0,062669 (0,2195)	-0,094772 (0,0489)	0,099298 (0,0188)	0,095342 (0,0626)	-0,008343 (0,8824)
Q1 (3m)	1,3884 %	0,0604	-0,000948 (0,5560)	1,073993 (0,0000)	0,156600 (0,0007)	-0,003225 (0,9442)	-0,123344 (0,0020)	-0,008977 (0,8756)
Q2 (3m)	1,4054 %	0,0609	-0,001325 (0,3308)	1,051783 (0,0000)	0,090395 (0,0289)	-0,041111 (0,2470)	-0,122842 (0,0012)	0,008233 (0,8699)
Q3 (3m)	1,4560 %	0,0608	-0,000424 (0,8201)	1,041563 (0,0000)	0,121001 (0,0074)	-0,006089 (0,9003)	-0,165008 (0,0001)	0,000439 (0,9942)
Q4 (3m)	1,0788 %	0,0563	-0,003506 (0,0967)	1,001612 (0,0000)	0,225914 (0,0015)	-0,068273 (0,3330)	-0,181314 (0,0105)	-0,047289 (0,5933)
Q1-Q4 (3m)	0,3096 %	0,0129	0,002558 (0,0837)	0,072381 (0,1099)	-0,069315 (0,1137)	0,065048 (0,1759)	0,057970 (0,1790)	0,038312 (0,5250)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 18: Five Factor regression (Sub period 4)

Portfolio	Excess monthly return	Std Dev	Alpha	Mkt	SMB	HML	RMW	CMA
EW all	0,9457 %	0,0265	0,002368 (0,0395)	0,870491 (0,0000)	0,078647 (0,0530)	-0,042400 (0,1718)	-0,068757 (0,0044)	-0,038913 (0,1034)
Q1 (12m)	1,0820 %	0,0274	0,004347 (0,0059)	0,838490 (0,0000)	0,074796 (0,1495)	-0,024431 (0,5890)	-0,126066 (0,0007)	-0,033043 (0,3154)
Q2 (12m)	0,9066 %	0,0276	0,001422 (0,2181)	0,919176 (0,0000)	0,075030 (0,0578)	-0,049125 (0,1177)	-0,028557 (0,1809)	-0,036060 (0,1195)
Q3 (12m)	0,9174 %	0,0264	0,002170 (0,1045)	0,863435 (0,0000)	0,057415 (0,1982)	-0,042026 (0,1913)	-0,037555 (0,1531)	-0,029391 (0,2658)
Q4 (12m)	0,9138 %	0,0274	0,001651 (0,2867)	0,877819 (0,0000)	0,124594 (0,0279)	-0,051714 (0,1659)	-0,084222 (0,0111)	-0,057697 (0,0898)
Q1-Q4 (12m)	0,1683 %	0,0118	0,002696 (0,1208)	-0,039329 (0,4693)	-0,049797 (0,3407)	0,027283 (0,5348)	-0,041844 (0,2716)	0,024654 (0,5093)
Q1 (3m)	0,9401 %	0,0274	0,002541 (0,0880)	0,864132 (0,0000)	0,078531 (0,0967)	-0,050590 (0,2561)	-0,092261 (0,0064)	-0,036059 (0,1926)
Q2 (3m)	0,9415 %	0,0268	0,001872 (0,0850)	0,889232 (0,0000)	0,094979 (0,0080)	-0,019666 (0,4645)	-0,070883 (0,0010)	-0,060432 (0,0138)
Q3 (3m)	0,9111 %	0,0274	0,001896 (0,1790)	0,894967 (0,0000)	0,053113 (0,2895)	-0,060197 (0,0583)	-0,034537 (0,1370)	-0,032196 (0,2107)
Q4 (3m)	1,0223 %	0,0263	0,003413 (0,0296)	0,838495 (0,0000)	0,095800 (0,0784)	-0,034793 (0,3608)	-0,081801 (0,0096)	-0,026560 (0,4518)
Q1-Q4 (3m)	-0,0822 %	0,0104	-0,000872 (0,5923)	0,025636 (0,5877)	-0,017269 (0,7512)	-0,015797 (0,6892)	-0,010461 (0,7155)	-0,009499 (0,7899)

*p-values in parentheses

Table description:

Mutual funds are sorted in quartile portfolios every January from the year 2000 to 2016. Given the characteristics of the sorting procedure the resulting time series of returns reaches from January 2001 to June 2017. Monthly equally weighting of the portfolios adjusts the weights whenever a fund disappears. The *EW all* portfolio is an equally weighted portfolio of all sample funds active at some point during the sample period. The top quartile (*Q1*) consist of the top 25 % performing funds the year prior to their respective holding periods of twelve months (*12m*) or three months (*3m*). The bottom quartile (*Q4*) consist of the worst performing funds. The "*top minus bottom*" (Q1-Q4) portfolio is a long Q1 and short Q4 portfolio. *Alpha* is the models intercept describing the portfolios' risk adjusted abnormal returns. *Mkt* is the market proxy (in excess terms). *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. The coefficients' p-values are in parentheses, marked green for statistical significance at a five percent level.

Appendix 19: List of funds

Code	Name
LP60047156	ALFRED BERG AKTIV
LP60046598	ALFRED BERG GAMBAK
LP60075464	ALFRED BERG HUMANFOND
LP60047923	ALFRED BERG NORGE +
LP60075463	ALFRED BERG NORGE ETISK
LP60046778	ALFRED BERG NORGE (CLASSIC)
LP68225172	C WORLD WIDE AKSJE NORGE III
LP60047432	C WORLD WIDE NORGE
LP60047368	DNB NOR KAPFORV. POSTBANKEN NORGE
LP65011608	DNB NOR KAPFORV.AVANSE NORGE II
LP65011629	DNB NOR KAPFORV.NORGE IV
LP65011630	DNB NORGE SELEKTIV (I)
LP60055273	DNB NOR KAPFORV.SMB
LP60047365	DANSKE INVEST NORGE I
LP60047228	DANSKE INVEST NORGE VEKST
LP60049111	DANSKE INVEST NORSKE AKSJER INSTITUSJON I
LP60047216	DELPHI FONDENE NORGE
LP60047933	STOREBRAND INT INV.FUND DELPHI VEKST
LP65011735	EIKA NORGE
LP60048422	EIKA SPAR
LP60048153	EIKA VEKST
LP68078038	FIRST GENERATOR S
LP68170072	FORTE NORGE
LP68207615	FORTE TRONDER
LP65011649	FONDSFINANS NORGE
LP68306329	HANDELSBANKEN NORGE (SEK)
LP60053436	HOLBERG NORGE
LP60048419	KLP AKSJE NORGE
LP65032717	LANDKREDITT NORGE
LP68203117	LANDKREDITT UTBYTTE
LP60047725	NB AKSJEFOND
LP65011690	NORDEA AVKASTNING
LP60047346	NORDEA KAPITAL
LP68148877	NORDEA NORGE PLUSS
LP60047582	NORDEA NORGE VERDI
LP60047754	NORDEA SMB
LP60047192	NORDEA VEKST
LP60046982	ODIN NORGE C
LP68063151	ODIN NORGE II
LP60047698	PLUSS AKSJE
LP60047376	PLUSS MARKEDSVERDI
LP65011706	PARETO AKSJE NORGE A
LP60046600	PARETO INVESTMENT FUND A
LP68352409	SBANKEN FRAMGANG SAMMEN
LP60047656	STOREBRAND INT INV.FUND AKSJE INNLAND
LP68416113	STOREBRAND GL MULTIFAKTOR VALUTASIKRET
LP60046592	STOREBRAND INTL.INV.FD. NORGE
LP65011597	STOREBRAND INT INV.FUND NORGE I
LP68086637	STOREBRAND INTL.INV. FUND NORGE I
LP66057273	STOREBRAND NORGE PLUSS
LP65011714	STOREBRAND INT INV.FUND OPTIMA NORGE A
LP60047822	STOREBRAND INTL.INV.FD. VEKST
LP60047964	STOREBRAND VERDI A
LP60048152	TERRA NORGE
LP60048050	VERDIPAPIRFONDET VIBRAND NORDEN

Table description:

The table contains every 55 funds selected to be a part of the sample according to the sorting procedures described in section *6.1*.

Appendix 20: Factor mimicking portfolios – Descriptive statistics for sub periods

	SMB	HML	RMW	CMA
Panel A				
Sub period 1				
Mean	0,70 %	0,91 %	-0,01 %	0,11 %
std dev	3,08 %	5,03 %	7,27 %	6,70 %
t-stat	1,57	1,26	-0,01	0,11
Panel B				
Sub period 2				
Mean	1,12 %	0,20 %	0,56 %	0,02 %
std dev	4,20 %	4,45 %	3,04 %	3,68 %
t-stat	1,85	0,31	1,28	0,04
Panel C				
Sub period 3				
Mean	-0,65 %	-0,97 %	-0,74 %	0,36 %
std dev	4,47 %	3,22 %	4,56 %	3,07 %
t-stat	-1,01	-2,08	-1,13	0,81
Panel D				
Sub period 4				
Mean	0,69 %	0,23 %	0,59 %	-0,72 %
std dev	2,96 %	3,56 %	4,44 %	4,39 %
t-stat	1,72	0,48	0,98	-1,21

Table description:

Descriptive statistics of monthly factor returns for the sub periods as described in section 6.2. Panel A, B and C contains 48 months of observations. Panel D contains 54 months of observations. *SMB*, *HML*, *RMW* and *CMA* are the Fama and French's factor mimicking portfolios for size, book-to-market equity, profitability and investments respectively. SMB and HML is provided by Ødegaard's public library. The profitability factor and investment factor are created with a 2x3 sort, first sorted on size, then on the respective factor. The operating profitability and investment groups are divided into robust/neutral/weak and conservative/neutral/aggressive for investment respectively, using 30% and 70% quantile breakpoints. RMW and CMA are calculated as the difference between the average return between the two robust and weak operating profitability portfolios, and the conservative and aggressive investment portfolios respectively. Mean and standard deviation is in percentage.

Appendix 21: Descriptive statistics for factor building blocks

Panel A				
RMW				
	Small Robust	Small Weak	Big Robust	Big Weak
Mean	0,24 %	0,47 %	0,28 %	-0,19 %
std dev	5,00 %	9,44 %	5,79 %	7,73 %
t-stat	0,67	0,70	0,67	-0,34
Panel B				
CMA				
	Small Conservative	Small Aggresive	Big Conservative	Big Aggresive
Mean	-0,31 %	0,31 %	0,50 %	0,04 %
std dev	7,86 %	6,81 %	7,24 %	7,47 %
t-stat	-0,55	0,63	0,97	0,08

Table description:

Descriptive statistics for the factor building blocks for the sample period as described in section 6.2. Stocks are sorted with a 2x3 sort, first sorted on size, then on the respective factor. The operating profitability and investment groups are divided into robust/neutral/weak and conservative/neutral/aggressive for investment respectively, using 30% and 70% quantile breakpoints. This produces two sets of three portfolios. This is the factor building blocks. The small robust/weak and big robust/weak portfolios for the RMW are displayed in Panel A. The small conservative/aggressive and big conservative/aggressive portfolios for the CMA are displayed in Panel B. RMW is the profitability factor and CMA are the investment factor. Mean and standard deviation is in percentage.