BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science

A Time-varying Performance Analysis of Norwegian Mutual Funds

Start: 02.03.2017 09.00

Finish: 01.09.2017 12.00

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Study programme: MSc in Business with major in Finance

Submission date: August 31, 2017

Abstract

We wish to enrichen the debate on whether actively managed mutual funds can earn excess returns to justify the fees carried by their investors. An important question to answer is whether mutual funds are able to earn excess returns net of fees, especially during the down markets, when we reckon it matters the most for their investors. We investigate Norwegian mutual fund's performance by employing Carhart's (1997) four-factor model and running bootstrap simulations similar to that of Kosowski et al. (2006) and Fama and French (2010). To investigate how performance relates to changing market conditions, we evaluate performance on both the entire sample period, as well as sub-samples representing bear- and bull markets. Persistence in performance is evaluated by employing Carhart's (1997) portfolio formation approach. Our findings indicate that some Norwegian mutual funds are skilled enough to generate abnormal returns net of fees for their investors. However, we find no evidence of performance persistence, suggesting that Norwegian markets are somewhat efficient.

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1.0 Introduction

The purpose of our study is firstly to investigate whether some actively managed mutual funds in Norway are able to earn abnormal returns, i.e. earn returns net of costs that are in excess of the returns expected by the financial theory. If so, is the performance due to fund managers' skill or luck? We define managerial skill in the same way as Kacperczyk et al. (2014); "as a general cognitive ability to either pick stocks or time the market at different times". Secondly, we consider the time-variability and investigate performance persistence regardless of changing market conditions. Lastly, we investigate whether the recorded performance persists. An important question to answer is whether mutual funds are able to earn excess returns net of fees for their investors, regardless of the fluctuations in market conditions. We argue that the "investors' marginal utility of wealth is high" (Kosowski, 2011) during bear-markets, as mentioned by Kosowski (2011) with regard to times of recessions.

Mutual fund performance has been extensively examined, and been the source of an academic debate throughout the years. Much of the previous research on this topic has shown vague and diverging results on whether mutual funds can in fact beat the market. The Norwegian mutual fund industry has so far only been extensively examined by few researchers (i.a. Sørensen, 2009; Gallefoss et al., 2015) and still remains an interesting field of study. From the investors perspective, the practical importance of this topic is that the fees carried have to be justified, while from the academic perspective the efficient market hypothesis is tested.

Based on previous research, we take what we assess to be the conservative approach, in favour of the efficient market hypothesis:

Actively managed mutual funds do not hold the relevant skills to outperform the market, regardless of the changing market conditions.

In this paper, we use a sample of 58 actively managed Norwegian mutual funds that is free from survivorship bias, covering the period from December 2002 to December 2016. We also divide the time period into bull and bear markets to see how the performance of funds changes during different economic conditions. When studying the performance of Norwegian mutual funds several measures are used. In order to see whether fund managers are able to generate abnormal returns we utilize the models of Jensen (1968) and Carhart (1997) and compare the results of the two models. All further research is conducted using Carhart's four-factor model, as we consider it more comprehensive. Because several studies (e.g. Berk and Van Binsbergen, 2015) emphasize that alpha alone cannot be considered as a measure of skill, we attempt to differentiate between skill and luck by employing a bootstrap procedure. Next, we examine whether performance persists over time and confirm the validity of our results with a bootstrap procedure mentioned earlier. Persistence in performance has an important academic implication as its existence would suggest that past performance is a good indicator of future performance, denying the efficient market hypothesis. This, in turn, would enable the investors to capitalize on past performance, which is an important practical implication.

Our results show that on average Norwegian mutual funds earn a positive alpha of 0,03% using the four-factor model, however not significant. When examining the funds separately over the whole sample period, we find that the best performing fund generates a monthly alpha of 1,53% that is statistically significant at 1% level. The worst performing fund shows a negative monthly alpha of -0,45%, indicating that it underperforms the market. Interestingly, the bear market period that captures the recent financial crisis shows that the best performing fund delivers a monthly alpha of 1,95%. This is the highest alpha among all sub-periods and also in the entire sample period. Moreover, our bootstrap simulations also reveal that during the bear market, the superior skills of fund managers become more prominent. This answers an important question raised by Kosowski (2011) whether mutual funds can deliver good performance when it matters the most to investors. Our bootstrap results for the entire sample period also indicate that superior (inferior) performance is attributed to good (poor) managerial skills. Despite this, we find no evidence of performance persistence among the top and bottom quintiles of funds. Furthermore, we find that momentum strategy generates a statistically significant negative alpha that persists over time. These results are in line with the findings of Sørensen (2009), but contradict the results of Gallefoss et al. (2015) who found short-term persistence.

The rest of the paper is structured as follows. Section 2 presents previous literature on mutual fund performance. Section 3 presents the data used in the analysis along with the benchmark and other factors. In section 4 we present detailed methodology and in section 5 we discuss the results followed by conclusion of the paper.

2.0 Theory and literature review

Section 2.1 presents classical performance evaluation measures that compare return relative to a benchmark as well as the studies associated with them. Section 2.2 expands the research by looking at more complex models that account for market timing and stock selectivity. In addition, it presents the studies on performance persistence among the funds. Finally, section 2.3 presents the research on the fund performance from Norway.

One of the important questions is whether the actively managed funds outperform the passive funds that track the market portfolio, consequentially giving rise to the question on whether they can justify the extra costs carried by their investors. According to the efficient markets hypothesis, on average, the pursuit to beat the market should be a zero sum game, as current prices reflect all available information; hence outperforming the market would be a matter of luck, or chance, rather than skill. The efficient markets and much of the prevailing financial theory does not support the idea that actively managed funds possess the skills necessary to outperform the market. Persistence in the performance by mutual funds provides us with information on whether the fund managers really possess these skills or not, but previous literature is inconsistent and the findings diverge.

2.1 Mutual fund performance evaluation

Building on Markowitz' (1952) portfolio theory, Sharpe (1964), Treynor (1962), Lintner (1965) and Mossin (1966) derived the Capital Asset Pricing Model (CAPM) that determines a linear relationship between a security's systematic risk and expected return. One of the first extensions to CAPM was Jensen's alpha developed by Jensen (1968), which is today one of the most general and widely used tools for evaluating fund managers' performance. Jensen (1968) found that mutual funds were on average unable to generate excess returns net of expenses. One major drawback of this model is the fact that, alike CAPM, it assumes the existence of the market portfolio, which is problematic to find in the real world. In contrast to

Jensen's results, Ippolito (1989) who also utilized Jensen's alpha as performance measure, found that actively managed US mutual funds outperformed the passive benchmarks net of the charged fees. Elton et al. (1993) found that the results of Ippolito (1989) were misrepresentative due to the wrong choice of the benchmark. After utilizing the correct benchmark, the authors found Jensen's alpha to be negative.

Shiller (1981) spiked the fire in the academic debate when he found that markets were too volatile than what could be reflected by the fundamentals – the financial theory. Marsh and Merton (1986) dismissed Shiller's findings on methodological grounds, defending the position of the financial theory. The contradictory results in academic literature even manifested themselves in the actions of Nobel Prize winner Robert Merton. He was later a co-founding partner in several actively managed hedge funds, seeking to take advantage of the same market inefficiencies that, according to his own arguments, did not exist. The Long-Term Capital Management hedge fund that he co-founded, together with Nobel Prize Winner Myron Scholes, later went bust and blew up when the identified mispricing persisted for longer than LTCM stayed solvent. This was later called a black swan event according to Taleb (2007, p. 62).

The widely used market proxies such as S&P 500 Index do not represent the true composition of the market portfolio as they exclude many of the risky assets, e.g. a variety of domestic and foreign stocks and bonds, real estate etc. (Reilly and Brown, 2011). This issue is referred to as a benchmark error, which was highlighted by Roll (1977) in his critique of the CAPM model. Several other studies underscore the importance of using the appropriate benchmark when evaluating performance. Lehmann and Modest (1987) concluded in their performance analysis of 130 US mutual funds that performance measures such as Jensen's alpha are highly sensitive to the chosen benchmark. Malkiel (1995) investigated performance of US mutual funds in the 1971-1991 period and concluded that on average mutual funds tended to underperformed relative to the market. However, the author demonstrated that the choice of benchmark was significantly influencing the results. This eventually led to the emergence of more complex models that sought to provide a better explanation of security returns.

In an attempt to extend the model of Jensen (1968), Fama and French (1993) proposed a Three Factor Model. The authors found that small-cap stocks outperformed the large-cap stocks and that value stocks outperformed the growth stocks. Consequently, in addition to market risk, Fama and French included two more factors that improve the explanatory power of the model, namely SMB (Small Minus Big) and HML (High Minus Low). The authors suggest that the Three Factor Model explains over 90% of the portfolio returns. Fama and French later expanded their model into a Five Factor model in 2015, including a profitability- and an investment pattern factors, arguing that the HML factor becomes redundant after accounting for the new factors. Including more variables in the model might also reduce the risk of artificially inflating the alpha value due to omitted variable bias.

Carhart (1997) extended the original model of Fama and French (1993) by accounting for the momentum effect, which was first documented by Jegadeesh and Titman (1993). The model became known as a Four Factor Model, where the additional one-year momentum factor measures the excess return of buying last year’s winners and selling last year’s losers. Carhart examined US mutual funds over the 1962-1993 period and found no support for the existence of managerial skill. He attributed excess returns of mutual funds to luck rather than the ability of employing momentum strategies. The author concludes that excess returns of some individual funds that do appear to follow momentum strategies are offset by the investment expenses.

Thus far, the research presented above is leaning towards underperformance of mutual funds, on average; and nonexistence of managerial skill, although it has not been able to fully answer this question. Nevertheless, the underperformance cannot explain the recent growth of actively managed mutual funds. Gruber (1996) and Zheng (1999) attempted to explain this puzzle by indicating that mutual fund investors can in fact pick superior funds to invest into. This raises the question if more extensive research and complex models can perhaps measure managerial skill.

2.2 Market timing, selectivity and persistence

Traditionally, a manager’s stock selection and market timing abilities are evaluated separately. Stock selection refers to the ability to pick the stocks that a manager considers “undervalued” at the current market prices. Such stocks might therefore offer profit at some future point of time. Market timing refers to the ability of switching between the two asset classes, namely stocks and bonds, depending on the manager’s belief about their performance in the near future. One of the first models to account for market timing and stock selection measures was proposed by Treynor and Mazuy (1966). Their findings suggest that the excess return that certain funds are able to generate comes from the fund managers’ capability of selecting underpriced stocks rather than timing the turns on the market. However, their model is based on Jensen’s alpha meaning that it suffers from the same limitations as the CAPM model. Similarly, Daniel et al. (1997) tested for stock selection and market timing abilities among fund managers and found that some funds showed stock picking abilities, while market timing ability was not confirmed. However, this outperformance was very close to the charged fees and therefore not much value was generated for the investors. On the contrary, Edelen (1999) documented that mutual funds underperform on average, but attributed it to the liquidity service that fund managers provide to investors rather than the lack of managerial skill. One of the recent studies on selectivity and market timing was carried out by Kacperczyk et al. (2014) who used unique methods for capturing fund manager skill. They found both market timing and stock selection abilities among fund managers and most importantly concluded that those managers who exhibit stock picking abilities are also able to time the market well.

Several other studies have documented that a number of actively managed funds are capable of generating abnormal returns (Gruber, 1996; Wermers, 2000). Despite the extensive research on the topic, it remains unclear if the ability to beat the market can simply be attributed to luck or if the fund managers indeed have market timing and stock selection skills. One way to differentiate between luck and skill is to examine whether superior performance of active funds persists over time. Performance persistence of mutual funds has been the subject of much empirical research as an attempt to study whether active management in fact pays off.

One of the early studies on performance persistence of mutual funds was done by Sharpe (1966) who ranked mutual funds in terms of their Sharpe ratios over the periods 1944-1953 and 1954-1963. He found a significant positive correlation between the two periods and concluded that mutual fund performance persistence might exist. Carlson (1970) examined equity mutual funds over the period of 1948-1967. The author found partial persistence within 5 years of fund returns, but no persistence over a longer period of 10 years. In the later studies, Grinblatt and Titman (1992) investigated 279 US equity funds in the 1975-1984 period using 8 portfolio benchmarks. Their evaluation periods consisted of 5 years and the authors found evidence of persistence for the following 5-year period. Building on their previous work Grinblatt and Titman (1993) studied CRSP listed quarterly holdings of mutual fund portfolios and found performance persistence. The authors demonstrated that funds that showed superior performance in the first half of the sample period were the ones that performed well in the second half, suggesting that superior performance could be predicted to some extent. Further studies also found that performance persists in the short run and that past performance could be an indicator of the future performance. (Goetzmann and Ibbotson, 1994; Brown and Goetzmann, 1995; Elton et al., 1996) However, as outlined by Malkiel (1995), the early studies might suffer from the survivorship bias which should be taken into account.

Hendricks et al. (1993) studied quarterly returns of 165 survivorship bias-free US equity funds over the 1974-1988 period and found short-term persistence (up to one year) driven by the "hot hands" phenomenon. This indicates that funds that outperformed the market in the past four quarters also performed well in the next four quarters. Furthermore, the authors showed that funds that performed poorly continued to be inferior in the following period, which is also known as the "icy hands" performance persistence. On the contrary, Carhart (1997) and Wermers (1997) argued that the "hot hands" result is explained by the one-year momentum effect of Jegadeesh and Titman (1993). Specifically, Wermers (1997) found that mutual funds actively practice momentum investment strategies and concluded that no persistence remained after controlling for the momentum effect.

Most of the previous studies focused on exploring long-term performance persistence in mutual funds and documented different results. One potential explanation for this might be the use of different methodologies[1]. Bollen and Busse (2005) examined 230 US mutual funds over the 1985-1995 period using daily data

[1] Specifically, these studies differ with respect to the time horizons, ranking measures and evaluation measures used.

and concluded that superior performance persistence exists, but is a short-lived phenomenon. Interestingly, when the authors adjusted their methodology to the one used by Carhart (1997) they found that performance persistence disappeared.

Kosowski et al. (2006) applied a bootstrap procedure to evaluate the performance of US mutual funds between the 1975 and 2002 period. The authors found evidence of superior performance net of fees and persistence among growth-oriented funds, which they concluded could not be explained solely by sampling variability, i.e. luck. Kosowski et al. (2006) also highlighted the importance of using the bootstrap approach when ranking mutual funds in order to eliminate the ex post sort problems. Similarly, Huij and Verbeek (2007) utilized an empirical Bayesian approach and found short-term performance persistence among top funds with the use of monthly data. In contrast, Cuthbertson et al. (2008) in an attempt to distinguish between skill and luck for UK mutual funds found little evidence of stock-picking abilities and attributed abnormal returns of the funds to “good luck”. The authors found no persistence among past-winner funds, while past-loser funds appeared to persist.

Although several studies have shown that active mutual funds can indeed deliver returns to their investors, it might not be the only explanation to why investors favor active management. Another explanation might be that the actively managed mutual funds provide better returns when investors need them the most, i.e. during the times of economic downturns. The next section takes a deeper look at the mutual fund studies performed on the Norwegian market.

2.3 Norwegian studies

Most studies on mutual fund performance is done in the US, and the existing literature on fund performance in Norway is highly limited. Gjerde and Sættem (1991) is the first ones to study Norwegian mutual fund performance, to our knowledge. Using a sample of 14 Norwegian mutual funds during the period of 1982-1990, they found outperformance in the period of 1982-1984, and that managers possessed market timing abilities. However, they found no evidence of managerial stock picking abilities.

Sørensen (2009) used a survivorship bias free sample when investigating the performance and persistence of Norwegian mutual funds. By employing the bootstrap simulation method proposed by Fama and French (2010), he found no evidence of persistence in performance. Contradictory to the results of Sørensen, Gallefoss et al. (2015) finds opposite results using daily data, in contrast to a sample of monthly data as used by the two previously mentioned studies on Norwegian funds. Gallefoss et al. (2015) is, to our knowledge, the first study outside of the US that use daily data, they find evidence of managerial skill, where top performers are better at both stock picking and market timing than bottom performers, and the performance persists for short time horizons of up to one year.

3.0 Data

3.1 Mutual Fund data

Fund data from 123 Norwegian registered mutual funds from the time-period of January 1990 up to December 2016, was collected from Morningstar's database. As of today, June 2017, there exists 63 Norwegian registered mutual funds, according to Morningstar[2].

To build a robust and more reliable sample, we exclude all funds with less than 25 observations. The sample contains 58 open-end Norwegian equity mutual funds, funds that primarily invest (at least 80% of their total assets) in Norwegian equities, with the time spanning from December 2002 until December 2016. The sample consists of both currently operating funds, as well as discontinued (dead) funds. Hence, we avoid the problem of survivorship bias, known as biasing the results upwards when excluding liquidated funds from the sample.

The data consists of fund returns, total net assets (TNAs), fund holdings and management fees. All data in our sample is at a monthly frequency. Additionally, we were also able to obtain manager history in order to evaluate how a particular fund's performance relates to the change of managers.

Fund returns downloaded from Morningstar are calculated based on the net asset values (NAV), equal to the respective funds total net assets divided by the number of outstanding shares, and is net of management fees and other administrative costs.

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[2] www.morningstar.no/no/fundquickrank/default.aspx

The monthly fund returns are defined as the change in NAV between time t and t-1 divided by the starting NAV (time t-1).

The TNA observations contained gaps. As the funds with some missing TNA values reported returns in the time-period, we created an implied TNA-value in order to fill in the gaps, by the following formulas:

1) $$TNA_{i,t+1} = TNA_{i,t}\left(1 + r_{i,t+1}\right)$$

2) $$TNA_{i,t-1} = \frac{TNA_{i,t}}{(1+r_{i,t+1})}$$

These formulas give us the implied TNAs for the next/previous period, however, we stress the fact that estimation errors might occur given that the returns will not fully capture the fund's net flows. The gaps with missing TNA values were only missing for a time-period of maximum two months; hence, we assume that the effect of estimation errors by the implied TNAs are limited.

Management fees are reported annually from Morningstar. Since we need monthly data, we transform the fees from annual to monthly by the following formula:

3) $$Management\ Fee_{monthly} = e^{fee_{annual}\frac{1}{12}} - 1$$

The observations of fees also contain gaps for some funds. Most funds have reported the fees as constant. For the funds with gaps in fee observations, we compare the management fees to the ones reported by the Norwegian mutual funds' association (VFF)[3]. If the fees reported there had changed, we create an average between the last reported fee by Morningstar and the last reported fee by VFF, given that the fund was still alive at the time of the missing fee observation.

3.3 Risk free rate

In order to carry out the analysis we need an estimate for the risk free rate of return. Much of the literature uses Treasury bills as a proxy for the risk free rate, however, Norwegian T-bills are considered less liquid due to the size of the market. Ødegaard (2017) suggests that the Norwegian Inter Bank Offered Rate (NIBOR) is more

[3] Verdipapirfondenes Forening: http://vff.no/fondsdata

suitable for a proxy of the risk free rate. Hence, we use a de-annualized one-month NIBOR rate obtained from Norges Bank for the period of December 2002 to November 2013, as the central bank stops reporting NIBOR after this date. The NIBOR for the remaining sample period was collected from Oslo Stock Exchange.

3.3 Market conditions

In order to perform the time-varying analysis on the data we need to define market conditions in Norway over the sample period. Much of the research done on time-varying performance has utilized the business cycles for defining the up- and down movements on the market. For instance, NBER provides official business cycles expansions and contractions on the U.S. market. Norwegian market, however, differs from the American, making it difficult to define the business cycles. We will therefore focus on the bull and bear markets instead. The bull market is defined as a point on the through of the OSEFX where the prices begin to increase until they reach the peak, while the bear market is defined as a point on the peak where the prices begin to fall until they reach the through.

3.4 Benchmark

Choosing an appropriate benchmark is an important part of the analysis as it should reflect the investment universe of the funds. This is essential to avoid biased results. The Norwegian equity mutual funds are required by law to invest in at least 16 different securities, where the weight of each company cannot exceed 10%. OSEFX is designed in compliance with the UCITS directives for regulating investments in mutual funds, which states that the maximum weight of an individual security is 10% and securities that exceed 5% must not combined exceed 40%. Therefore, we judge OSEFX to be the most suitable benchmark for our analysis as it meets the requirements for the Norwegian mutual funds. From the Bloomberg database we obtain the historical prices of OSEFX along with its holdings and prices of the securities traded. Table 1 depicts descriptive statistics of monthly returns on the OSEFX benchmark and equally-weighted portfolios of all funds and funds that have been liquidated. Panel A shows results for the entire sample period. We see that the equally weighted portfolio of all 58 funds tends to outperform the benchmark with an average monthly return of 1.28% and a standard deviation of 5.89%. We see that all returns are negatively skewed, indicating a greater chance to incur larger losses.

We also observe excess kurtosis, suggesting a high volatility of returns. During the first bull market period (Panel B) the all funds portfolio shows superior performance, while the funds that will be liquidated lag far behind, even before the bear market takes place. Panel C reflects the financial crisis, although the mean returns are negative, all funds portfolio seems to have slightly smaller losses. Here we also see that the standard deviation has more than doubled, indicating a larger degree of risk. In the post-crisis period (Panel D) the all funds portfolio once again outperforms the benchmark. The funds that will be liquidated show the worst performance and it is also during this period that most of them are liquidated or merged. We also observe a reversion in skewness from negative to positive.

Table 1: Summary statistics for mutual funds and benchmark returns.

Panel A: Entire sample 2002m12-2016m12						
	Mean	St.dev	Min	Max	Skewness	Kurtosis
OSEFX	1.2040	6.2812	-27.1660	16.5207	-1.2154	7.2311
EW(All)	1.2766	5.8902	-25.5864	15.7174	-1.0459	6.2890
EW(Dead)	1.0754	6.0823	-25.0690	15.3357	-0.9831	5.9761
Panel B: Sample period 2002m12-2008m4						
	Mean	St.dev	Min	Max	Skewness	Kurtosis
OSEFX	2.0546	6.0110	-20.2212	14.2375	-0.8549	4.5409
EW(All)	2.1126	5.8752	-17.7466	13.0747	-0.7179	3.6963
EW(Dead)	0.9574	5.9362	-17.8118	13.3435	-0.7287	3.7943
Panel C: Sample period 2008m5-2009m2						
	Mean	St.dev	Min	Max	Skewness	Kurtosis
OSEFX	-5.6998	13.0750	-27.1660	5.8629	-0.6144	2.2865
EW(All)	-5.0497	11.4645	-25.5864	6.0293	-0.6341	2.3382
EW(Dead)	-6.6994	9.8508	-25.0690	6.1254	-0.8749	2.9368
Panel D: Sample period 2009m3-2016m12						
	Mean	St.dev	Min	Max	Skewness	Kurtosis
OSEFX	1.3321	4.9539	-11.0974	16.5207	0.1149	3.8443
EW(All)	1.3501	4.6578	-10.4255	15.7174	0.0514	4.1208
EW(Dead)	1.1772	4.8586	-10.7659	15.3357	0.0584	4.0917

Table 1: This table shows mean, standard deviation, max and min values, skewness and kurtosis for the mutual funds and benchmark (OSEFX) returns over the different market conditions (Panels A-D). EW(All) represents an equally weighted portfolio comprising 58 funds. EW(Dead) represents the funds that have been liquidated. All numbers are calculated on a monthly basis and reported in percent, except for skewness and kurtosis.

3.5 Potential biases

Survivorship bias occurs when funds that have been liquidated or merged with another entity are excluded from the sample. Previous literature argues that it is important to include both surviving and non-surviving funds when selecting the sample to avoid biasing the performance results upward (Malkiel, 1995; Elton et al., 1996b). This is illustrated in Figure 1 where the portfolio of dead funds has lower returns than the portfolio of all funds, indicating that the problem of survivorship bias would arise if the liquidated funds were excluded from the sample. Our funds data consists of both currently operating and liquidated funds, hence, survivorship bias is not a problem.

A look-ahead bias can arise when the analysis is conducted using the data that would not have been available during the timeframe of the analysis. This bias typically occurs in historical studies, leading to inaccurate results. Therefore, we make sure to include only the information that has been available during the period being analysed.

Another potential bias associated with our study comes from the usage of factor models. When using the factor models for performance analysis we assume the factors to be alternative (passive) investment opportunities. However, Berk and Van Binsbergen (2015) argue that such assumption is only valid when the factors are tradable portfolios. Taking this argument into account, we recognize that the factors used in our analysis are non-tradable and the transaction costs could therefore potentially lower the abnormal returns further.

Figure 1: Cumulative returns of funds and the benchmark

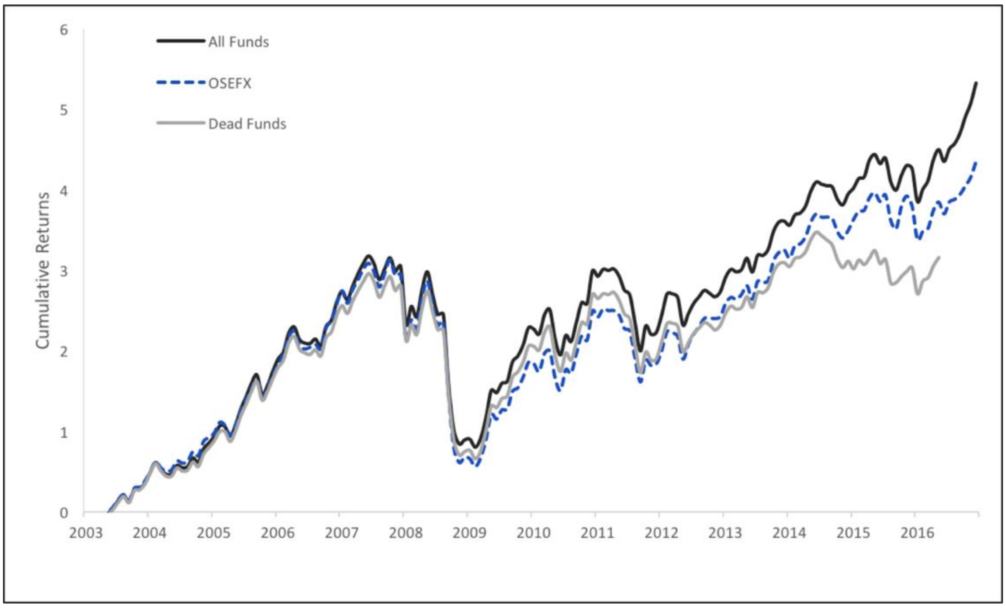

Figure 1: The graph illustrates cumulative returns on the equally weighted portfolio comprising all available funds, funds that have been liquidated and the OSEFX benchmark.

4.0 Methodology

Because our study is threefold, we present our methodology in the following way. We start our research by investigating whether fund managers are actually able to beat the market, i.e. deliver abnormal return measured as the net alpha. Even though the net alpha is commonly used as a measure of skill (Berk and Van Binsbergen, 2015), we adapt different methodologies to separate skill from luck when identifying abnormal returns.

4.1 Fund performance: Factor Models

In this sub-section, we establish which of the various factor models will be used to evaluate the performance of Norwegian mutual funds. Whether a fund over- or underperforms is determined by the respective fund's alphas, and whether they are positive or negative and statistically significant.

4.1.1 Jensens's alpha

One of the cornerstones in today's finance is the CAPM, developed by Sharpe (1964), Treynor (1962), Lintner (1965) and Mossin (1966). Jensen (1968) proposed an extension to the CAPM, where he regressed the return of fund *i* net of the risk free rate, upon the single factor of the market return exceeding the risk free rate, as presented below:

4) $$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \varepsilon_{i,t}$$

Where $R_{i,t}$ represents the expected return of fund *i* at time *t*, $R_{f,t}$ is the risk free rate, $R_{m,t}$ represents the market return and $\beta_{i,m}$ is the markets systematic risk factor, $\varepsilon_{i,t}$ is the unsystematic, idiosyncratic, risk which is assumed to be diversified away towards zero. According to Jensen (1968), a fund's performance is measured by a significant non-zero alpha. A significantly positive alpha would represent abnormal performance, in favour of fund manager skill, and vice versa for a significantly negative alpha.

4.1.2 Carhart's alpha

As we have mentioned previously, at least some of the assumptions that CAPM relies on are unrealistic in the real world. Jensen's simple extension of the model was later expanded into multifactor models, in order to account for various anomalies observed in the market that could predict deviations from the expected returns consistent with the CAPM.

Fama and French (1993) added two additional variables to Jensen's single factor model: HML and SMB, which is the factor of high minus low book-to-market ratio (HML), and small minus big (SMB). These factors account for the size- and the book-to-market anomalies, which have been observed to be good return predictors, but are inconsistent with the return levels of the CAPM.

Carhart's (1997) four-factor model is a further extension of Fama and French's three factor model. He introduced one additional factor that captured the momentum anomaly, that good- or bad performance continued the following periods. Carhart's four factor model is specified below:

5) $$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \varepsilon_{i,t}$$

Where the first part of the model is the same as for Jensen's alpha, the MKT variable is the excess market return, SMB and HML factors are the contributions from Fama and French (1993) for the size- and book-to-market returns, while the MOM factor is the Carhart's additional factor that accounts for the momentum. The alpha-interpretation is the same as for Jensen's alpha, as a predictor of fund performance when the alpha is statistically significant and different from zero.

We will mainly focus on this multifactor model in our research. We account for the changing market conditions by running the multifactor model on the entire sample, as well as the different sub-samples representing the changing market conditions from a bull market, to a bear market, and back to the bull market again.

4.2 Luck vs. Skill

In this section we further investigate whether fund performance is due to managerial skill or luck.

4.2.1 Bootstrapping

Returns data is not normally distributed, and is therefore hard to reconcile with the conventional ordinary least squares approach, as it relies on assumptions of normality. The bootstrap procedure proposed by Kosowski (2006) is a suiting approach to disentangle skill from luck, because it does not rely on any normality assumption. The bootstrapping simulations assume that the future returns (or in this case residuals) will be drawn from the same distribution as the historical observations (McDonald, 2013, 806). This approach will create a cross-sectional distribution of mutual fund alphas, enabling us to evaluate the managerial skill when comparing the simulated alphas to each fund's true alpha estimate. Furthermore, we assess the bootstrapping to be especially appropriate to the Norwegian market, because of its importance when having a small number of funds, and/or when having a sample of funds with short life spans (Kosowski et al, 2006; Sørensen, 2009), as is the case in our study.

Some of the recent studies employing the bootstrap procedure (Sørensen, 2009; Gallefoss et al, 2015; and others) are employing the modifications made by Fama and French (2010) to Kosowski et al's (2006) bootstrapping procedure. This involves jointly sampling of fund- and explanatory returns, rather than running simulations on each fund independently. Because the population of Norwegian mutual funds are so scarce, we have a very small sample of mutual funds, compared to that of Kosowski et al. (2006), Fama and French (2010) and even the Norwegian studies of Sørensen (2009) and Gallefoss et al. (2015). In comparison to our sample, the sample of Sørensen included the entire history of monthly returns on Norwegian mutual funds, and even though Gallefoss et al. (2015) has a time span of only 11 years, they are working on daily data, providing them with a much bigger set of observations than that of ours. Therefore, we choose to focus on Kosowski et al's (2006) bootstrapping procedure, and not adopt the modifications made by Fama and French (2010).

Implementation

The main model of our research is Carhart's four-factor model (5), and will be used to obtain the OLS estimated alphas, the respective factor coefficients and residuals. Each respective fund *i*'s coefficient estimates ($\hat{\alpha}_i, \widehat{\beta}_{i,MKT}, \hat{\beta}_{i,SMB}, \hat{\beta}_{i,HML}, \hat{\beta}_{i,MOM}$), the time series of the residuals ($\hat{\varepsilon}_{i,t}$, t=1,…,T), where t=1 to T represents the first and the last observation of fund *i*'s monthly returns, and the alpha t-statistic ($\hat{t}_{\hat{\alpha}_i}$) is then saved.

By drawing a random sample of fund *i*'s residuals, with replacement, we build a fictitious time-series of resampled residuals ($\hat{\varepsilon}_{i,t}^{b}, t = 1, \dots, T$), Where *b* denotes the bootstrap number. Each simulation run equals the numbers of monthly returns for each fund respectively. This produces a random vector of time-points, with replacement, from the historical distribution of fund *i*'s residuals (Kosowski et al. 2006; Sørensen,2009), with equal length as the vector of initial residuals.

A time series of artificial monthly excess returns (6) are constructed by using the random sample of fund residuals, as well as the saved coefficient estimates from (5), with $\alpha_i = 0$. By setting $\alpha_i = 0$ we impose our *no-skill-to-outperform* null hypothesis.

6) $$r_{i,t}^{b} = \hat{\beta}_{i,MKT}MKT_t + \hat{\beta}_{i,SMB}SMB_t + \hat{\beta}_{i,HML}HML_t + \hat{\beta}_{i,MOM}MOM_t + \hat{\varepsilon}_{i,t}^{b}$$

The time-series of pseudo monthly returns has, by construction, a zero true alpha. By regressing this pseudo time-series onto the four-factor model again (5), we obtain a simulated alpha ($\hat{\alpha}_i^{b}$). Repeating the above steps for all bootstrap replications ($b = 1, \dots, 1000$) generates a distribution of cross-sectional bootstrapped alphas and alpha t-statistics ($\hat{t}_{\hat{\alpha},i}^{b}$).

By calculating the fraction of times the simulated alpha (or t-alpha value) is greater than the true alpha (or t-alpha), we will assess the presence of managerial skill. The following formulas are adopted from Sørensen (2009):

7) $$P(\alpha) = \frac{1}{S}\sum_{s=1}^{S} 1[\alpha(s) > \alpha^{act}]$$

8) $$P(t_\alpha) = \frac{1}{S}\sum_{s=1}^{S} 1[t_\alpha(s) > t_\alpha^{act}]$$

Where S is the number of bootstrap iterations (1000), while act denotes the actual value of alpha and t-alpha respectively.

We look specifically at whether the bootstrap replications generate far fewer values of $\hat{\alpha}_i^{b}$ (or $\hat{t}_{\hat{\alpha},i}^{b}$) that are more positive than the actual alphas (or alpha t-statistics), in accordance with Kosowski et al. (2006).

We perform this procedure on all pre-defined time periods to observe if there is any change in managerial skill and performance during the different market conditions.

4.2.2 Persistence: The Portfolio Formation Approach

Mutual fund performance persistence has important academic- and practical implications, as mentioned in previous sections. We investigate the existence of performance persistence by using the portfolio formation approach (Hendricks et al, 1993; Carhart 1997).

We sort the funds into five equally weighted quintile portfolios where the first quintile portfolio consists of the best performing funds in our sample, and vice versa for the fifth quintile portfolio. Fund performance is measured based on their one year-, 6 month- and 3 month lagged returns, and each portfolio is held for either 3, 6- or 12 months before it is rebalanced according to the same ranking requirements. This enables us to investigate fund performance both short- and longer term. In addition to the five quintile portfolios, we are generating a portfolio that replicates a hypothetical strategy of going long on the portfolio of the past best performing funds and short on the worst performing funds[4], calculated as the difference between the best- and worst performing funds.

Funds that die during the holding period are included in the portfolio, the weights adjust accordingly when the funds disappear, replicating that the money is redistributed onto the funds remaining in the respective portfolio. This gives us a time series of monthly returns on each quintile portfolio, allowing us to compute each portfolios four-factor alphas (and alpha t-statistic).

Kosowski et al (2006) argues that the problem with this approach alone is that luck might also persist for some time-period. By applying the bootstrap method described in the previous section, we assess the statistical significance of our results as the two methods complement each other (Kosowski et al 2006; Sørensen 2009).

5.0 Results

5.1 Fund performance

Table 2 reports the results of the Norwegian mutual fund performance over the entire sample period, December 2002 until December 2016. Results tables for all defined sub-periods, illustrating fund performance over the different market

[4] The portfolio is hypothetical, because short-selling is not allowed in the Norwegian mutual fund industry.

conditions can be seen in the appendix (Appendix 1-3). In panel A, we compare the Jensen's single-factor model to Carhart's four-factor model, using an equally weighted portfolio of all funds in our sample. This is done over all sub-periods as well. We see that the alpha measure (and the alpha t-statistic) consistently lowers for all time-periods when we move from the single-factor to the four-factor model. This is also illustrated by the graph in Figure 2, where we see that the single-factor alphas are greater than the four-factor alphas for the majority of time in our sample period.

Figure 2: Cross-sectional alphas for the single- and four-factor model

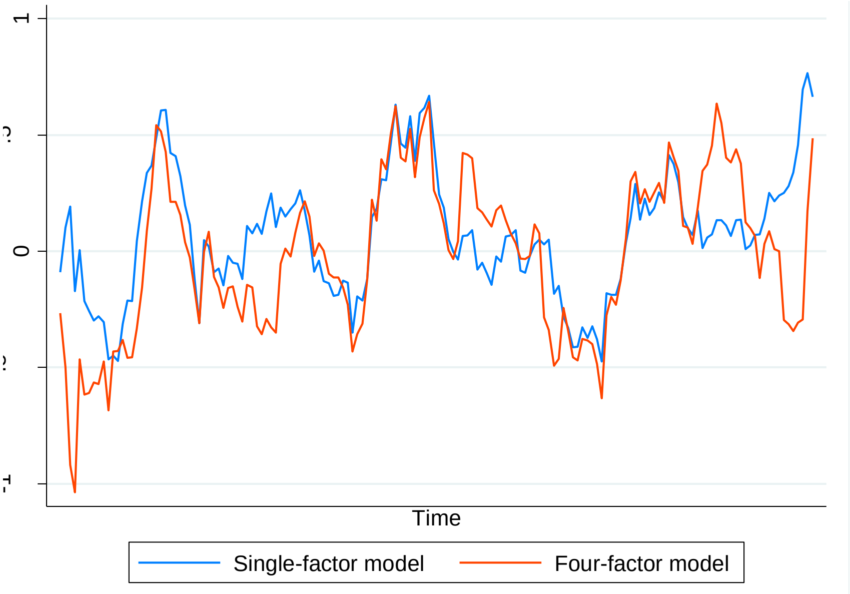

Figure 2: The graph illustrates and compares the single- and four-factor alphas over the sample period. The red line shows the alphas generated by Carhart's four-factor model, while the blue line show the alphas generated by Jensen's single-factor model.

Going forward, we consider Carhart's four-factor model to be our main model of interest. The model controls for more undiversifiable risk-factors than that of Jensen, and we see it as a better fit as it is less likely to artificially inflate the alpha estimate.

Table 2: Norwegian mutual fund performance

Panel A: Performance of EW portfolio						
Model	α	β MKT	β SMB	β HML	β MOM	Adj. R^2
Jensens single-factor	0.14**	0.93				0.98
	(2.16)					
Carharts four-factor	0.03	0.97	0.12	-0.01	0.02	0.98
	(0.42)					
Panel B: Individual fund performance using Carhart's four-factor model						
Worst	-0.45*	1.07	0.57	-0.05	-0.10	0.84
(NordeaSMB)	(-1.90)					
2nd	-0.24	1.00	0.36	-0.05	-0.12	0.88
(EikaSMB)	(-1.11)					
3rd	-0.23	1.01	0.32	-0.06	-0.03	0.87
(DelphiVekst)	(-1.03)					
Median	0.03	1.15	0.51	0.00	-0.06	0.81
(DNBSMB)	(0.11)					
3rd	0.46	1.23	0.16	0.09	-0.08	0.76
(FIRSTGenerator)	(1.28)					
2nd	0.48	0.65	0.15	0.08	0.07	0.56
(LandkredittUtbytte)	(1.55)					
Best	1.53***	0.52	-0.05	-0.03	-0.14	0.38
(FORTETrønder)	(3.35)					

Table 2: The table shows the OLS estimated alphas, factor loadings and adjusted R^2 for the entire sample period of December 2002 to December 2016. The number in parenthesis below alphas is the alpha t-statistic. The numbers are in percent. Panel A shows the results of an equally weighted portfolio of all funds comparing the different factor models. Panel B shows the results of the bottom- median- and top performing funds against Carhart's four-factor model. The stars indicate the significance level at 10%(*), 5%(**) and 1%(***) level.

Interpreting the results in panel A, both models indicate that the Norwegian mutual fund industry on average earns abnormal returns. However, only the single-factor model shows statistically significant over-performance, raising the question of whether this might be due to omitted variable bias. On average, the mutual funds are loading heavily on the market proxy, with the beta coefficient almost equal to 1. This is however not surprising given that the funds in our sample has the majority of assets invested in Norwegian equities.

In panel B, we have ranked the bottom- median and top performing funds based on their Carhart's alpha estimate. The worst-performing fund significantly underperforms the market, while the best performing fund significantly outperforms the market, at 10% and 1% significance level respectively. It seems that the best performing funds invest in securities that are far less volatile than the market. Furthermore, the factors explaining the variation in excess returns for the best performing fund is as low as 38%, indicating that the excess return is not explained by the funds' factor exposure.

When examining the fund performance during the sub-periods representing the bull- and bear markets, we see that different funds perform differently. We find significant alpha estimates at both ends of the scale for the sub-periods representing bull markets, but only the alphas of the top performing funds are significant for the bear market sub-period. We also see that the alphas on both ends of the scale are far more positive/negative during the bear markets compared to those during bull markets, except for Forte Trønder, which has a considerably shorter lifespan than most of the other funds in our sample. This is an interesting finding indicating that funds tend to earn higher abnormal returns, or outperform at a larger scale, compared to the market during the down-markets. All top three performing funds delivered alphas significant at 10% level. This finding might shed light onto the question raised by Kosowski (2011), on whether funds are able to earn excess returns net of fees for their investors, when the "investors marginal utility of wealth is high" (Kosowski, 2011).

In our overall sample period, a total of seven alphas are found significant. One alpha is positive at 1% level, two at 5% level and two at 10% level, while two negative alphas are significant at 10% level. For the first sub-period, six alphas are significantly negative, whilst one alpha is significant and positive at 10% level. The second sub-period, representing the bear-market, also has a total of seven significant (both positive and negative) alphas, however none at 1% level. The last sub-period, representing a bull market, delivers one positive alpha significant at 1% level, two negative and one positive alpha at both 5% and 10% level. The complete results table can be found in Appendix 1-3.

We have found that some funds are able to deliver positive, and statistically significant, alphas during all periods in our sample. Following the alpha interpretation of Jensen (1968), we can conclude that there are signs that some mutual funds in the Norwegian market are able to outperform the market. Even though the alpha is commonly interpreted as a measure of skill, we want to emphasize the arguments from Berk and Van Binsbergen (2015); that the alpha is just a measure of abnormal return, and not a skill measure that reflects the quality of the manager.

5.2.1 Bootstrap Simulations

Since abnormal returns are not a sufficient and satisfying measure of managerial skill, we proceed with the bootstrapping approach in order to identify whether the abnormal returns really are due to skill, or luck. The bootstrap approach is less likely to use skill as a justifying argument for performance, rather than luck, disregarding that luck may also persist (Kosowski, 2006).

Even though the intercept (alpha) from the factor models is commonly used to capture fund performance, several researchers argue that one should evaluate performance based on the alpha t-statistics rather than the alpha estimates (Sørensen 2009; Fama and French, 2010). According to Fama and French (2010), the t-alpha value can be interpreted as a "precision adjusted alpha estimate". In order to stay consistent with theory, we have chosen to rank the funds based on both their alpha estimates, and their t-alpha values. Ranking the funds by their t-alpha values might also be particularly appropriate given the short length of returns history in our sample, since the precision of the alpha increase with the length of the return history (Sørensen, 2009).

In Table 3 we show the results from the bootstrap simulations, based on 1,000 bootstrap iterations. Panel A shows the results from the bootstrap simulations on the entire sample period, while panels B-D show the bootstrapped results for all sub-periods. The three far left columns show results when funds are ranked by their ex post (true) alpha estimates, while the three far right columns show the results when funds are ranked by their true t-alpha statistics. Columns 2 and 5, named Sim, show the average simulated value based on 1,000 simulations. The 3rd and 6th columns show how many times the simulated values exceeded the actual values, reported as a percentage.

Table 3: Separating skill from luck by bootstrapping

Panel A: Entire sample period (2002m12-2016m12)						
	Alphas			T-statistics		
	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
Worst	-0.4480	0.0058	97.70	-1.9035	0.0140	96.70
2	-0.2410	0.0050	87.70	-1.7743	0.0476	96.70
3	-0.2320	0.0022	88.10	-1.4286	-0.0503	91.10
4	-0.1898	-0.0036	86.00	-1.1083	0.0109	86.80
5	-0.1831	0.0039	96.50	-1.0837	-0.0009	86.20
10 %	-0.1796	-0.0024	92.90	-1.0307	0.0175	88.00
20 %	-0.0692	0.0000	78.10	-0.6278	-0.0241	73.20
30 %	-0.0235	0.0007	66.80	-0.1773	-0.0257	54.30
40 %	0.0022	-0.0011	48.10	0.0253	0.0079	47.80
50 %	0.0336	-0.0041	41.50	0.1967	0.0061	41.40
60 %	0.0486	-0.0036	22.90	0.5653	-0.0048	29.30
70 %	0.0872	-0.0038	13.20	0.7158	-0.0842	20.70
80 %	0.1075	-0.0013	18.90	1.0064	-0.0174	15.70
90 %	0.2413	-0.0002	19.60	1.2837	-0.0248	10.00
5	0.2775	0.0084	13.30	1.7588	0.0344	3.30
4	0.2796	0.0027	0.60	1.7946	-0.0187	3.60
3	0.4613	0.0019	10.40	2.2413	0.0108	0.60
2	0.4822	-0.0099	3.80	2.6140	-0.0072	0.30
Best	1.5289	0.0001	0	3.3518	-0.0274	0.00

Panel B: Sample period 2002m12-2008m4						
	Alphas			T-statistics		
	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
Worst	-0.6482	0.7980	100.00	-2.8294	1.6404	100.00
2	-0.5741	0.2849	99.50	-2.2452	1.9746	100.00
3	-0.5267	0.2720	100.00	-2.2122	1.9457	100.00
4	-0.3742	0.4687	97.60	-1.9747	0.8374	99.70
5	-0.3525	0.3518	100.00	-1.8860	0.7665	99.40
20 %	-0.2697	0.2227	100.00	-1.2923	0.4559	95.80
30 %	-0.1856	0.1953	99.80	-0.8747	1.2402	98.20
40 %	-0.1121	0.1114	68.20	-0.5771	0.6995	89.90
50 %	-0.0695	-0.0719	48.70	-0.3404	-0.4642	46.40
60 %	-0.0345	0.0281	62.10	-0.2769	0.1103	65.30
70 %	0.0099	-0.2298	23.80	0.0877	-0.0466	45.10
80 %	0.1034	-0.6122	2.90	0.3870	-0.2022	28.50
90 %	0.1851	-0.0934	5.70	0.7999	0.1132	25.50
5	0.1932	-0.0730	26.60	0.9674	-0.7158	5.80
4	0.1992	0.0327	25.20	0.9683	-1.3584	1.60
3	0.3004	-0.3710	1.20	1.0748	-0.6521	6.50
2	0.3194	-0.3432	0.10	1.4113	-1.5824	0.10
Best	0.4987	-0.3362	0.1	1.8198	-1.4833	0.10

Panel C: Sample period 2008m5-2009m2						
	Alphas			T-statistics		
	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
Worst	-2.5179	1.3646	98.10	-3.3710	1.8193	98.80
2	-2.1085	1.9839	99.90	-2.9067	1.3398	98.30
3	-1.8991	0.6226	95.30	-2.0420	1.4493	91.90
4	-1.4698	0.8988	95.30	-1.8817	1.1463	76.00
5	-1.4351	1.0289	96.30	-1.8457	0.8072	72.10
20 %	-1.1580	1.2741	99.30	-0.8970	-0.0512	76.00
30 %	-0.4456	0.5664	96.20	-0.7174	-0.0800	82.80
40 %	-0.3025	0.2162	78.70	-0.5617	1.6749	68.20
50 %	-0.2531	0.2245	89.40	-0.5120	0.2753	23.20
60 %	-0.1849	-0.0486	57.00	-0.1761	-0.2145	41.70
70 %	-0.0354	-0.2154	35.20	-0.0596	-0.5470	17.70
80 %	0.1971	-0.0405	26.10	0.3886	-0.0977	21.50
90 %	0.4402	0.1092	33.20	1.0378	-0.4468	51.00
5	1.5144	-1.6173	0.00	1.7148	-1.5388	0.10
4	1.5280	-0.8545	0.10	2.0524	-1.5031	0.90
3	1.7174	-1.0595	0.00	2.0552	-1.6599	1.20
2	1.7516	-0.9902	0.00	2.1819	-1.9875	0.00
Best	1.9516	-1.2902	0.00	2.7258	-2.0138	2.10

Panel D: Sample period 2009m3-2016m12						
	Alphas			T-statistics		
	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
Worst	-0.7590	0.5592	99.90	-2.3966	1.5396	100.00
2	-0.3511	0.3324	99.80	-2.0523	0.8972	99.70
3	-0.2238	0.2246	97.40	-1.8594	1.4039	100.00
4	-0.2118	-0.0485	68.50	-1.8296	0.7012	99.30
5	-0.1938	0.2318	98.10	-1.4447	0.9605	99.10
10 %	-0.1772	0.1255	99.20	-1.0298	0.9126	98.1
20 %	-0.0653	0.0736	71.60	-0.4731	-0.5834	45.40
30 %	-0.0391	0.1219	73.60	-0.2117	-0.9323	23.10
40 %	0.0114	0.1415	79.30	0.1018	-0.1376	41.40
50 %	0.0515	0.1190	72.50	0.3206	1.0495	76.10
60 %	0.0737	-0.0077	24.70	0.6306	0.0354	28.00
70 %	0.1022	0.0231	26.00	0.7286	0.7723	51.40
80 %	0.1210	0.0326	28.80	0.9824	0.0938	18.70
90 %	0.2689	-0.1412	1.70	1.3722	-0.7340	1.90
5	0.4060	-0.2620	0.00	1.5549	-0.0341	4.90
4	0.4613	0.0019	10.40	1.6199	-0.4754	2.50
3	0.4822	-0.0099	3.80	1.9824	-1.2299	0.00
2	0.7289	-0.4010	0.00	2.2931	-1.4336	0.00
Best	1.5289	0.0001	0.00	3.3518	-0.0274	0.00

Table 3: The table presents the bottom- and top performing funds ranked on their respective true alpha and t-alpha values over the entire sample period and all sub-sample periods. The three left columns show the bottom- and top performing funds ranked by their true alpha estimate, with their respective average bootstrapped alpha estimates, as well as the percentage number of times the simulated alpha is higher than the actual alpha estimate. The three right columns show the bottom- and top performing funds ranked by their actual/ true t-alpha value. The alphas are in percent per month.

From panel A, we see that multiple funds show signs of skills, in both the left and right tail. Surprisingly, even when reviewing the findings at 1% in the right tail, the best- and fourth best funds exhibit true alphas greater than the simulated alphas when ranked based on their alpha values. This is even more apparent when ranking the funds based on their precision adjusted performance estimators (t_α). The findings are indicating that the returns are due to skill (both superior and inferior) rather than luck. The findings in the right tail are particularly interesting in light of the research of Sørensen (2009), who concluded that skills were not present in the Norwegian mutual fund industry.

Figure 3: Alpha distribution of top- and bottom funds during the entire sample period

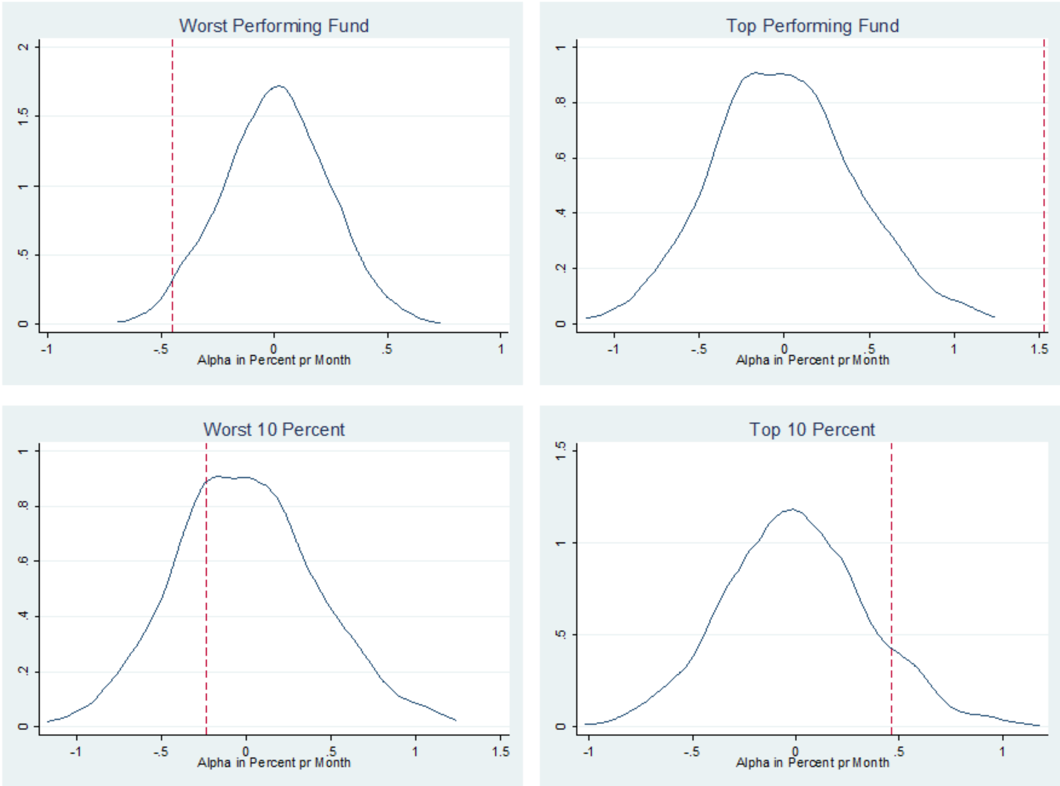

Figure 3: The figure plots the kernel density estimates of the worst- and best performing funds, as well as the 10th percentile top and bottom performing funds, ranked on their true t-alpha value. The X-axis shows the true alphas (red dotted line) versus the bootstrapped alpha distribution (solid line) of each fund respectively.

We will mainly focus on the results of the funds based on their t-alpha statistics from here on, due to the short length of the return history of the funds included in our sample. We argue that these results have a higher precision than those ranked by the alpha-estimates. Table 3, Panel A shows that the simulated alphas are greater than the actual alphas in more than 90% of the draws for the third worst fund. The two worst funds exhibit simulated alphas greater than their actual alpha, respectively, in more than 95% of the simulations. In the right tail, we see that the actual alphas for the top five funds are greater than the simulated alphas for more than 95% of the draws, and the three top funds even produce an actual alpha greater than the simulated alphas for more than 99% of the simulations. Figure 3 above illustrates the distribution of simulated alphas versus true alpha estimates for the top- and bottom funds during the entire sample period. The alpha distribution during each sub-period can be seen in the appendix (Appendix 4-6).

The results separating skill from luck during the different market conditions, still show signs of both superior and inferior skills in the top- and bottom performing mutual funds. However, it seems that there are fewer funds in the left tail with poor performance due to poor managerial skills in the bear markets (Table 3, Panel C), compared to the number of funds with simulated alphas greater than actual alphas for more than 90% of the draws, during the bull markets (Table 3, Panels B and D). This indicates that poor performance due to (bad) luck is greater during the bear markets compared to the bull markets. On the other side, the superior skill becomes more prominent during the bear markets compared to the bull markets. The top five funds during bear markets all have a true alpha greater than the simulated alpha for more than 99% of the time. However, it seems that there are more funds exhibiting managerial skills (both superior and inferior) during the bull markets compared to the bear markets, evaluating skill at 10% on each side. Yet, the performance during the bull markets is less extreme compared to the bear markets.

5.2.2 Persistence

Table 4 below represents 5 equally weighted portfolios based on their ranking period and consisting of lagged 3 to 12 months returns. The holding period suggests how often these portfolios are rebalanced and runs from 3 to 12 months. Judging by the raw returns alone, it is clear that the top ranked portfolio generates larger excess return as compared to the bottom portfolio. We can also see that excess return decreases when the rebalancing period increases.

When looking at the risk-adjusted alphas we cannot see any clear patterns, except for the fact that the top quintile generates a slightly higher average monthly alpha compared to the bottom quintile (0,05% vs. 0,03%). However, none of these alphas are statistically significant; indicating no evidence of persistence among the top or bottom portfolios of funds. This confirms the findings of Bollen and Busse (2005) who found that persistence disappears when using longer ranking periods (above 3 months) and monthly data. As for the other quintiles, we find significantly positive alpha of 0,14% for the 4th quintile portfolio in the 6-month ranking and 3-month holding strategy. Another significantly positive alpha of 0,12% was found for the 3rd quintile portfolio in the 12-month ranking and 12-month holding strategy. We also identify reversion towards the mean, where the funds that produced the highest returns the prior period actually underperform, whereas the funds that delivered the lowest returns the previous period show a positive alpha (not significant).

It is also interesting to see that the spread portfolio, which resembles the momentum strategy, shows negative alpha with a significant -0,20% in the 12 months ranking and 3 months holding strategy as well as -0,27% in the 12 months ranking and 12 months holding strategy. Overall, the momentum strategy delivers an average alpha of -2,4% and average excess return of -0,6% in annualized terms. This implies that an investor going long past winner funds and shorting past loser funds (were it allowed to short on the Norwegian market) would ultimately suffer losses. These results confirm the findings of Sørensen (2009) and suggest that the Norwegian markets are somewhat efficient and are in line with the prevailing financial theory. Gallefoss et al. (2015), on the other hand, found short-term persistence among the top and bottom funds. One explanation for the difference could be that Gallefoss et al. (2015) use daily data that enables them to estimate the alphas more precisely. The validity of our results has been assessed by the bootstrapping simulations, which confirmed their significance. The complete results table along with the parametric and bootstrapped p-values can be found in Appendix 7.

Table 4: Risk-adjusted alphas and excess returns of portfolios formed on lagged returns

Ranking Period		Alpha			Excess Return		
		Holding Period			Holding Period		
		3	6	12	3	6	12
Top Quintile	3	0,09	0,09	0,05	1,3552	1,1959	1,0445
	6	0,09	0,06	0,06	1,2148	1,1601	1,0184
	12	0,04	-0,01	-0,03	1,0364	1,0126	0,9789
2nd Quintile	3	0,05	0,08	0,02	1,2020	1,0861	0,9182
	6	-0,03	-0,01	-0,03	1,0091	1,0321	0,8477
	12	0,05	0,10	0,07	0,9838	1,0322	0,9753
3rd Quintile	3	0,07	0,02	-0,01	1,2338	1,0703	0,8774
	6	-0,04	0,07	0,10	0,9936	1,1202	1,0504
	12	0,04	0,08	0,12*	0,9320	0,9581	0,9970
4th Quintile	3	0,00	0,04	0,10	1,1344	1,0217	0,9764
	6	0,14**	0,06	0,11	1,1281	1,0746	0,9897
	12	0,00	0,04	0,05	0,8666	0,8807	0,9260
5th Quintile	3	-0,04	0,03	0,09	1,0697	1,0345	0,9468
	6	0,04	0,06	0,01	0,9913	0,9963	0,8723
	12	0,02	0,05	0,02	0,8520	0,8989	0,8845
Long Best Short Worst	3	-0,10	-0,16	-0,26	0,0706	-0,0497	-0,1115
	6	-0,18	-0,21	-0,17	0,0125	-0,0472	-0,0631
	12	-0,20*	-0,28	-0,27***	-0,0248	-0,0955	-0,1149

Table 4: This table represents post-formation alphas and excess returns of five equally-weighted quintile portfolios of funds along with the spread portfolio. The ranking periods run from 3 to 12 months and the portfolios are rebalanced every 3 to 12 months. All figures are in percent and computed on a monthly basis. The stars (*) denote the statistical significance, where the alphas are significant with both the parametric and the bootstrapped p-values. * is sign. at 10%, ** at 5% and *** at 1%.

5.3 Conclusion

We examine the Norwegian mutual fund industry over the period of December 2002 to December 2016 using both Jensen's single factor and Carhart's four factor models. Both models show that on average the Norwegian mutual funds are capable of generating abnormal returns, however, only the single factor model provides statistically significant results. We identify FORTE Trønder as the best performing fund, delivering a monthly abnormal return of 1,53% (sign. at 1%) and Nordea SMB as the worst performing fund with a negative monthly abnormal return of -0,45% (sign. at 10%) based on the Carhart's alpha estimate. We further divide our sample period into bear and bull markets to look at how the performance of funds relates to the states of the economy. This is where we make an interesting finding, namely, we find that the best performing fund delivers an abnormal return of 1,95% (sign. at 10%). This indicates that the best performing fund outperforms the market to a greater extent during the bear market period compared to all sub-periods and the entire sample period. This answers an important question raised by Kosowski (2011) whether active management is able to deliver good performance during economic downturns, when the investors' marginal utility of wealth is high.

Although we identify that some funds are able to generate statistically significant alpha, it is still not a convincing measure of managerial skill. Taking into account the arguments of Berk and Van Binsbergen (2015) that alpha is a measure of abnormal return rather than skill, we want to further test market efficiency and see whether the superior performance is due to luck. By adopting a bootstrap approach, we find that superior (inferior) performance of funds can indeed be attributed to good (poor) managerial skill rather than mere chance. This is in contrast to the findings of Sørensen (2009) who reports that managerial skill is absent in the Norwegian mutual fund industry. Additionally, we find that superior skills become more prominent during the down-market, which confirms our earlier findings that some funds are able to add value when it matters most to investors. Nevertheless, our results also show that during the bull markets more funds exhibit managerial skills as compared to the bear markets. This can be an indication that Norwegian fund managers are better stock-pickers, than market-timers[5].

[5] Kacperczyk et al. (2014) show that an average fund manager exhibits stock-picking skills in economic expansions and market-timing skills in recessions.

The final aspect of our study is to see whether performance persists over time. This is done by implementing a portfolio formation approach and applying a bootstrap procedure to confirm the validity of our results. Our findings show no statistically significant abnormal return in the top and bottom quintile portfolios over all ranking and holding periods, indicating no evidence of performance persistence. Interestingly, our hypothetical spread portfolio where you go long previous winners and short previous losers, in fact, generates a negative monthly alpha of -0,20% in the 12 months ranking and 3 months holding strategy as well as -0,27% in the 12 months ranking and 12 months holding strategy, both statistically significant. This suggests that chasing performance of Norwegian mutual funds is not a good strategy for the investors.

We conclude that some actively managed Norwegian mutual funds are capable of generating abnormal returns net of fees for their investors. Some funds even show extraordinary performance when the market is in contraction. We therefore deny our hypothesis as we find that some funds hold the relevant skills. However, such superior performance is not possible to identify *ex ante*, as mutual fund performance does not persist.

For further research, we suggest to extend the standard four-factor model by adding profitability (RMW) and investment (CMA) factors proposed by Fama and French (2015). It would also be interesting to compare these results to the other Nordic countries or analyse the Nordic mutual fund market as a whole, using the five-factor model. When analyzing managerial skill, we recommend to investigate if it is due to market timing or stock-picking abilities (or both) of the fund managers, as some US based data (e.g. Kacperczyk et al., 2014) indicates.

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Appendix

Appendix 1: Mutual fund performance sub-sample period 2002m12-2008m4

Panel A: Performance of EW portfolio						
Model	α	β MKT	β SMB	β HML	β MOM	Adj. R^2
Jensens single-factor	0.10	0.96				0.98
	(0.89)					
Carharts four-factor	-0.08	1.00	0.14	-0.02	0.03	0.98
	(-0.74)					
Panel B: Individual fund performance using Carhart's four-factor model						
Worst	-0.65**	1.06	0.31	-0.27	-0.13	0.90
(Storebrand Vekst)	(-2.21)					
2nd	-0.57*	1.04	0.32	-0.13	-0.08	0.89
(Eika SMB)	(-1.97)					
3rd	-0.53***	1.04	0.18	-0.09	-0.01	0.96
(Nordea Vekst)	(-2.83)					
Median	-0.07	1.01	0.10	-0.01	0.12	0.95
(Atlas Norge)	(-0.34)					
3rd	0.30	0.98	0.32	-0.03	0.02	0.86
(Holberg Norge)	(0.97)					
2nd	0.32	0.89	-0.15	0.18	0.24	0.93
(Storebrand Verdi)	(1.41)					
Best	0.50*	0.96	0.01	0.07	-0.01	0.95
(Storebrand Norge H)	(1.82)					

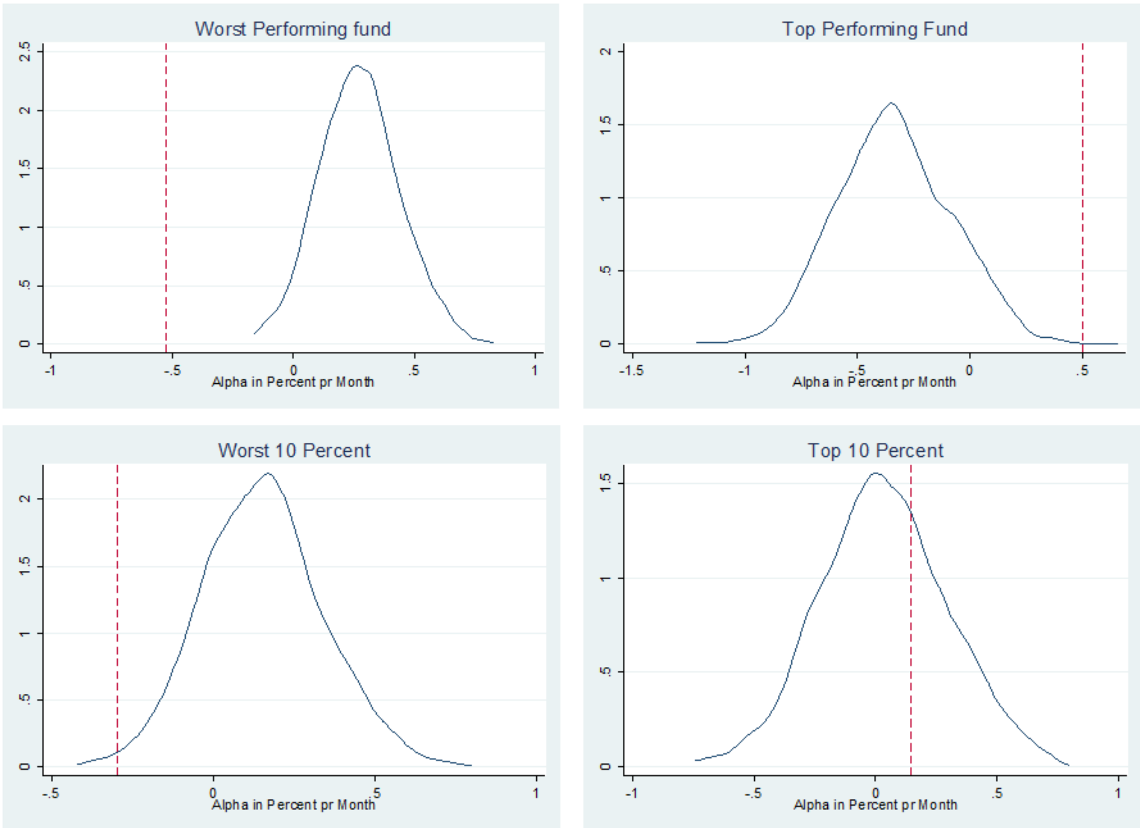
Appendix 2: Mutual fund performance subsample 2008m5-2009m2

Panel A: Performance of EW portfolio						
Model	α	β MKT	β SMB	β HML	β MOM	Adj. R^2
Jensens single-factor	-0.07	0.88				0.99
	(-0.15)					
Carharts four-factor	-0.26	0.95	0.11	-0.04	0.15	0.99
	(-0.51)					
Panel B: Individual fund performance using Carhart's four-factor model						
Worst	-2.52	1.28	0.82	0.00	0.76	0.89
(DNB SMB)	(-1.85)					
2nd	-2.11	0.85	0.63	-0.42	-0.02	0.90
(ODIN Norge C)	(-1.83)					
3rd	-1.90	1.17	0.71	0.11	0.54	0.85
(Nordea SMB)	(-1.29)					
Median	-0.25	1.01	0.02	-0.02	0.16	1.00
(Alfred Berg Norge Classic)	(-1.01)					
3rd	1.72*	0.81	-0.24	0.16	-0.24	0.97
(Danske Invest Norge I)	(2.06)					
2nd	1.75*	0.79	-0.24	0.16	-0.25	0.96
(Danske Invest Norge II)	(2.05)					
Best	1.95*	0.81	-0.41	0.26	-0.09	0.96
(Danske Invest Norske Aksjer Inst	(2.18)					

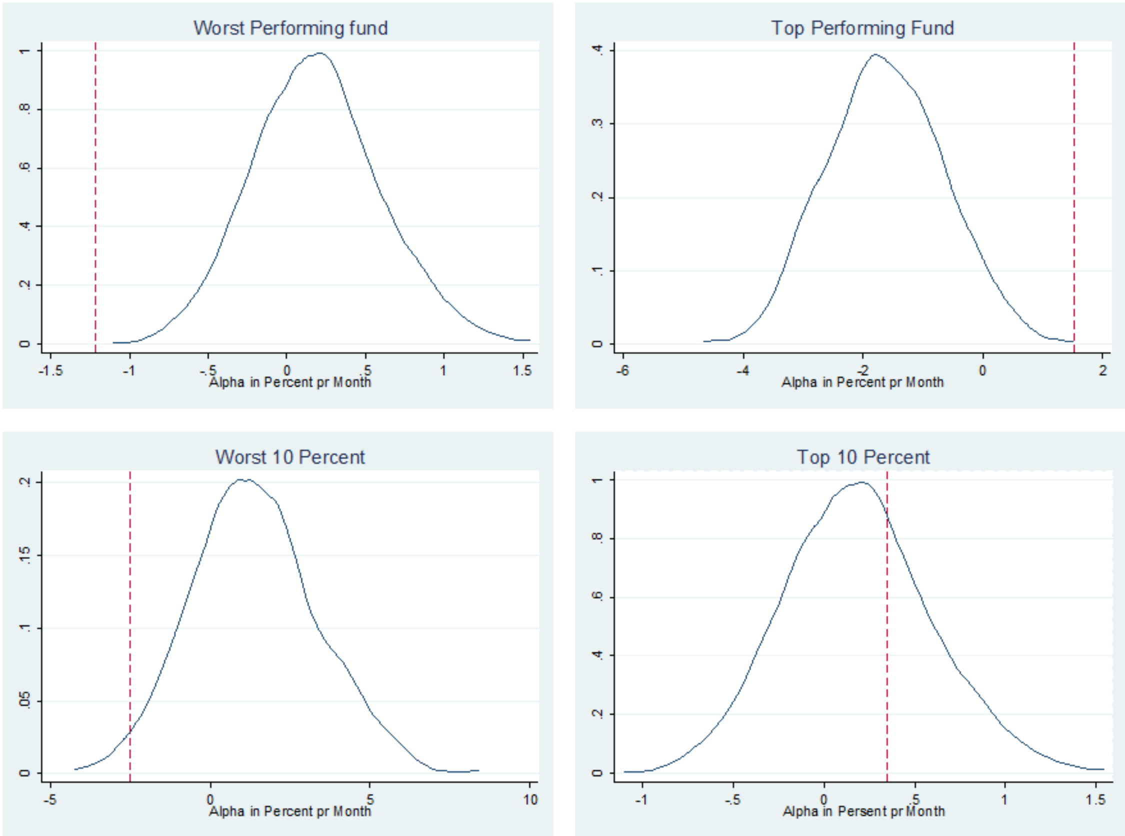
Appendix 3: Mutual fund performance subsample 2009m3-2016m12

Panel A: Performance of EW portfolio						
Model	α	β MKT	β SMB	β HML	β MOM	Adj. R^2
Jensens single-factor	0.11	0.93				0.97
	(1.32)					
Carharts four-factor	0.07	0.98	0.11	0.01	-0.02	0.98
	(0.87)					
Panel B: Individual fund performance using Carhart's four-factor model						
Worst	-0.76**	1.06	0.58	-0.01	-0.31	0.81
(Nordea SMB)	(-2.40)					
2nd	-0.35*	1.02	0.26	0.04	-0.04	0.88
(Holberg Norge)	-1.86					
3rd	-0.22	0.92	0.21	0.05	-0.02	0.82
(ODIN Norge C)	(-1.03)					
Median	0.05	0.98	0.05	0.01	0.06	0.97
(Alfred Berg Humanfond)	(0.52)					
3rd	0.48	0.65	0.15	0.08	0.07	0.56
(Landkreditt Utbytte)	(1.55)					
2nd	0.73*	0.95	0.14	-0.13	-0.12	0.66
(Storebrand Vekst)	(1.98)					
Best	1.53***	0.52	-0.05	-0.03	-0.14	0.38
(FORTE Trønder)	(3.35)					

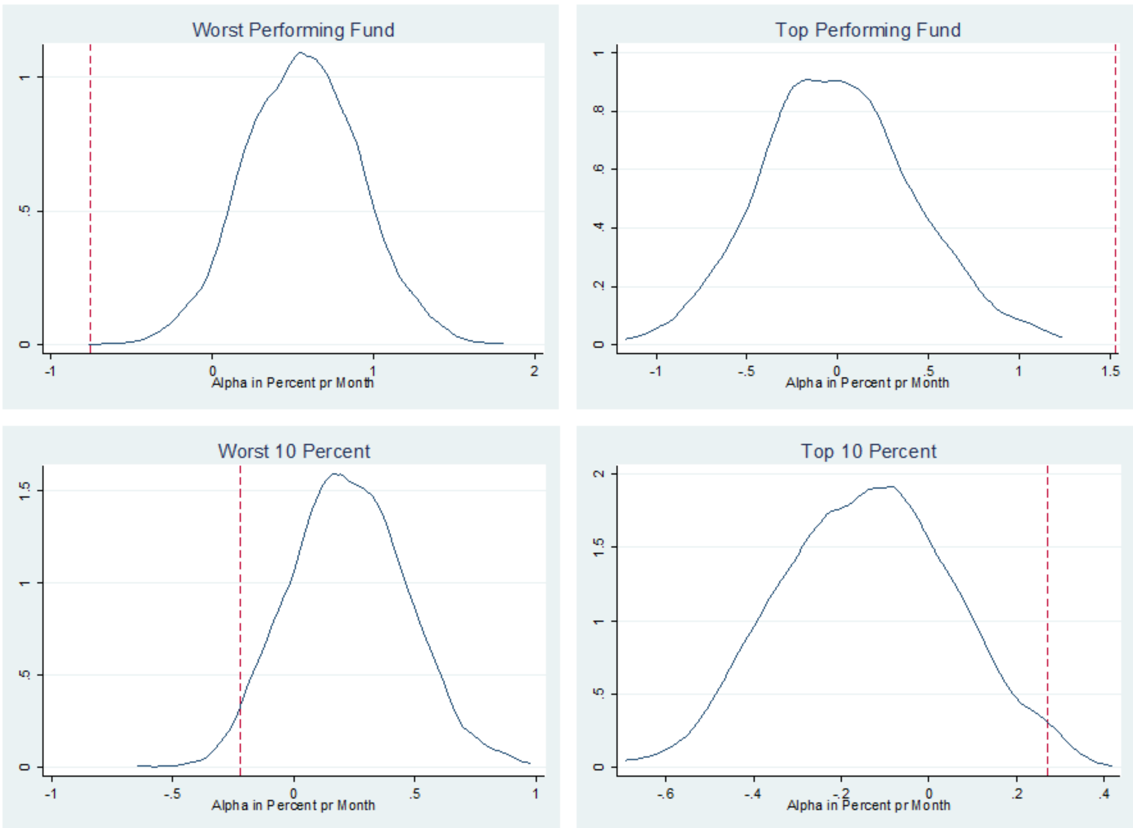
Appendix 4: Bootstrapped alpha distribution, sub-sample period 2002m12-2008m4



Appendix 5: Bootstrapped alpha distribution, sub-sample period 2008m5-2009m2



Appendix 6: Bootstrapped alpha distribution, sub-sample period 2009m3-2016m12



Appendix 7: Persistence results of post-formation portfolios

Ranking Period		Alpha			Excess Return			Standard Deviation			One-tailed Parametric p-Alpha			Bootstr. p-Alpha (right-tailed)		
		Holding Period			Holding Period			Holding Period			Holding Period			Holding Period		
		3	6	12	3	6	12	3	6	12	3	6	12	3	6	12
Top Quintile	3	0,09	0,09	0,05	1,3552	1,1959	1,0445	6,03	6,00	6,00	0,38	0,34	0,65	0,19	0,16	0,31
	6	0,09	0,06	0,06	1,2148	1,1601	1,0184	5,98	5,97	5,87	0,38	0,52	0,51	0,18	0,25	0,24
	12	0,04	-0,01	-0,03	1,0364	1,0126	0,9789	5,99	6,02	5,96	0,71	0,94	0,71	0,34	0,51	0,65
2nd Quintile	3	0,05	0,08	0,02	1,2020	1,0861	0,9182	5,87	5,85	5,84	0,52	0,24	0,73	0,24	0,11	0,35
	6	-0,03	-0,01	-0,03	1,0091	1,0321	0,8477	5,87	5,82	5,83	0,62	0,83	0,66	0,69	0,566	0,64
	12	0,05	0,10	0,07	0,9838	1,0322	0,9753	5,83	5,80	5,80	0,50	0,15	0,33	0,24	0,06	0,15
3rd Quintile	3	0,07	0,02	-0,01	1,2338	1,0703	0,8774	5,92	5,93	5,94	0,27	0,70	0,83	0,13	0,36	0,57
	6	-0,04	0,07	0,10	0,9936	1,1202	1,0504	5,92	5,92	6,00	0,55	0,37	0,16	0,74	0,19	0,09
	12	0,04	0,08	0,12*	0,9320	0,9581	0,9970	5,85	5,83	5,90	0,49	0,19	**0,07**	0,26	0,09	**0,03**
4th Quintile	3	0,00	0,04	0,10	1,1344	1,0217	0,9764	5,91	5,87	5,72	0,96	0,58	0,18	0,46	0,29	0,09
	6	0,14**	0,06	0,11	1,1281	1,0746	0,9897	5,83	5,92	5,78	**0,04**	0,40	0,15	**0,03**	0,17	0,07
	12	0,00	0,04	0,05	0,8666	0,8807	0,9260	5,76	5,84	5,83	0,95	0,54	0,51	0,47	0,25	0,26
5th Quintile	3	-0,04	0,03	0,09	1,0697	1,0345	0,9468	5,77	5,69	5,64	0,72	0,78	0,43	0,64	0,38	0,23
	6	0,04	0,06	0,01	0,9913	0,9963	0,8723	5,66	5,70	5,68	0,70	0,59	0,94	0,34	0,30	0,48
	12	0,02	0,05	0,02	0,8520	0,8989	0,8845	5,57	5,62	5,61	0,86	0,64	0,86	0,42	0,29	0,42
Long Best	3	-0,10	-0,16	-0,26	0,0706	-0,0497	-0,1115	1,54	1,50	1,42	0,39	0,19	0,02	0,79	0,89	0,99
Short	6	-0,18	-0,21	-0,17	0,0125	-0,0472	-0,0631	1,63	1,44	1,42	0,18	0,07	0,17	0,91	0,50	0,91
Worst	12	-0,20*	-0,28	-0,27***	-0,0248	-0,0955	-0,1149	1,49	1,41	1,38	0,07	0,01	0,01	0,97	0,99	0,99

Appendix 7: This table reports post-formation alpha, excess return, standard deviation, parametric p-values and bootstrapped p-values of five equally-weighted quintile portfolios of funds and the spread portfolio. P-values for negative alpha estimates should be computed as 1- right-tailed p-value. The ranking periods run from 3 to 12 months and the portfolios are rebalanced every 3 to 12 months. All figures are in percent and computed on a monthly basis. The stars (*) denote the statistical significance, where * are sign. at 10%, ** at 5% and *** at 1%.