Norwegian mutual fund performance based on Fama and French´s five-factor model

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Abstract

The following paper uses a dataset free of survivorship bias for the period 2002-2011. We investigate whether Norwegian mutual funds possess enough skills to outperform a passive benchmark based on Fama and French's five-factor model. Our results suggest that the mutual fund industry exhibits significant excess returns on a 10% level in the recent financial crisis. Further, we examine whether the results obtained by the five-factor model are greater than the results obtained by the three-factor model. Our findings indicate that the five-factor model is better to explain the volatility in returns compared to previous models. Moreover, we do not find any evidence of performance persistence among Norwegian mutual funds. The bootstrapping results indicate significant inferior performance in the whole sample and the *pre-crisis* period. However, we do find evidence of managerial skills for the two best performing funds in the *crisis* period.

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1. INTRODUCTION

Sharpe (1964), Lintner (1965) and Mossin (1966) laid the foundation of modern finance theory. They introduced the capital asset-pricing model (CAPM), which is a single factor model that explains the relationship between risk- and average return. In 1968, Jensen conducted one of the earliest papers in this field, where he used CAPM to introduce Jensen's alpha, which he defined as an absolute measure of manager's skill and ability to outperform the market. He concluded that mutual funds were not able to beat the market when accounting for manager fees.

In 1993, Fama and French introduced two new factors in addition to the market factor. The new variables, size (*SMB*) and book-to-market equity (*HML*), combined with the market factor represent the Fama and French three-factor model. The asset-pricing model developed by Fama and French (1993) predicts expected stock market returns better than the classical CAPM model, thus it shows more precise measurement of fund performance. However, past research argues that the three-factor model does not capture Jegadeesh and Titman's (1993) momentum effect, nor explains the phenomenon of *hot hands* described by Hendricks, Patel and Zeckhauser (1993).

In 1997, four years after the studies of Fama and French, Carhart suggested a new explanatory variable to the three-factor model, namely momentum. By including this fourth factor, it would better encounter the issues discussed by Jagadeesh and Titman in their studies from 1993. Furthermore, Carhart's four-factor model is commonly used for measuring mutual fund performance. The momentum factor is constructed by investing in past winners and selling past losers.

In 2013, Fama and French presented for the first time a draft of a new asset-pricing model, consisting of two new explanatory variables, namely profitability (*RMW*) and investment (*CMA*). Thus, the five-factor model is an extension of the three-factor model. Fama and French's first draft of the five-factor model is the motivating paper to our thesis. The purpose of this paper is to test Norwegian mutual fund performance based on Fama and French's five-factor model (2015a). Moreover, we will compare the results obtained from both the three- and five-factor model. We need to construct the two new factors for the Norwegian equity market in order to apply the five-factor model. We want to emphasize that construction of these factors is our main contribution to the field of finance. Further, we will divide the dataset into two subsamples in order to see the effect of the recent financial crisis on fund performance. One sample will consist of data from 2002 to the end of 2006, defined as *pre-crisis*. The second sample will consist of data from January 2007 to the end of 2011, defined as *crisis.* To test mutual fund performance, we use a dataset free of survivorship bias consisting of 57 actively managed mutual funds, spanning from 2002 until the end of 2011 where we cover the recent financial crisis.

Our results show weak evidence of abnormal fund performance in our dataset period based on the five-factor model. The results suggest that the mutual fund industry as a whole was able to gain excess risk-adjusted returns on a 10% significance level during the *crisis* period. Furthermore, our findings indicate that the results obtained by the five-factor model are superior to the three-factor results for the whole period as well for the subsamples. Further, we do not find any evidence of persistence in fund performance, indicating that the Norwegian market is efficient. The bootstrap analysis does not show any evidence of superior funds in the right tail of the cross-section of alpha estimates in the whole period. The findings from the whole sample and the *pre-crisis* period imply that funds in the left tail of the distribution have a lack of skills. Finally, the bootstrapping analysis does not show any skills in the right tail for the managers during the crisis, except for the two best performing funds.

The remainder of this paper proceeds as follows. The second section presents a literature review. In the third section, we present mutual fund data, benchmarks, interest rates and factor returns. In addition, we discuss the importance of survivorship bias. In section four, we present the five-factor model and explain the procedure we apply in order to create the two new factors. Moreover, in section five we present and discuss results of both the aggregate portfolio of funds and individual funds. Section six sort mutual funds into portfolios and measure the persistence of their returns over time. The seventh section presents the bootstrap technique and evidence where we separate skill from luck. Finally, in the last section we submit our conclusion and share our thoughts on possible further research on this topic.

2. LITERATURE REVIEW

Evaluation of mutual fund performance has been a debated topic for a long time in the field of finance. Academics as well as investors have a great interest in this topic for several reasons. Academics try to see whether the market is efficient, which means it should not be possible to outperform the market. If mutual fund managers are able to beat the market persistently, it will support a rejection of efficient market hypothesis of the semi-strong form (Fama, 1970). Further, investors are interested in the possibility of outperforming the market since it will indicate if it is worth investing in an active fund and pay the extra costs compared to a passively managed fund.

In 1995, Malkiel observed the development of different mutual funds, and he concluded that these funds were underperforming compared to the market index even prior to accounting for manager fees. The research of Fama and French from 2010 supported the conclusion that mutual funds do not deliver positive abnormal returns net of management expenses.

Sharpe (1991) argues that the sum of returns from active- and passive funds have to *break-even*. He states that if one of the funds is able to deliver abnormal returns, it is on expense of other funds. Hence, not every fund can utilize the market and earn abnormal returns. Moreover, Sharpe argues that if mutual funds as a group cannot deliver positive alphas, it does not conclude that none of the funds is able to deliver excess returns. Kosowski et al. conducted a research in 2006 concluding that some mutual funds were able to earn high enough alphas to cover their expenses, and that these funds performance persisted over time.

As mentioned earlier, manager's skill is evaluated based on persistence. Outperforming the market once does not mean that the manager possesses skills. According to Grinblatt and Titman (1992), funds that continue to deliver abnormal returns over time are said to be persistent. Furthermore, Hendrick, Patel and Zeckhauser (1993) and Goetzmann and Ibbotson (1994) argue that by investing in past winners investors could earn positive abnormal returns, and they find evidence of persistence in fund performances over a period of one to three years. Persistence can be a useful indicator when concluding on which funds to avoid and which to invest in. However, Brown and Goetzmann (1995) state that using persistence to select funds that will constantly deliver excess returns has no strong evidence.

Most of the research on mutual fund performance is conducted on U.S. data much due to their extensive market. However, with time, researches have focused on European markets in addition to the U.S. market. Active managed Norwegian mutual funds are perhaps more likely to perform well on the Oslo Stock Exchange (OSE) since the presence of strong market efficiency may be weaker, and it seems to be easier to obtain a positive alpha. Regarding the Norwegian market, there are limited studies on mutual funds. The paper closest to ours, and the most extensive research conducted on Norwegian mutual funds is the unpublished paper by Sørensen (2009). He used a dataset free of survivorship bias, ranging from 1982 to 2008, and concluded that active fund managers were unable to gain abnormal returns in the long-term. However, his study does not include the recent financial crisis and he applies the three-factor model in his paper, while we use the five-factor model to evaluate fund performance.

2.1 Fama and French five-factor model

In 2013, Fama and French presented for the first time a draft of a new asset-pricing model, consisting of two new explanatory variables, namely profitability and investment. Two years later, they published a paper regarding the five-factor model that includes the two new factors. Available evidence indicates that a significant part of the volatility in returns related to profitability and investment is left unexplained by the three-factor model (Fama and French, 2015a). Hence, Fama and French include profitability and investment as factors in a new model and explain why these variables are related to average returns through the dividend discount model.

Fama and French (2015a) conducted research on U.S. data to analyze whether the five-factor model explains average returns on portfolios formed to produce large spread in *SMB*, *HML*, *RMW* and *CMA*. They argue that a five-factor model directed at capturing patterns in the average stock returns perform better than the three-factor model. However, the GRS-test conducted by Fama and French (2015a) rejects the five-factor model. Thus, the five-factor model is imperfect. Nonetheless, it is still able to explain between 71% and 94% of expected returns' volatility for the portfolios they examined (Fama and French, 2015a). The authors conclude that the five-factor model is superior to the three-factor model. However, the five-factor model's main problem is its failure to capture the low average returns on small stocks whose returns behave similar to the firms that invest a lot despite their weak profitability.

Furthermore, Fama and French (2015c) conduct the same research on international markets. The paper's main goals are to examine whether the patterns in U.S. average stock returns related to the five-factor model show up in other markets, and to test whether the new model captures the patterns in average stock returns better than the three-factor model (Fama and French, 2015c). Fama and French conclude that with the exception of Japan, the first goal is fulfilled internationally. The reason is that average returns show little relation to profitability or investment. Regarding the second goal, the three- and five-factor model perform poorly in tests on regional portfolios. Moreover, the three-factor model does not perform well when using local versions. However, local versions of the five-factor model are better to describe the patterns in average returns (Fama and French, 2015c).

In a recent unpublished study, Fama and French (2015b) use portfolios formed on anomaly variables that are not directly targeted by the five-factor model in their tests on U.S. data. Their findings indicate that the list of anomalies shrink when applying the five-factor model, since the anomaly returns become less anomalous and because the returns for different anomalies have similar five-factor exposures (Fama and French, 2015b).

To our knowledge, there are no papers, which have conducted a study of the five-factor model explicitly on the Norwegian equity market. Based on the recent findings by Fama and French (2015a,b,c), we believe that the five-factor model will be superior to previous models when applied on Norwegian data as well.

3. DATA

3.1 Norwegian Mutual Funds

The mutual funds data consists of monthly returns, which is gathered through Oslo Børs Informasjon (OBI)[1]. According to OBI, mutual fund returns are corrected for dividends and other adjustments. The database consists of both existing and defunct mutual funds, thus we will avoid the issue of survivorship bias. We have only included funds that primarily invest in Norwegian equities.

[1] The OBI database contains Oslo Stock Exchange data and is available to students at BI Norwegian Business School.

However, we allow funds where 20% of the assets can be placed in international markets. It is easier to detect the effectiveness of Norwegian market conditions if we focus on funds primarily investing in Norwegian stocks. Moreover, we omit any passively managed funds and funds that primarily invest in money market and bonds. Further, we have included funds that have perished or started during our sample period. We require that each fund has functioned at least for more than 12 months in order to be included in the dataset. After accounting for these criteria, we end up with a dataset of 57 actively managed Norwegian mutual funds ranging from the beginning of 2002 to the end of 2011. However, the *pre-crisis* subsample contains 55 funds since *Landkreditt Norge* does not have enough observations, while *Danske Invest Aksje Institutt II* does not have any observations in the subsample. Additionally, the *crisis* sample only contains 50 funds since seven of the funds have died prior to the *crisis* period.

Even though this paper's main goal is to construct the two new factors for the Norwegian market, it is interesting to see how Norwegian funds perform in troubled times measured against the five-factor model. Therefore, we have divided the dataset into two subsamples. In the whole sample, there are 6114 observations of monthly returns consisting of all the funds. The subsample *pre-crisis* contains 3117 monthly returns, while *crisis* contains 2997 monthly observations.

3.2 Benchmark index

In order to measure fund performance, a convenient benchmark is required. Choosing the right benchmark is crucial since the conclusion could be bias if we use an inappropriate index. The most common index is Oslo Børs Benchmark Index (OSEBX), which is a representation of the most traded companies on the OSE. However, we use Oslo Børs Mutual Fund Index (OSEFX) collected from OBI, which is a weight-adjusted version of OSEBX. Furthermore, OSEFX is adjusted to meet particular diversification requirements and to satisfy the EU directives set forth in UCITS, which regulate investments in mutual funds. As regulated by the Norwegian law, mutual funds must hold at least 16 different stocks and none of the stocks can have a weight exceeding 10% of the portfolio (Sørensen, 2009).

We assess OSEFX as most suitable for our research as it is designed to meet Norwegian mutual funds regulations. However, OSEFX is not meanvariance efficient. It has the highest standard deviation, lowest mean return, highest negative skewness and is the most leptokurtic of all indexes (table 1). Hence, as mentioned by Sørensen (2009), OSEFX makes it easier to draw a conclusion. If the mutual funds cannot beat the benchmark with the weakest market return, then we can conclude that these funds cannot outperform any other benchmark either.

3.3 Interest rates

In order to evaluate fund performance, we require a proxy for the risk-free rate. We decided to use three-month treasury bill as the risk-free rate, which we collected through the database of Norway's central bank. The three-month treasury bill is the most common rate used as the risk-free rate when applying asset-pricing models. Since the central bank of Norway does not have data of three-month treasury bills prior to 2003, we extracted interest rates for 2002 from the Bloomberg terminal[2]. The monthly yields are computed as follows:

$$(1) \quad r_t^M = (1 + r_t^{3M})^{1/12} - 1,$$

where r_t^M is the monthly yield for the risk-free rate and r_t^{3M} is the annualized three-month rate.

3.4 Survivorship bias

Survivorship bias occurs when returns of defunct funds are excluded from the sample. To avoid any survivorship bias in the dataset, we have included funds that have either perished or initiated during the sample period. By omitting funds that have died, we might end up with only high-performing funds, since funds that usually underperform are the ones that get defunct. By neglecting the effect of dead funds it will consequently lead to inaccurate measurements as several studies has shown (Brown et al., 1992; Brown and Goetzmann, 1995). Thus, to have a representative data sample we have included both funds that have died, and funds that have been initiated between 2002 and 2011 in our sample.

In table 2, we have exhibited all the funds in our dataset and marked those mutual funds that have either died or initiated during the period in order to

[2] Bloomberg Terminal is available to students at BI Norwegian Business School

distinguish them from the rest. Those are marked with † and * respectively. We see from figure 1 that seven funds have perished prior to the financial crisis, and we see that these funds performed poorly measured against OSEFX on a monthly basis compared to funds that stayed alive. Figure 1 plots the cumulative returns on the equal-weighted portfolio of funds that are alive (EW), funds that have perished during the sample period (EW dead) and the cumulative return on OSEFX.

3.5 Factor returns

We have collected Fama and French's factor returns *SMB* and *HML* for the Norwegian stock market from Ødegaard[3], which he has made available through the OBI database. As for the *MKT*, we have calculated the factor by subtracting risk-free rate from OSEFX. We mentioned earlier that the factors profitability and investment are not available for the Norwegian equity market. Hence, we have constructed these factors for our dataset period 2002-2011 in order to apply the five-factor model. The procedure behind the factor construction will be explained later. We are willing to share the factors with professors, students and others that might be interested.

In table 3, we highlight the descriptive statistics of the different factor returns for all the periods in our dataset. Panel A presents the descriptive statistics for the whole sample period, while panel B and C exhibit descriptive statistics for *pre-crisis* and *crisis* period, respectively. Panel A shows that all the factors have positive mean returns for the whole sample period, likewise for the subsample *pre-crisis*. Furthermore, in the subsample *crisis*, *MKT* and *HML* have negative mean returns. The *MKT* factor has negative returns in the *crisis* period due to the recession. Moreover, the mean returns of *SMB*, *RMW* and *CMA* decrease from *pre-crisis* to *crisis* period.

For the whole period, the factor correlations are close to zero, which means the factors share no particular relationship. However, *SMB* and *RMW* have correlations equal to -0,63 and -0,42 with the market premium. Further, panel B and C illustrate that the correlation coefficients mentioned above are high in the *pre-crisis* and *crisis* period. Moreover, the relationship between *RMW* and *CMA* is

[3] Bernt A. Ødegaard has made factor returns for the Norwegian equity market available to BI-students through OBI.

-0,45 during the *crisis* period, while the correlation between *SMB* and *MKT* is -0,78 during the crisis.

4. METHODOLOGY

In the following section, we will describe the five-factor model in depth and give an explanation for applying the model when evaluating performance of Norwegian mutual funds. Furthermore, we will describe the procedure for creating the factors profitability and investment. Finally, we will present the method we use to evaluate fund performance.

4.1 Five-factor model

As mentioned earlier, Fama and French presented a draft of the five-factor model for the first time in 2013. It includes two new variables, profitability (RMW_t) and investment (CMA_t).

The equation for the five-factor model is formulated as follows:

$$(2)\quad E(R_{i,t}) = \alpha_i + \beta_{i,m}\big(E(R_{m,t}) - R_{f,t}\big) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + e_{i,t}.$$

The $R_{f,t}$ is the risk-free rate and the $\beta_{i,m}$ represents the covariance risk for the fund. $E(R_{m,t})$ is the expected market return and $e_{i,t}$ represents the error term in the regression. *SMB* and *HML* are factors related to respectively size and the book-to-market equity, while the profitability factor *RMW* is the difference between the returns on portfolios of stocks with robust- and weak profitability. Moreover, the investment factor *CMA* is the difference between the returns on portfolios of the stocks of low and high investment firms, defined as conservative and aggressive (Fama and French 2015a).

4.2 Factor construction

In order to test mutual fund performance based on the five-factor model, we have constructed the factors profitability (*RMW*) and investment (*CMA*) for the Norwegian equity market. We have followed the same procedure as described by Fama and French (2015a). The first step was to collect monthly returns for all stocks listed at the OSE in the period 2002-2011, which we gathered from OBI. However, we have only included stocks that have been present at the OSE for at least 12 months. Thereafter, we collected financial data from Bloomberg of all the firms listed at OSE in our dataset period in order to create the variables operating profitability and investment. According to Fama and French's website[4], operating profitability is defined as revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book value of equity for the last fiscal year, t-1. These calculations had to be done manually for each firm. Furthermore, investment is defined as the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by total assets t-2. The next step was to plot the returns of the different firms and their financial data together.

The collected returns from OBI contained companies with A- and B stocks and we encountered the issue by computing value-weighted returns. The rest of the subsection describes the steps applied to obtain the returns. Firstly, we gathered equity prices adjusted for dividends and number of shares outstanding through OBI. The prices and number of shares outstanding were used to compute market values for A- and B shares. Finally, we used the market values to compute value-weighted returns.

In June of each year t from 2002 to the end of 2011, all OSE firms are ranked on market cap and profitability or market cap and investment, resulting in four portfolios for each factor (table 4). The portfolios for profitability are created by first computing the breakpoints, which is determined by the median values in our paper. Thereafter, we ranked the stocks on profitability, resulting in robust and weak portfolios. Finally, by dividing the robust and weak portfolios into small- and big stocks determined by the median value for market cap, we obtained small robust (SR), big robust (BR), small weak (SW) and big weak (BW). The procedure for creating the portfolios for investment is similar. The first step is again to compute the median values, rank the stocks on investment, resulting in aggressive and conservative portfolios. Finally, divide the portfolios into small and big stocks to obtain small conservative (SC), big conservative (BC), small aggressive (SA) and big aggressive (BA).

We have used 2x2 sorts to construct the factors and used the median as breakpoints. The reason is that using 2x3 sorts would be a problem since it uses

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/variable_definitions.html

30th and 70th percentiles as breakpoints resulting in very few observations. Further, we have calculated value-weighted returns for the eight portfolios from July of year t to June of t+1, and the portfolios are reformed in June of t+1. We have calculated returns beginning in July of year t to make sure that the financial data for t-1 is known (Fama and French, 1993). In our case, this means that returns from the first half of 2002 is ranked on financial data from 2000, while the second half is ranked on data from 2001, and so forth. The profitability factor RMW is calculated by taking the average of SR and BR minus the average of SW and BW. Moreover, the investment factor is created by taking the average of SC and BC minus the average of SA and BA (table 4).

Table 4: factor construction

Portfolio categorization		**Measurement of factors**
Profitability		***RMW-factor***
Robust	***Weak***	RMW = (SR+BR)/2 - (SW+BW)/2
Small Robust (SR)	Small Weak (SW)	
Big Robust (BR)	Big Weak (BW)	
Investment		***CMA-factor***
Conservative	***Aggressive***	CMA = (SC+BC)/2 - (SA+BA)/2
Small Conservative (SC)	Small Aggressive (SA)	
Big Conservative (BC)	Big Aggressive (BA)	

4.3 Performance evaluation

Existing literature proposes a number of methods to evaluate fund performance. We assess performance based on the intercept of a time-series regression, defined as the alpha by Jensen (1968). We apply the following factor model in order to measure mutual fund performance, as suggested by Jensen (1968):

$$(3)\quad \alpha_i = E(R_{i,t}) - [R_{f,t} + \beta_{i,m}\big(E(R_{m,t}) - R_{f,t}\big) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t],$$

where $R_{i,t}$ is the return on mutual fund *i* and the alpha (α) represents the excess return of the funds that is not explained by the factor model. A significant positive or negative alpha indicates either positive or negative excess return. We rank funds based on the t-statistics rather than the alpha estimates since the precision of the alpha varies across funds. The length of the fund's return history and the degree of diversification affects the precision of the alpha estimate in each fund.

However, we will report both for completeness. The null hypothesis is set so that the alpha is equal to zero, meaning that managers do not possess superior skills.

5. PERFORMANCE

We use OLS time-series regressions to measure risk-adjusted returns with the five-factor model. As mentioned earlier, we assess fund performance based on the intercept (alpha), and the corresponding t-statistics. However, we rank the funds based on the t-statistics rather than the alpha estimates for reasons mentioned earlier. We have chosen to list all the funds with significant alphas in table 5-7, while the rest are sorted into percentiles[5]. Table 5-7 exhibits alphas, factor loadings and adjusted R^2 for both aggregate- and individual fund performance. However, we only report alphas obtained from the three-factor model on fund industry level.

We compare the results for the aggregate fund industry obtained by the five- and three-factor model. Further, we expect our findings, based on the five-factor model to be superior to the three-factor results. Sørensen (2009) argues that the momentum factor is insignificant when measuring Norwegian mutual fund performance. Hence, we do not apply the momentum factor in this research. Finally, we suspect the *crisis* results to be greater than the findings in the *pre-crisis* period.

The remainder of this section proceeds as follows. The first subsection presents the results for the whole period. Moreover, we will present the findings for the pre-crisis and crisis period in the second and third subsection, respectively.

5.1 Whole period results

Table 5 summarizes the results for the whole period (2002-2011), of which panel A exhibits aggregate fund performance for the fund industry while panel B presents individual fund performance measured against the five-factor model. Further, the aggregate fund industry exhibits non-significant alphas. The whole sample contains 34 positive alphas where six funds have significant alphas on a 10% level and two funds on a 5% level. Finally, *Fondsfinans Spar* exhibits

[5] The reported percentiles are not actual percentiles, but the marginal fund. This means that it shows the fund closest to, but less than, the percentile t-statistic. We do this in order to report factor loadings and t-statistics for these funds.

significant alpha based on a 1% significance level. Moreover, the sample consists of 23 funds with negative alphas of which none of the funds are significant.

The results show weak evidence of abnormal fund performance on an individual level for the whole sample. *Fondsfinans Spar* is the best performing fund in the whole period. The findings obtained from the three- and five-factor model suggest that the alpha's t-value for the fund industry increases when we apply the five-factor model.

5.2 Pre-crisis results

Table 6 reports the estimates of *pre-crisis* performance for the three- and five-factor model. The aggregate exposure towards the market is 1,012 for the five-factor model, and 1,043 for the three-factor model. The corresponding t-values of the coefficients for both the fund industry and individual funds are statistically significant, except for *Pareto Verdi.* Hence, we reject the null hypothesis that the beta is equal to 1. The aggregate industry has statistically significant exposure towards *SMB*, *HML* and *RMW*, while the *CMA* factor is non-significant for the five-factor model. As for the three-factor model, the mutual fund industry has significant exposure towards all the factors.

Furthermore, table 6 reports negative non-significant alphas for the aggregate mutual fund industry measured with the five- and three-factor model. The *pre-crisis* period contains 55 funds of which 18 funds exhibit positive alphas measured with the five-factor model. However, only four funds have a significant excess return among these funds. *Eika Norge* exhibits significant positive alpha on a 1% level, while *Fondsfinans Spar* and *Holberg Norge* are significant on a 5% level. Finally, *Pareto Verdi* is significant on a 10% level. Moreover, 37 of the mutual funds in our research show sign of poor performance, whereas only eight of these funds have significant alphas with confidence levels 90-95%.

Evidence presented in table 6 suggests that the aggregate mutual fund industry was not able to gain positive risk-adjusted returns. However, the results obtained by the five-factor model are superior to the three-factor results, which indicate that the five-factor model is able to capture the variation in returns to a greater extent. We see that funds that underperform outweigh funds with positive abnormal returns, as proposed by Sharpe (1991).

5.3 Crisis results

As reported in panel A in table 7, the equal-weighted aggregate fund returns exposure towards the market is 0,932 for the five-factor model, and 0,950 for the three-factor model. The corresponding t-statistics of the coefficients for both the fund industry and individual funds reject the null hypothesis that beta is equal to 1. The mutual fund industry has statistically significant exposures toward *SMB* and *RMW,* while *HML* and *CMA* are non-significant for the five-factor model. Further, the *HML* factor is non-significant for the three-factor model. Hence, there is no evidence that the value factor had any significant impact on the aggregate mutual fund industry, as stated by Zhang (2005). He argues that value stocks are more exposed to risk during recessions compared to growth stocks since value stocks are concerned with more unproductive capital, which makes them suffer when price risk is high. Furthermore, Fama and French (2015a) state that when profitability and investment factors are added to the three-factor model, the *HML* factor becomes redundant for describing average returns, at least for the U.S. data in the period 1963-2013. Moreover, they argue that the *HML* return is absorbed by the exposures of *HML* to the other four factors, mainly the profitability and investment factors.

Comparing the two subsamples *pre-crisis* and *crisis* there seems to be a noteworthy difference in performance as 42 of 50 funds exhibit positive alphas in the crisis. This is an extensive deviation from the *pre-crisis* subsample. The mutual fund industry, as reported in table 7, has a significant alpha on a 10% significance level measured against the five-factor model. However, alpha for the fund industry is not significant measured against the three-factor model. The *crisis* period contains 11 funds with significant positive alphas. Five of the funds are significant on a 10% significance level, while four of the funds are significant on a 5% level. Finally, two of the reported funds in table 7 are significant on a 1% level.

The results suggest that the mutual fund industry is able to outperform the market based on the five-factor model. However, the same results do not apply with the three-factor model. The corresponding t-values are 1,68 and 1,30 for the models, respectively. Hence, our findings from the Norwegian equity market are in line with Fama and French's results from 2015 that the five-factor model is superior to the three-factor model. The results imply that a significant part of the volatility in returns related to profitability and investment is indeed unexplained by the three-factor model. Moreover, the five-factor model is able to explain the variation in returns greater than the three-factor model, which is emphasized in the *crisis* period. Thus, we will recommend researchers to apply the five-factor model when evaluating mutual fund performance in the Norwegian and U.S. equity market in the future.

Additionally, our findings suggest that fund performance is superior in recessions. The results are in line with the perception that mutual funds are able to gain positive abnormal returns during financial crises. Based on our findings, fund managers are to some extent able to protect investors from major losses during the recent financial crisis. Manager's skills and abilities are emphasized during financial downturns since these managers seem to pick good stocks to a greater extent when the market is underperforming. However, we will use the bootstrapping method in order to distinguish skill from luck in section seven.

6. PERSISTENCE

In this analysis we try to assess whether it is possible to earn risk-adjusted returns persistently by examining good performing funds ex ante. If persistence in abnormal performance is present, it challenges the efficient market view as discussed by Fama (1970). In efficient markets, unexpected returns only reflect news, which is considered unpredictable. Moreover, evidence supporting the presence of persistence could confirm that investors might be able to distinguish good performing funds from the bad ones in one period and construct a portfolio of those funds. By investing in the constructed portfolio, investors could be able to earn abnormal returns for the subsequent period.

Research conducted by Grinblatt and Titman (1992) suggests that performance of mutual funds is persistent in the U.S. market. These findings support the popular investment strategy *hot hands*. Briefly described, the strategy involves investing in stocks with superior performance and selling those that underperform compared to the market. Sørensen (2009) found that the Norwegian market did not exhibit evidence of persistence in fund performance. Hence, the *hot hands* strategy gains no support in the Norwegian market. However, we will examine the persistence in returns for the Norwegian mutual fund market by applying the five-factor model.

In this section, we will use the methodology adopted from Carhart (1997) and Sørensen (2009). On January of each year, we rank all funds based on lagged-one year returns and sort them into five equal-weighted quintile portfolios. The portfolios are formed from the extreme winners to extreme losers, with quintile 1 consisting of the worst performing funds, while quintile 5 consists of the best performing funds. The rebalancing frequency corresponds to the formation period, which means that portfolios are hold for one year and then rebalanced. Fund that die during the evaluation period are included in the equal-weighted average until they disappear, then money are redistributed from dead funds equally across the remaining funds in the particular quintile. Moreover, we construct a long-short portfolio, which is a hypothetical self-financing portfolio that is long quintile 5 and short quintile 1. This corresponds to a strategy that invest in past winners and sells past losers. The result is a time-series of monthly returns on each portfolio ranging from 2002 to 2011. Finally, we estimate the alphas on each portfolio by applying the five-factor model. The results are reported in table 8.

6.1 Results

The results imply that none of the alphas for the portfolios are statistically significant measured against the five-factor model. Thus, none of the funds was able to gain risk-adjusted returns persistently. Funds that earned abnormal returns in the formation period are not likely to obtain same results in the subsequent period. Consequently, there is no evidence of persistence in the Norwegian mutual fund industry. As for the long-short portfolio, 5-1, there is no statistically significant alpha. As stated in the introduction, previous U.S. literature has found *hot hands* strategy to be profitable. However, our findings contradict with the investment strategy at least for the Norwegian market. Additionally, this suggests that the Norwegian market is somewhat efficient (Fama, 1970). On the other hand, the fact that persistence is non-existing might indicate that skilled managers after a good performing period moves on to more lucrative businesses such as hedge funds or international equity funds as argued by Sørensen (2009).

7. BOOTSTRAP – Distinguishing skill from luck

Even though managers as a group have not been able to produce significant positive abnormal returns, it is possible that some mutual funds possess superior managerial skills. If we assume managers do not exhibit superior abilities, some managers will outperform the market, while some will perform poorly simply due to chance. For that reason, we apply the bootstrapping method in order to distinguish between skill and luck among fund managers. Further, it is assumed that the residuals from the estimation are normally distributed when analyzing funds with OLS regression technique (Kosowski et al. 2006). The assumption may not be true since stock returns can often be drawn from a non-normal distribution and exhibit significant higher moments. However, the bootstrap method overcomes the issues of non-normality, skewness and kurtosis (Kosowski et al. 2006; Fama and French 2010). By implementing the bootstrap approach, we seek to examine whether the true alpha is different from zero. In particular, we examine whether there are too many excess returns in the left and/or right tail of the distribution compared to a null hypothesis of zero true alpha.

We use the bootstrap technique proposed by Kosowski et al. (2006) with the modifications suggested by Fama and French (2010), which involves sampling the fund residuals and factor returns jointly. This is implemented to account for correlation in fund alphas, which may occur because the chosen benchmark model does not capture all the variation in fund returns (Fama and French, 2010).

Carhart's (1997) portfolio formation approach, which we applied in the previous section, examines whether mutual funds can deliver abnormal returns persistently. The weakness of this method is that it does not take into consideration that good or bad luck can persist over time. Thus, one cannot conclude whether abnormal returns are delivered out of skill or luck using the portfolio formation approach. Hence, the bootstrapping technique is aimed to account for this issue.

7.1 The procedure

We start the procedure by imposing a multi-factor model to obtain the OLS estimates such as alphas, returns and the residuals by using the time-series of monthly excess returns for mutual funds:

$$(4)\quad R_{i,t}^{e} = R_{i,t} - R_{f,t} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j} f_{j,t} + e_{i,t}$$

Where $R_{i,t}^{e}$ represents the excess return, while $R_{i,t}$ is the return on mutual fund *i* and $R_{f,t}$ is the risk-free rate. Further, $\hat{\beta}_{i,j}$ indicates the risk exposure of fund *i*. $f_{j,t}$ is the return on the *j*-th factor, while *K* denotes the number of factors. The last term, $e_{i,t}$, represents the residuals in the factor model. We save the alphas and corresponding t-statistics (α_i, t_i), as well as the coefficient estimates for the factor exposures ($\beta_{i,j}$) and time-series of the estimated residuals of each individual fund. The residuals are stored in a vector ($e_{i,t}$,t = $T_{i0}, \dots, T_{i1}$), where T_{i0} and T_{i1} indicate the first and the last excess return available for fund *i*.

We implement the five-factor model in order to run the simulations. For every simulation we run, we draw a random vector, T_s, from the uniform distribution ($U_t(0{,}1)_{t=1}^{T}$). The *T* denotes the number of observations in the sample. We then round to the nearest integer, which yields the following vector:

$$(5)\quad T_s = round(T \times \{U_t(0{,}1)\}_{t=1}^{T}, \text{ where s = 1,…,S.}$$

By this process, the bootstrapping technique draws a random vector of time points with replacement from the historical distribution. The next step is to construct a pseudo-time series of return using properties of zero true alphas with jointly sampled factor returns and residuals. This makes sure that the new set of constructed returns has the same properties as the actual set of returns. However, the new set of returns has zero alphas by construction:

$$(6)\quad R_i^{e}(T_s) = f(T_s)\beta_i + e_i(T_S).$$

Finally, from the simulations we attain an estimation of alpha and the corresponding *t*-statistics, which is obtained by the pseudo-time series of returns that is regressed on the factor model given in equation (5). The procedure explained above is repeated for N bootstrap repetitions, where N equals 10 000. This process establishes a distribution of simulated alphas $\{\alpha_i, i = 1, \dots, N\}$ and their *t*-statistics $\{t_{\alpha_i}, i = 1, \dots, N\}$ for each fund, which result entirely from sampling variation while imposing the null of a true alpha equal to zero. We jointly sample the residuals and the factor returns simultaneously when building the pseudo-times series of simulated returns, as suggested by Fama and French (2010).

To be able to draw a conclusion from the distribution of alphas and the *t*-statistics, we calculate the fraction of the number of times the simulated alpha (7) and *t*-statistic (8) exceed the actual alpha and *t*-statistic for the best and worst performing funds and for the percentiles of funds from 10th to 90th:

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

and the fraction of the number of times the simulated *t*-statistic exceeds the actual *t*-statistic:

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

The conclusion is based on the probabilities above, which shows the percentage of the simulated distribution of alphas and t-statistics that is greater than the actual alphas and t-statistics. For more details on the bootstrapping procedure, see Kosowski et al. (2006) and Fama and French (2010).

7.2 Results

The results obtained from the bootstrapping method are reported in table 9-10. Table 9 shows the results for the whole period, while table 10 reports the results for both subsamples. The left column in the tables list the five worst performing funds, 10th to 90th percentiles, and finally the five top performing funds according to either their alphas or t-statistics.

The results for the whole sample period show that the simulated alphas and t-statistics are greater than the actual values in the left tail of the distribution. In more than 95% of the draws, the simulated t-statistic is higher than the actual t-statistic for the four worst performing funds. This confirms that four of the funds in the left tail show signs of poor skills. Moreover, in the right tail, the actual alphas are less than the simulated alphas for the reported funds. However, ranking funds based on t-statistics rather than alphas does not yield similar results. The actual t-statistics are greater than the simulated t-statistics for the 80th percentile to the best performing fund in the right tail. Overall, none of the funds has simulated t-statistics greater than the actual values in more than 5% of the draws. This implies that none of the funds possesses skills at least for the period 2002-2011.

The findings for the subsample pre-crisis indicate that the actual alphas and t-statistics are less than the simulated values in the left tail. The simulated t-statistics are greater than the actual values for all the funds in more than 96% of the draws. We can therefore conclude the existence of funds with inferior managerial skills. Further, the simulated alphas and t-statistics are higher than the actual values with a few exceptions in the right tail. The simulated t-statistic of the best performing fund is less than the actual t-statistic in 4,4% of the draws. Hence, the highest ranked fund might be able to deliver abnormal returns due to skills, and not purely by chance.

The results from the recent financial crisis look very different compared to the pre-crisis period. We do not find any evidence of inferior performance in the left tail of the distribution. However, in the right tail, we find evidence of skills based on t-statistics. The simulated t-statistics are greater than the actual values for the two best performing funds in less than 5% of the draws. Overall, our findings in the crisis period suggest that returns during the crisis are far more driven by chance compared to the pre-crisis period. Even though fund managers are able to deliver abnormal returns in the *crisis* period, we do not find significant evidence of managerial skills based on the bootstrapping procedure. Figure 2-7 in the appendix exhibits visual presentations of the simulated distributions of alphas and t-statistics and their corresponding actual values for the whole period as well for the subsamples.

8. CONCLUSION

In this paper, we investigate Norwegian mutual fund performance using a dataset free of survivorship bias ranging from 2002 to the end of 2011. The purpose of this paper is to evaluate fund performance based on Fama and French's five-factor model. In addition, we examine whether the results obtained by the five-factor model are superior to the three-factor results. Furthermore, we divide the dataset into two subsamples to study the effect of the latest financial crisis on fund industry. Moreover, we measure the persistence of mutual fund returns over time. Finally, we apply the bootstrapping technique proposed by Kosowski et al. (2006)

with modifications suggested by Fama and French (2010) in order to investigate if fund managers possess skills.

Our findings indicate that Norwegian mutual funds are not able to gain risk-adjusted abnormal returns in the whole sample period. However, on an individual level, we find weak evidence of excess returns. In the *pre-crisis* period, we do not find any evidence of abnormal performance. The results for the *crisis* period are more encouraging, as the fund industry exhibits positive significant alpha on a 10% level measured against the five-factor model. Our findings from the *crisis* period indicate that some of the active funds are able to protect their investors during the recent financial crisis.

The results for the whole period and the subsamples are in line with our assumption that the five-factor model is able to explain the volatility in returns better than the three-factor model. This is highlighted in the recent crisis as we find evidence of superior performance on industry level only with the five-factor model. Furthermore, our findings imply that mutual fund performance do not persist over time. Finally, we find substantial evidence of inferior skills among managers in the whole sample and the *pre-crisis* period. However, only the best fund in the *pre-crisis* period shows sign of superior skills. During the recession, we only find superior skills among the two best performing funds.

For further research it would be interesting to examine how Norwegian mutual funds perform in other recessions measured against the five-factor model, and see whether fund managers are able to take advantage of the market conditions or not. Evaluation of international mutual fund performance based on the five-factor model would also be interesting, where one investigates if international funds are able to deliver positive abnormal returns.

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APPENDIX A – Tables and Figures

Table 1: Descriptive statistics of benchmarks and fund returns

The table shows mean, standard deviation, minimum and maximum return, skewness and kurtosis for different market indexes and the equal-weighted aggregate return for the mutual fund industry. All of the statistics are presented monthly. The indexes are the Oslo Stock Exchange All Share Index (OSEAX), Oslo Stock Exchange Benchmark Index (OSEBX) and the Oslo Stock Exchange Mutual fund Index (OSEFX). EW is the equal-weighted aggregate fund return. Panel A shows the statistics for 2002-2011, Panel B shows the statistics for the first subsample period, 2002 to 2006, while Panel C shows the second subsample period, 2007-2011.

	Mean	**Std.dev**	**Min**	**Max**	**Skewness**	**Kurtosis**
			Panel A: 2002-2011			
OSEAX	0,0108	0,0670	-0,24	0,15	-0,93	4,75
OSEBX	0,0096	0,0714	-0,25	0,16	-0,89	4,54
OSEFX	0,0092	0,0751	-0,27	0,17	-1,01	5,12
EW	0,0098	0,0717	-0,26	0,16	-0,86	4,38
			Panel B: 2002-2006			
OSEAX	0,02073	0,05763	-0,15	0,12	-0,48	2,67
OSEBX	0,01812	0,06223	-0,16	0,13	-0,50	2,69
OSEFX	0,01842	0,06336	-0,16	0,14	-0,52	2,82
EW	0,01826	0,06511	-0,18	0,13	-0,59	2,94
			Panel C: 2007-2011			
OSEAX	0,0008	0,0744	-0,2	0,2	-1,0	4,8
OSEBX	0,0010	0,0791	-0,3	0,2	-1,0	4,7
OSEFX	-0,0001	0,0847	-0,3	0,2	-1,1	5,1
EW	0,0013	0,0771	-0,3	0,2	-0,9	4,8

Table 2: List of mutual funds

The table shows a list of all mutual funds in our sample period, 2002-2011, sorted alphabetically. Some funds have not existed for the entire sample period. Some funds have started operation during our sample and are marked with*, while other funds have died during our sample period and are marked with †. The dates of the event are listed at the bottom of the table.

Fund Number and Fund Name	
1 ABIF Norge ++ †	30 Globus Norge I †
2 Aksjefondet Pluss Markedsverdi	31 Globus Norge II †
3 Alfred Berg Aktiv	32 Handelsbanken Norgefond
4 Alfred Berg Aktiv II	33 Holberg Norge
5 Alfred Berg Gambak	34 KLP Aksje Invest †
6 Alfred Berg Humanfond	35 KLP Aksje Norge
7 Alfred Berg Norge	36 Landkreditt Norge*
8 Alfred Berg Norge Etisk*	37 NB Aksjefond
9 Alfred Berg Norge Pluss	38 Nordea Avkastning
10 Atlas Norge	39 Nordea Kapital
11 Carnegie Aksje Norge	40 Nordea Kapital II †
12 Danske Invest Aksje Institutt I	41 Nordea Kapital III †
13 Danske Invest Aksje Institutt II*	42 Nordea Norge Verdi
14 Danske Invest Norge I	43 Nordea SMB
15 Danske Invest Norge II	44 Nordea Vekst
16 Danske Invest Norge Vekst	45 ODIN Norge
17 Delphi Norge	46 Orkla Finans 30 †
18 Delphi Vekst	47 Orkla Finans Invest
19 DNB Norge Avanse I	48 Pareto Aksje Norge
20 DNB Norge Avanse II	49 Pareto Verdi*
21 DNB Norge I	50 Pluss Aksjefond
22 DNB Norge III	51 Storebrand Aksje Innland
23 DNB Norge IV*	52 Storebrand Norge
24 DNB Norge Selektiv I	53 Storebrand Norge I
25 DNB Norge Selektiv III	54 Storebrand Optima Norge
26 DNB SMB	55 Storebrand Vekst
27 Eika Norge*	56 Storebrand Verdi
28 Fondsfinans Aktiv	57 Terra Norge
29 Fondsfinans Spar*	

*8: 042002-122011, 13: 012007-122011, 23: 122002-122011, 27: 102003-122011, 29: 012003-122011, 36: 072006-122011, 49: 012006-122011.

†1: 012002-112004, 30: 012002-112006, 31: 012002-112006, 34: 012002-082003, 40: 012002-112005, 41: 012002-042006, 46: 012002-062006.

Table 3: Descriptive statistics of factors

The table shows summary statistics of the factors applied in our research for the whole sample, pre-crisis subsample and the crisis subsample period. MKT is the excess market return (given by the OSEFX) above the risk-free rate. SMB and HML are factors related to respectively size and book-to-market equity as given by Fama and French (1993). RMW and CMA are the two new factors created by us for the Norwegian equity market as given by Fama and French (2015). RMW is the factor related to profitability, while CMA is related to investment. Column one reports the monthly average return, the second column reports the monthly standard deviation and column 4 to 8 report the correlation between the five factors.

Panel A: Factor returns, standard deviations and correlations: whole sample							
Factor	Monthly Average Return	Standard Deviation	Correlations				
			MKT	SMB	HML	RMW	CMA
MKT	0,0755	-0,2763	1,00				
SMB	0,0419	-0,1123	-0,63	1,00			
HML	0,0413	-0,1224	-0,16	0,22	1,00		
RMW	0,0396	-0,1313	-0,42	0,05	0,06	1,00	
CMA	0,0384	-0,1374	-0,12	0,26	0,06	-0,25	1,00

Panel B: Factor returns, standard deviations and correlations: pre-crisis							
Factor	Monthly Average Return	Standard Deviation	Correlations				
			MKT	SMB	HML	RMW	CMA
MKT	0,0639	-0,1691	1,00				
SMB	0,0330	-0,1077	-0,38	1,00			
HML	0,0444	-0,1224	-0,12	0,19	1,00		
RMW	0,0426	-0,1313	-0,44	-0,12	0,14	1,00	
CMA	0,0448	-0,1374	0,05	0,19	-0,02	-0,45	1,00

Panel C: Factors returns, standard deviations and correlations: crisis							
Factor	Monthly Average Return	Standard Deviation	Correlations				
			MKT	SMB	HML	RMW	CMA
MKT	-0,0027	0,0851	1,00				
SMB	0,0007	0,0493	-0,78	1,00			
HML	-0,0023	0,0380	-0,24	0,26	1,00		
RMW	0,0064	0,0367	-0,42	0,20	-0,04	1,00	
CMA	0,0054	0,0309	-0,34	0,35	0,18	0,10	1,00

Table 5: Fund performance - whole period

The table shows alphas, factor returns and adjusted R^2 obtained from the first-pass time-series regressions of excess mutual fund returns. The estimates are stated in monthly numbers. The numbers in parentheses below the point estimates are their corresponding *t*-statistics. The standard errors used in the computation of t-statistics are robust. The null hypothesis for the *t*-statistics of the slope on the excess market returns is $\beta_{MKT}=1$. Panel A shows the results for an equal-weighted portfolio of mutual funds return (EW) measured against the five-and three-factor model. Panel B reports individual fund performances and percentiles result against the five-factor model. The sample period is January 2002 to the end of December 2011. Footnotes describe funds, which have initiated and died during our sample period. Those are marked with * and †, respectively. The dates at which the event occurred are listed in the bottom of the table. Asterisks *, ** and *** in the second column indicate the level of significance for the alphas at respectively the 10, 5 and 1 percent significance level.

Panel A: Aggregate performance for the mutual fund industry: whole sample							
Model	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$R^2_{Adj.}$
Fama French five-factor	0,000	0,964	0,104	-0,036	-0,078	0,036	0,988
	(0,60)	(43,89)	(4,64)	(-1,74)	(-3,76)	(1,46)	
Fama French three-factor	0,000	0,992	0,140	-0,038			0,986
	(0,12)	(44,69)	(6,34)	(-1,95)			
Panel B: Individual fund performance based on five-factor: whole sample							
Rank	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$R^2_{Adj.}$
Worst	-0,002	0,950	0,098	0,022	-0,103	0,022	0,970
NB-aksjefond	(-1,58)	(32,48)	(2,57)	(0,60)	(-2,27)	(0,49)	
2	-0,003	0,999	0,311	-0,138	-0,140	0,077	0,901
Delphi Vekst	(-1,26)	(22,65)	(4,25)	(-2,49)	(-2,07)	(1,23)	
3	-0,001	0,981	0,076	-0,059	-0,112	0,027	0,973
Nordea Vekst	(-1,19)	(42,75)	(1,99)	(-2,03)	(-3,15)	(0,83)	
15 %	-0,001	0,969	0,395	0,088	-0,124	0,017	0,891
ODIN Norge	(-0,59)	(19,34)	(6,13)	(1,32)	(-1,91)	(0,26)	
Median	0,000	0,900	-0,020	-0,016	-0,038	0,079	0,965
Pluss Aksjefond	(0,16)	(25,05)	(-0,64)	(-0,56)	(-0,93)	(2,20)	
85 %	0,006	0,743	-0,009	0,043	-0,008	-0,046	0,760
Eika Norge *	(1,65)	(6,62)	(-0,09)	(0,43)	(-0,09)	(-0,41)	
9	0,002*	0,993	0,072	-0,050	-0,029	0,034	0,985
Alfred Berg Norge	(1,71)	(60,14)	(2,62)	(-2,43)	(-1,14)	(1,45)	
8	0,002*	0,968	0,056	-0,038	-0,090	-0,047	0,971
Storebrand Norge I	(1,71)	(25,56)	(1,39)	(-1,32)	(-2,46)	(-1,30)	
7	0,002*	0,938	-0,001	-0,024	-0,016	0,054	0,978
DNB Norge Selektiv III	(1,72)	(34,46)	(-0,03)	(-0,97)	(-0,54)	(1,86)	
6	0,005*	0,808	-0,128	0,044	0,024	0,049	0,888
DNB Norge IV **	(1,73)	(8,62)	(-1,34)	(1,14)	(0,54)	(0,91)	
5	0,001*	0,913	-0,047	0,002	-0,049	0,036	0,987
Aksjefondet Pluss Markedsverdi	(1,75)	(50,92)	(-2,35)	(0,15)	(-1,74)	(1,41)	
4	0,004*	0,882	0,217	0,048	-0,018	-0,043	0,879
Pareto Aksje Norge	(1,86)	(19,32)	(3,11)	(0,82)	(-0,24)	(-0,65)	
3	0,002**	0,992	0,069	-0,050	-0,031	0,034	0,985
Alfred Berg Norge Pluss	(2,15)	(60,41)	(2,52)	(-2,43)	(-1,22)	(1,45)	
2	0,002**	0,943	0,014	-0,003	-0,009	-0,024	0,982
Storebrand Aksje Innland	(2,18)	(30,98)	(0,37)	(-0,14)	(-0,30)	(-0,83)	
Best	0,008***	0,772	0,127	0,067	-0,068	0,089	0,839
Fondsfinans Spar ***	(2,76)	(10,72)	(-1,54)	(1,08)	(-0,76)	(1,43)	

*102003 **122002 ***012003

Table 6: Fund performance - pre-crisis

The table shows alphas, factor returns and adjusted R^2 obtained from the first-pass time-series regressions of excess mutual fund returns. The estimates are stated in monthly numbers. The numbers in parentheses below the point estimates are their corresponding *t*-statistics. The standard errors used in the computation of *t*-statistics are robust. The null hypothesis for the *t*-statistics of the slope on the excess market returns is $\beta_{MKT}=1$. Panel A shows the results for an equal-weighted portfolio of mutual funds return (EW) measured against the five- and three-factor model. Panel B reports individual fund performances and percentiles result against the five-factor model. The sample period is January 2002 to the end of December 2006. Footnotes in the first column describe funds, which have initiated and died during our sample period. Those are marked with * and †, respectively. The dates at which the event occurred are listed in the bottom of the table. Asterisks *, ** and *** in the second column indicate the level of significance for the alphas at respectively the 10, 5 and 1 percent significance level.

Panel A: Aggregate performance for the mutual fund industry: pre-crisis							
Model	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$R^2_{Adj.}$
Fama French five-factor	-0,001	1,012	0,102	-0,061	-0,072	0,035	0,986
	(-0,87)	(49,10)	(2,80)	(-2,58)	(-2,25)	(1,33)	
Fama French three-factor	-0,002	1,043	0,148	-0,073			0,983
	(-1,33)	(55,51)	(4,04)	(-2,87)			
Panel B: Individual fund performance based on five-factor: pre-crisis							
Rank	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$R^2_{Adj.}$
Worst	-0,005**	1,019	0,011	-0,055	-0,028	0,034	0,970
Pluss Aksjefond	(-2,63)	(33,47)	(0,21)	(-1,56)	(-0,60)	(0,88)	
2	-0,012**	1,050	0,056	-0,187	-0,470	0,239	0,851
Globus Norge II †	(-2,42)	(11,83)	(0,36)	(-1,82)	(-3,39)	(2,12)	
3	-0,010**	1,030	0,075	-0,216	-0,500	0,206	0,856
Globus Norge I ††	(-2,08)	(11,94)	(0,49)	(-2,17)	(-3,70)	(1,88)	
4	-0,007**	0,902	0,023	0,011	-0,072	0,132	0,874
Nordea Kapital II †††	(-2,04)	(12,6)	(0,21)	(0,12)	(-0,9)	(2,05)	
5	-0,003*	1,026	0,072	-0,053	-0,063	0,003	0,985
Nordea Avkastning	(-1,98)	(49,92)	(1,70)	(-1,73)	(-1,12)	(0,14)	
6	-0,003*	0,962	0,042	-0,057	-0,034	0,068	0,977
NB-Aksjefond	(-1,90)	(38,48)	(0,95)	(-1,99)	(-0,86)	(2,15)	
7	-0,006*	1,096	0,231	-0,224	-0,167	0,083	0,896
Delphi Vekst	(-1,73)	(16,80)	(2,00)	(-2,96)	(-1,64)	(1,00)	
8	-0,004*	0,913	0,100	-0,101	0,017	0,167	0,920
Orkla Finans 30 ††††	(-1,71)	(20,26)	(1,25)	(-1,94)	(0,24)	(2,92)	
15 %	-0,003	1,044	0,107	-0,096	-0,070	0,025	0,964
Nordea Vekst	(-1,67)	(30,72)	(1,78)	(-2,44)	(-1,32)	(0,59)	
Median	-0,003	1,165	0,513	-0,268	-0,120	0,000	0,862
Alfred Berg Gambak	(-0,69)	(15,04)	(3,73)	(-3,00)	(-0,99)	(0,00)	
85 %	0,001	1,009	0,076	-0,059	0,004	0,053	0,976
Alfred Berg Norge	(0,62)	(38,19)	(1,61)	(-1,92)	(0,10)	(1,57)	
4	0,004*	0,069	-0,044	0,034	0,030	-0,088	0,702
Pareto Verdi *	(1,70)	(1,61)	(-0,58)	(0,68)	(0,45)	(-1,62)	
3	0,007**	0,946	0,136	-0,095	-0,220	0,055	0,915
Holberg Norge	(2,27)	(18,31)	(1,49)	(-1,59)	(-2,73)	(0,84)	
2	0,013**	0,596	-0,196	0,048	0,020	0,204	0,644
Fondsfinans Spar **	(2,33)	(4,95)	(-1,35)	(0,58)	(0,14)	(2,31)	
Best	0,016***	0,463	0,063	-0,087	0,101	0,035	0,443
Eika Norge ***	(3,19)	(4,96)	(0,4)	(-0,82)	(0,67)	(0,3)	

*012006 **012003 ***102003
†112006 ††112006 †††112005 ††††062006

Table 7: Fund performance - crisis

The table shows alphas, factor returns and adjusted R^2 obtained from the first-pass time-series regressions of excess mutual fund returns. The estimates are stated in monthly numbers. The numbers in parentheses below the point estimates are their corresponding *t*-statistics. The standard errors used in the computation of *t*-statistics are robust. The null hypothesis for the *t*-statistics of the slope on the excess market returns is $\beta_{MKT}=1$. Panel A shows the results for an equal-weighted portfolio of mutual funds return (EW) measured against the five- and three-factor model. Panel B reports individual fund performances and percentiles result against the five-factor model. The sample period is January 2007 to the end of December 2011. Asterisks *, ** and *** in the second column indicate the level of significance for the alphas at respectively the 10, 5 and 1 percent significance level.

Panel A: Aggregate performance for the mutual fund industry: crisis							
Model	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$R^2_{Adj.}$
Fama French five-factor	0,001*	0,932	0,076	0,011	-0,064	0,011	0,992
	(1,68)	(30,3)	(2,39)	(0,37)	(-2,21)	(0,24)	
Fama French three-factor	0,001	0,950	0,092	0,019			0,991
	(1,30)	(31,77)	(3,38)	(0,75)			

Panel B: Individual fund performance based on five-factor: crisis							
Rank	α	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	$R^2_{Adj.}$
Worst	-0,003	0,934	0,448	0,146	-0,226	-0,254	0,903
Nordea SMB	(-1,07)	(12,23)	(4,74)	(1,56)	(-2,58)	(-1,89)	
2	-0,004	0,877	0,315	0,084	-0,148	-0,002	0,861
ODIN Norge	(-1,04)	(12,29)	(2,76)	(0,90)	(-1,40)	(-0,02)	
3	-0,002	0,863	0,113	0,096	-0,102	0,118	0,932
Holberg Norge	(-0,82)	(12,31)	(1,31)	(0,89)	(-1,24)	(1,16)	
25 %	0,001	1,073	0,191	-0,060	-0,012	-0,090	0,974
Handelsbanken Norgefond	(0,30)	(27,82)	(3,10)	(-1,19)	(-0,21)	(-1,40)	
Median	0,002	1,006	0,117	0,081	-0,083	-0,057	0,972
Terra Norge	(0,98)	(16,78)	(1,93)	(1,07)	(-1,08)	(-0,78)	
75 %	0,001	0,937	-0,029	0,002	-0,044	0,058	0,992
Nordea Kapital	(1,53)	(47,68)	-(0,93)	(0,07)	-(1,52)	(1,78)	
11	0,006*	0,953	0,164	-0,118	0,085	-0,191	0,882
Storebrand Vekst	(1,67)	(9,72)	(1,20)	(-1,15)	(0,91)	(-1,47)	
10	0,002*	0,981	0,068	-0,044	-0,055	0,014	0,990
Alfred Berg Norge	(1,72)	(42,78)	(1,87)	(-1,46)	(-1,61)	(0,38)	
9	0,003*	0,885	-0,016	-0,020	-0,066	-0,077	0,980
Storebrand Norge I	(1,82)	(17,86)	(-0,32)	(-0,44)	(-1,54)	(-1,30)	
8	0,004*	0,817	0,123	0,042	-0,091	0,034	0,955
Fondsfinans Aktiv	(1,85)	(13,44)	(1,93)	(0,76)	(-1,59)	(0,39)	
7	0,002*	0,869	-0,058	-0,028	-0,024	-0,052	0,986
Storebrand Aksje Innland	(1,87)	(21,52)	(-1,22)	(-0,72)	(-0,63)	(-1,05)	
6	0,002**	0,981	0,068	-0,043	-0,056	0,010	0,990
Alfred Berg Norge Pluss	(2,06)	(42,52)	(1,84)	(-1,40)	(-1,62)	(0,27)	
5	0,003**	0,889	-0,040	-0,027	0,006	-0,023	0,989
DNB Norge IV	(2,22)	(24,78)	(-0,88)	(-0,78)	(0,15)	(-0,49)	
4	0,004**	0,877	-0,061	-0,029	-0,027	0,036	0,975
DNB Norge Selektiv III	(2,29)	(26,11)	(-1,14)	(-0,67)	(-0,54)	(0,64)	
3	0,003**	0,820	-0,107	0,055	-0,028	0,120	0,978
Pluss Aksjefond	(2,40)	(21,91)	(-2,20)	(1,60)	(-0,67)	(2,15)	
2	0,003***	0,893	-0,075	0,036	-0,068	0,083	0,990
Aksjefondet Pluss Markedsverdi	(2,81)	(41,08)	(-2,16)	(1,24)	(-2,10)	(2,30)	
Best	0,006***	0,942	0,090	0,064	-0,151	0,008	0,963
Fondsfinans Spar	(3,39)	(14,56)	(1,28)	(1,00)	(-2,67)	(0,09)	

Table 8: Performance persistence across quintiles for portfolios of mutual funds

The table reports formation period returns and post-formation period returns for mutual funds sorted on lagged 1-year performance. The formation period returns and standard deviations are annual and correspond to the one-year lagged return on the quintile portfolios leading up to the formation date. All the returns in the formation- and post-formation period are given in percentage. Quintile 1 contains the worst performing funds and quintile 5 consists of the best performing funds during the portfolio formation period. The post-formation period returns are the monthly returns on the quintile portfolios in the year after formation. The *t*-statistics are reported in parenthesis, and is computed against a null hypothesis with a coefficient of 1, except for the long-short portfolio, 5-1, where the null is that the coefficient is 0. The sample period is 2002-2011.

Table 8: Portfolios sorted on 12-month returns, time period 2002-2011

	Formation period		Post-formation period		Fama and French five-factor model						
Quintile	R^e	$\sigma(R^e)$	R^e	$\sigma(R^e)$	α	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	$R^2_{Adj.}$
1	3,09	3,58	1,15	6,76	0,010	-0,025	0,311	0,121	-0,282	0,016	0,03
					(1,10)	(-0,20)	(1,37)	(0,93)	(-1,31)	(0,08)	
2	10,13	3,52	1,20	7,01	0,010	0,023	0,400	0,101	-0,269	-0,023	0,04
					(1,12)	(0,19)	(1,77)	(0,74)	(-1,20)	(-0,12)	
3	12,23	3,48	1,20	7,09	0,010	0,031	0,401	0,095	-0,257	-0,012	0,03
					(1,09)	(0,26)	(1,70)	(0,68)	(-1,17)	(-0,06)	
4	15,10	3,43	1,24	6,95	0,010	0,021	0,372	0,109	-0,263	-0,016	0,03
					(1,19)	(0,18)	(1,62)	(0,79)	(-1,22)	(-0,08)	
5	22,74	3,49	1,13	7,08	0,010	0,030	0,402	0,126	-0,246	-0,037	0,03
					(1,01)	(0,25)	(1,68)	(0,89)	(-1,14)	(-0,18)	
5-1	19,12	0,42	-0,02	1,46	-0,001	0,055	0,091	0,005	0,036	-0,053	0,02
					(-0,55)	(2,04)	(2,02)	(0,15)	(0,81)	(-1,37)	

Table 9: Bootstrapping results – distinguishing skill from luck, whole period.

The table reports the distribution of actual and average simulated alphas and t-statistics of the Fama and French's five-factor model. The left column lists the five worst performing funds, 10th to 90th percentiles, and finally the five top performing funds according to either their alphas or t-statistics. Alphas are in percentage per month.

	Alphas			t-statistics		
	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
Panel A: measured against OSEFX, whole period 2002-2011						
Worst	-0,20	0,43	81,30	-1,58	0,61	**98,60**
2	-0,30	0,45	83,20	-1,26	0,60	**96,10**
3	-0,10	0,48	78,20	-1,19	0,64	**96,50**
4	-0,05	0,59	80,40	-0,84	0,81	**95,00**
5	-0,23	-0,05	70,10	-0,67	-0,16	68,10
10 %	-0,08	0,60	81,60	-0,63	0,79	92,50
20 %	-0,21	0,31	80,80	-0,45	0,51	82,60
30 %	-0,06	0,62	84,90	-0,30	0,95	89,90
40 %	-0,02	0,12	61,20	-0,06	0,22	61,40
50 %	0,07	0,79	81,20	0,32	1,00	73,90
60 %	0,06	0,69	81,20	0,65	0,97	60,80
70 %	0,26	1,09	84,10	0,96	1,34	63,40
80 %	0,13	0,76	81,20	1,36	1,07	39,30
90 %	0,19	0,82	81,20	1,72	1,15	31,00
5	0,10	0,72	81,00	1,75	1,03	26,70
4	0,40	1,03	82,40	1,86	1,59	41,60
3	0,20	0,86	81,40	2,15	1,17	21,20
2	0,20	0,80	80,10	2,18	1,14	19,20
Best	0,80	1,28	75,90	2,76	1,92	24,80

Table 10: Bootstrapping results – distinguishing skill from luck, subsamples.

The table reports the distribution of actual and average simulated alphas and t-statistics of the Fama and French's five-factor model. The left column lists the five worst performing funds, 10th to 90th percentiles, and finally the five top performing funds according to either their alphas or t-statistics. Panel A reports the results from pre-crisis period 2002-2007, while panel B shows the results from crisis period 2007-2011. Alphas are in percentage per month.

	Alphas			t-statistics		
	Act	Sim	%(Sim>Act)	Act	Sim	%(Sim>Act)
Panel A: measured against OSEFX, pre-crisis 2002-2007						
Worst	-0,50	1,11	94,50	-2,63	1,13	**100,00**
2	-1,20	0,46	89,00	-2,42	0,36	**99,80**
3	-1,00	0,60	88,30	-2,08	0,47	**99,50**
4	-0,70	0,80	93,10	-2,04	0,86	**99,80**
5	-0,30	1,33	94,40	-1,98	1,35	**99,90**
10 %	-0,30	1,25	94,60	-1,90	1,36	**99,90**
20 %	-0,60	0,56	92,10	-1,52	0,70	**99,00**
30 %	-0,14	1,48	94,40	-1,17	1,55	**99,70**
40 %	-0,14	1,45	93,70	-0,93	1,49	**99,20**
50 %	-0,30	1,72	**95,50**	-0,69	1,46	**98,20**
60 %	-0,96	1,59	**98,80**	-0,43	1,47	**96,90**
70 %	0,02	1,96	**96,40**	0,08	1,95	95,60
80 %	0,14	1,75	**95,20**	0,51	1,92	91,30
90 %	0,43	2,60	**96,60**	1,12	2,18	84,00
5	0,95	2,07	92,50	1,64	2,62	84,00
4	0,40	0,43	51,90	1,70	1,79	54,60
3	0,70	0,75	47,00	2,27	2,21	47,50
2	1,30	1,28	42,60	2,33	3,00	11,90
Best	1,60	1,32	20,70	3,19	2,14	**4,40**
Panel B: measured against OSEFX, crisis period 2007-2011						
Worst	-0,30	-0,88	29,30	-1,07	-0,90	57,70
2	-0,40	-0,69	39,20	-1,04	-0,74	63,30
3	-0,20	-0,43	41,70	-0,82	-0,45	65,90
4	-0,06	-0,35	40,80	-0,36	-0,32	52,70
5	-0,08	-0,25	45,30	-0,30	-0,25	53,00
10 %	-0,08	-0,25	45,30	-0,30	-0,25	53,00
20 %	0,03	0,08	40,20	0,13	0,19	42,80
30 %	0,14	0,17	30,40	0,36	0,41	35,60
40 %	0,21	0,29	38,20	0,67	0,71	31,20
50 %	0,19	0,23	39,20	0,98	1,10	28,50
60 %	0,28	0,33	40,40	1,24	1,28	30,40
70 %	0,17	0,19	41,50	1,44	1,35	18,30
80 %	0,61	0,64	41,90	1,67	1,59	21,70
90 %	0,23	-0,01	46,20	2,06	0,12	15,90
5	0,30	0,37	40,20	2,22	1,43	13,20
4	0,40	0,32	49,00	2,29	0,29	17,70
3	0,30	0,25	45,00	2,40	1,17	8,40
2	0,30	0,39	42,70	2,81	1,26	**4,20**
Best	0,60	0,54	47,80	3,39	0,42	**3,70**

Figure 1: Cumulative return on equal-weighted aggregated funds and OSEFX

The figure below shows the cumulative return on the equal-weighted return of funds that are alive today, cumulative return of OSEFX and funds that have died during our sample period. The sample period is 2002-2011.

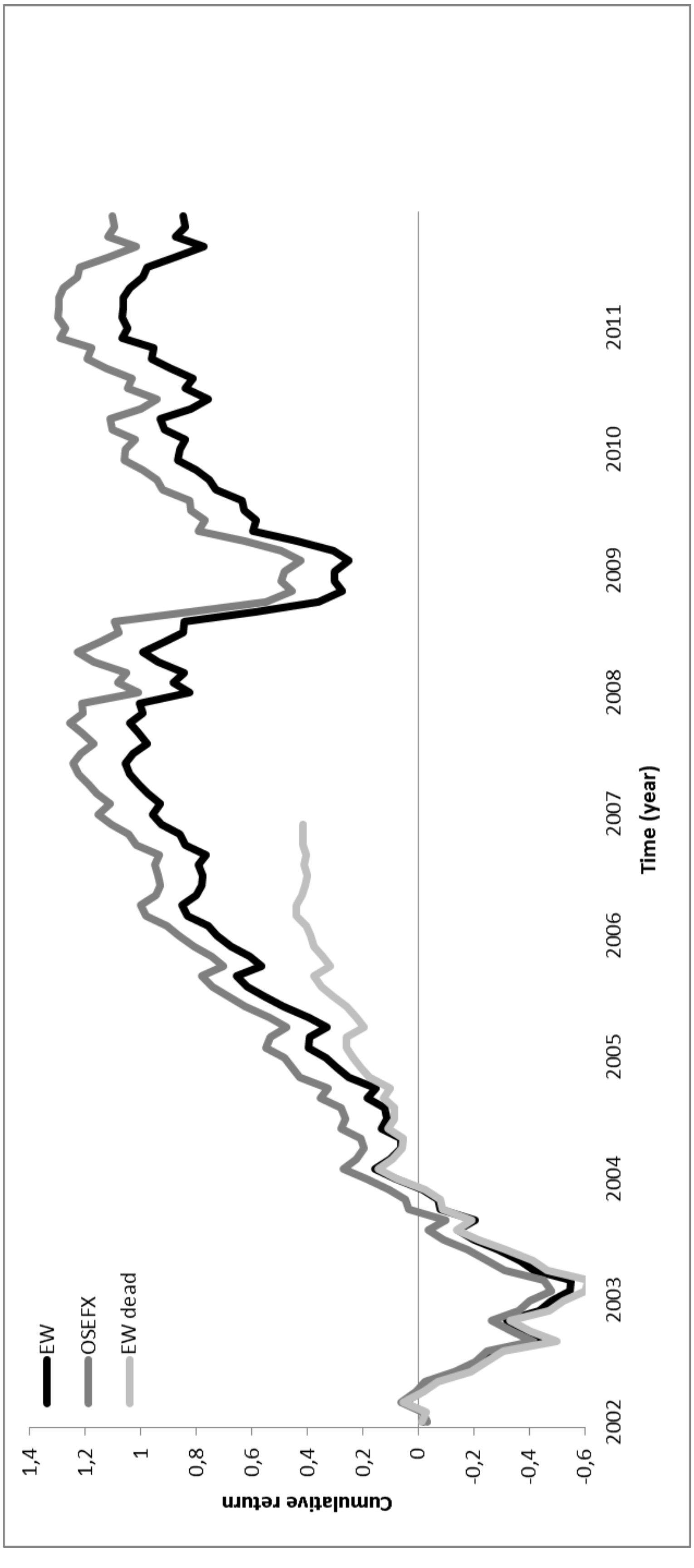


Figure 2: Estimated alpha versus simulated alpha distribution, whole period.

This figure plots the kernel density estimates of the bootstrapped distribution of mutual fund alpha estimates from the Fama and French's five-factor model for Norwegian equity mutual funds for the period 2002-2011. The x-axis illustrates the alpha value in percent per month, while the y-axis represents the kernel density estimate. The dashed vertical line shows the actual estimated alpha. Panel A1-A3 shows several funds on the left tail of the distribution, and panel B1-B3 reports the corresponding funds in the right tail of the distribution. The percentiles represent marginal funds, that is, the 5th percentile fund shows the alpha at the top of the 5th percentile of the distribution.

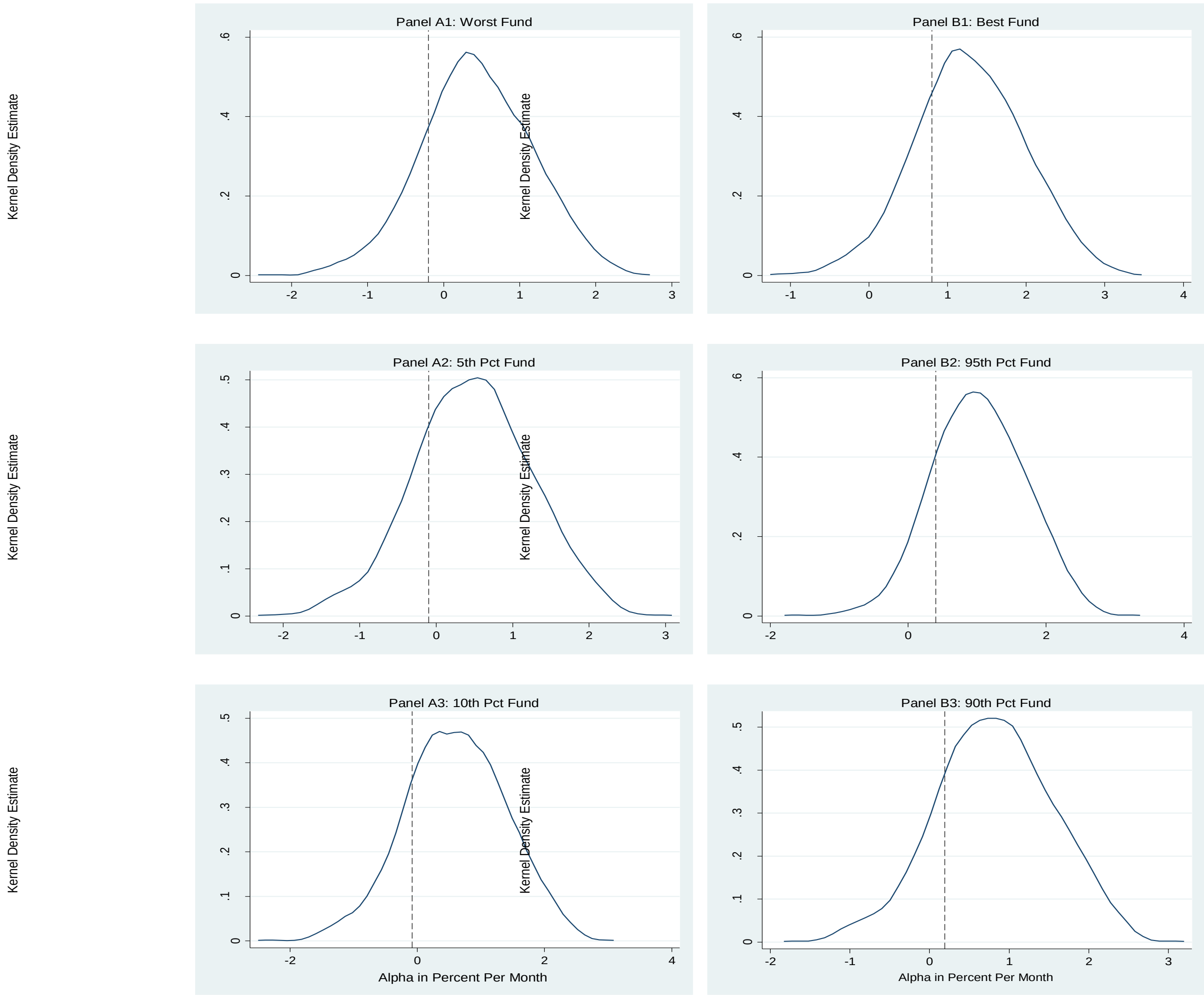


Figure 3: Estimated alpha versus simulated alpha distribution, pre-crisis.

This figure plots the kernel density estimates of the bootstrapped distribution of mutual fund alpha estimates from the Fama and French's five-factor model for Norwegian equity mutual funds for the period 2002-2007. The x-axis illustrates the alpha value in percent per month, while the y-axis represents the kernel density estimate. The dashed vertical line shows the actual estimated alpha. Panel A1-A3 shows several funds on the left tail of the distribution, and panel B1-B3 reports the corresponding funds in the right tail of the distribution. The percentiles represent marginal funds, that is, the 5^{th} percentile fund shows the alpha at the top of the 5^{th} percentile of the distribution.

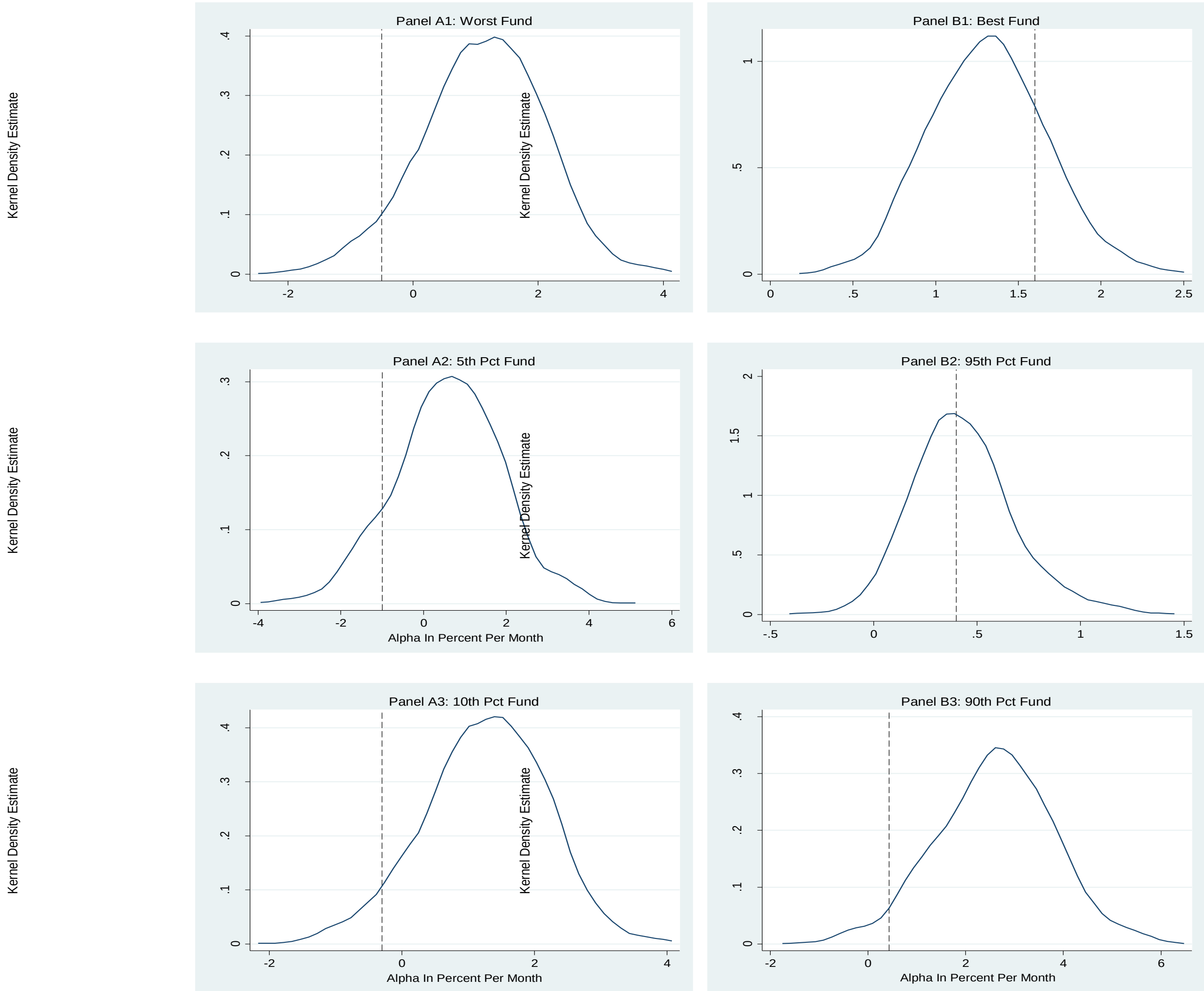


Figure 4: Estimated alpha versus simulated alpha distribution, crisis.

This figure plots the kernel density estimates of the bootstrapped distribution of mutual fund alpha estimates from the Fama and French's five-factor model for Norwegian equity mutual funds for the period 2007-2011. The x-axis illustrates the alpha value in percent per month, while the y-axis represents the kernel density estimate. The dashed vertical line shows the actual estimated alpha. Panel A1-A3 shows several funds on the left tail of the distribution, and panel B1-B3 reports the corresponding funds in the right tail of the distribution. The percentiles represent marginal funds, that is, the 5th percentile fund shows the alpha at the top of the 5th percentile of the distribution.

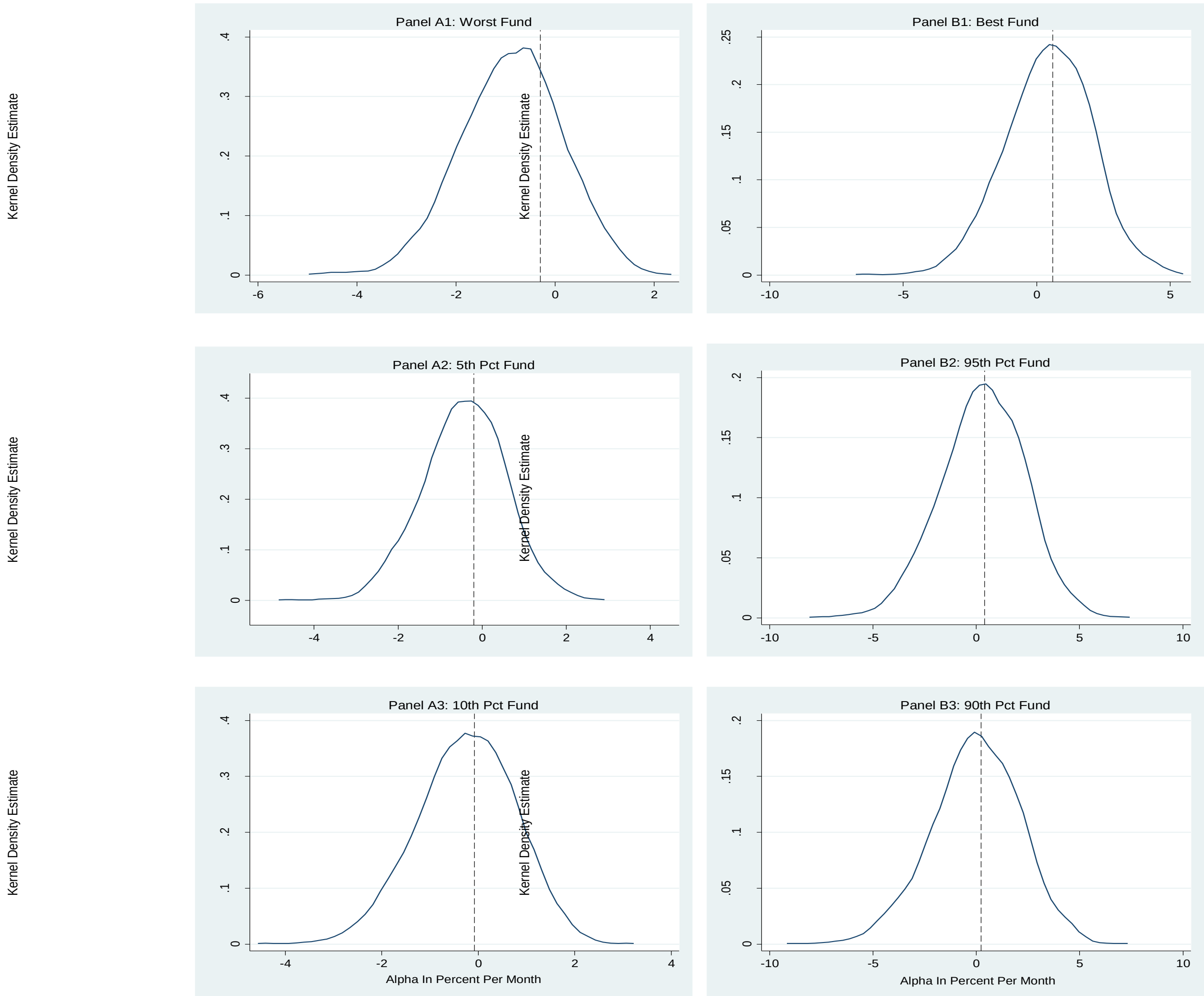


Figure 5: Estimated t-statistics versus simulated t-statistics distribution, whole period.

The panels below represent the kernel density estimates of the bootstrapped distribution of alpha t-statistics for Norwegian equity mutual funds in the period 2002-2011 based on Fama and French's five-factor model. Panel A1-A3 illustrates funds for different percentiles in the left tail of the distribution, and panels B1-B3 reports percentiles for the right tail distribution of bootstrapped alpha t-statistics. The x-axis represents the t-statistic and the y-axis shows the kernel density. The dashed vertical line represents the actual t-statistic of alpha.

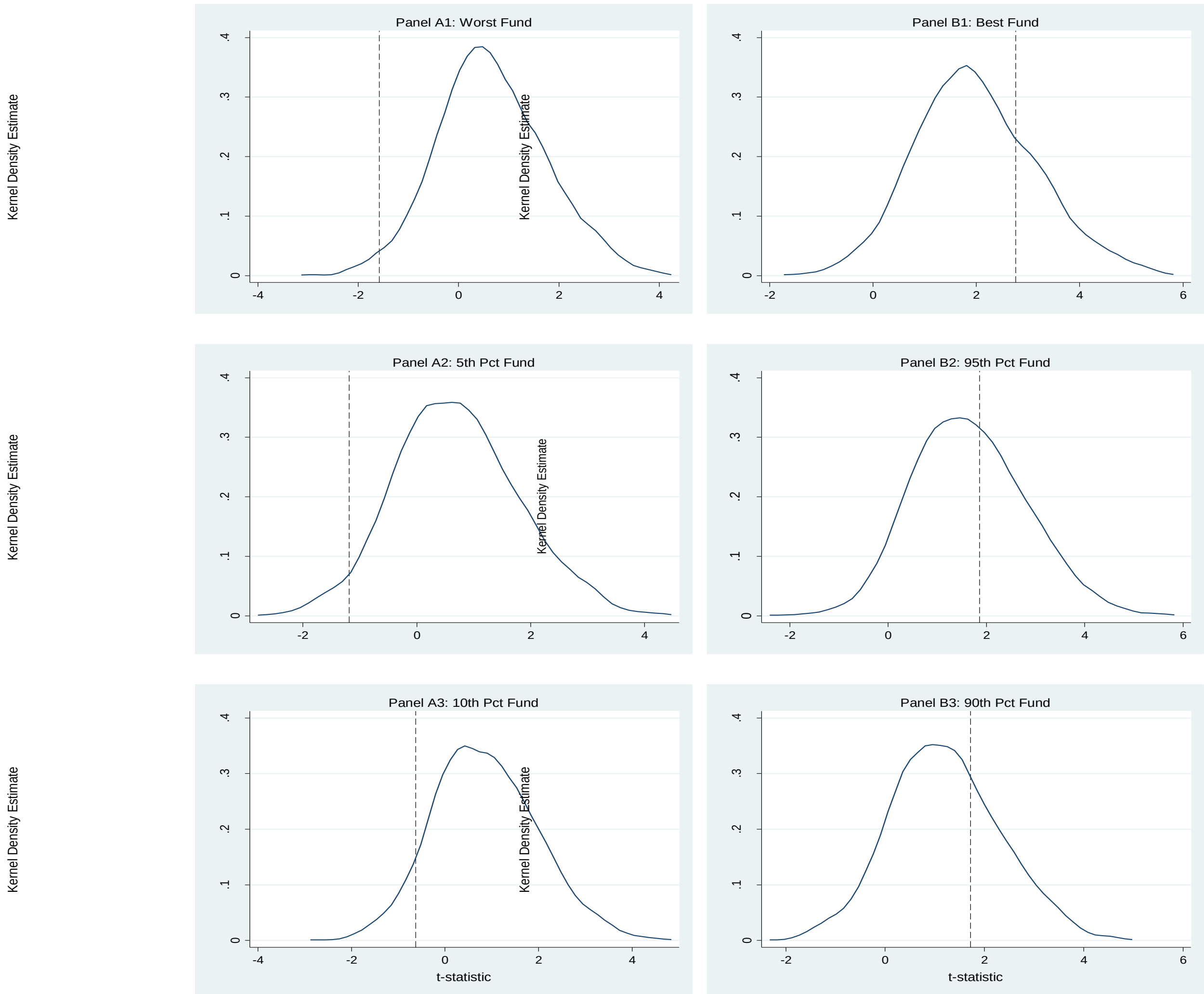


Figure 6: Estimated t-statistics versus simulated t-statistics distribution, pre-crisis.

The panels below represent the kernel density estimates of the bootstrapped distribution of alpha t-statistics for Norwegian equity mutual funds in the period 2002-2007 based on Fama and French's five-factor model. Panel A1-A3 illustrates funds for different percentiles in the left tail of the distribution, and panels B1-B3 reports percentiles for the right tail distribution of bootstrapped alpha t-statistics. The x-axis represents the t-statistic and the y-axis shows the kernel density. The dashed vertical line represents the actual t-statistic of alpha.

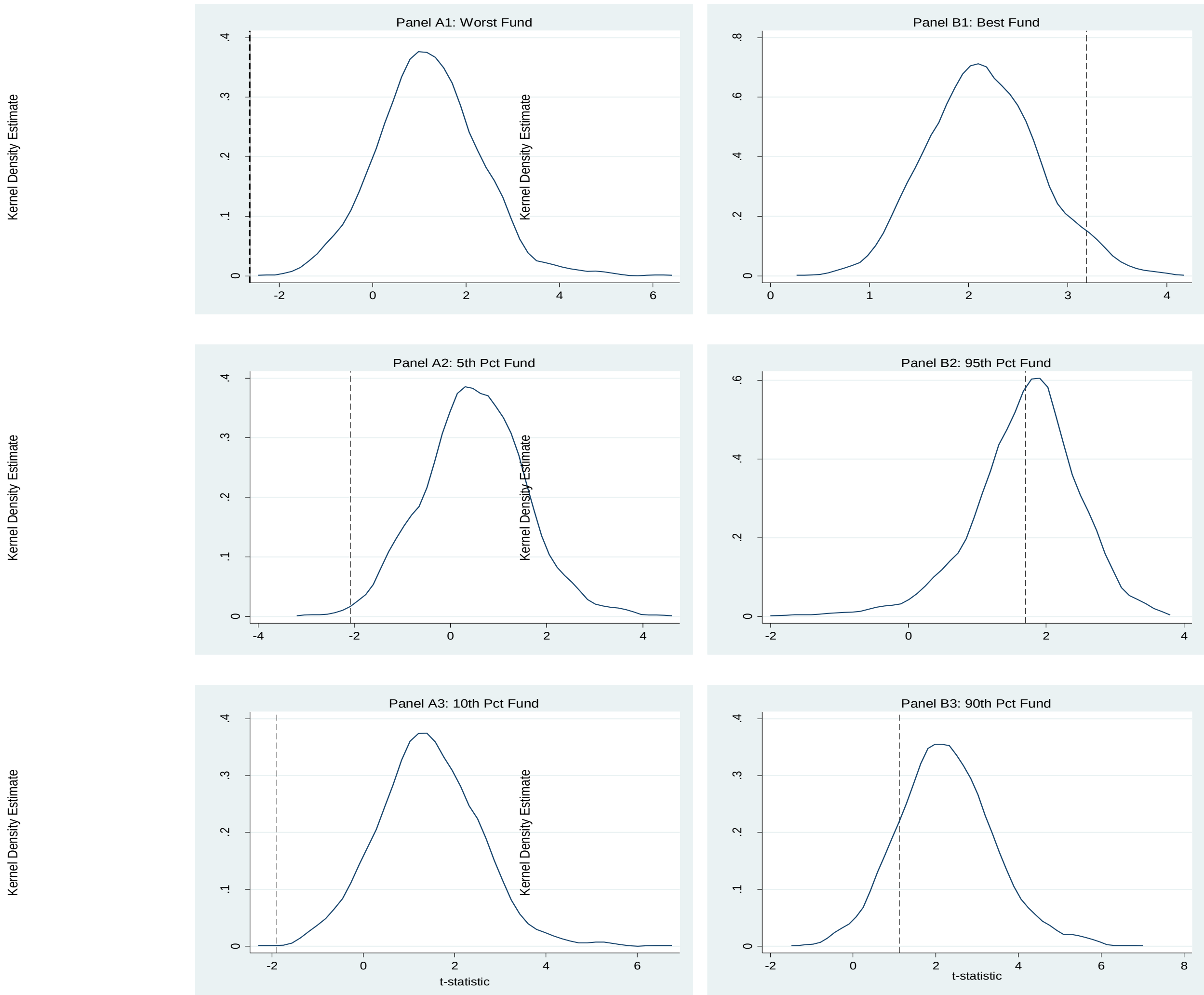
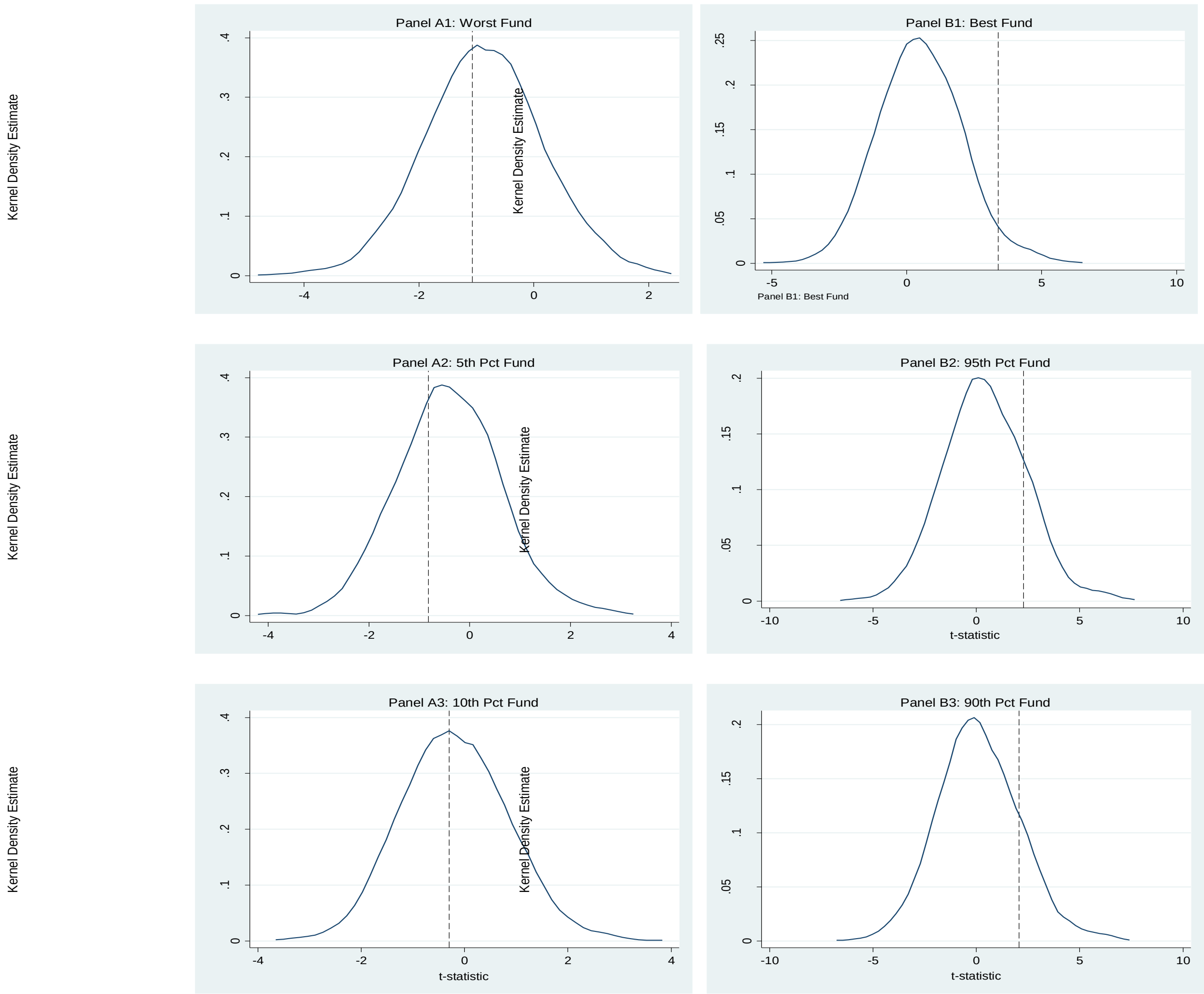


Figure 7: Estimated t-statistics versus simulated t-statistics distribution, crisis.

The panels above represent the kernel density estimates of the bootstrapped distribution of alpha t-statistics for Norwegian equity mutual funds in the period 2007-2011 based on Fama and French's five-factor model. Panel A1-A3 illustrates funds for different percentiles in the left tail of the distribution, and panels B1-B3 reports percentiles for the right tail distribution of bootstrapped alpha t-statistics. The x-axis represents the t-statistic and the y-axis shows the kernel density. The dashed vertical line represents the actual t-statistic of alpha.



APPENDIX B – Preliminary Thesis Report

BI Norwegian Business School – Preliminary Thesis Report

Norwegian Mutual Fund Performance based on the 5-Factor Model

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Abstract

In this paper our main goal is to examine Norwegian mutual fund performance based on Fama and French's 5-factor model. Past research show that managing fees of active funds are baffling, since they underperform on average compared to passive index funds. Recent findings by Fama and French (2015) suggest that the 5-factor model is superior to previous models. Hence, our study aims at discovering whether it is profitable for investors to invest in active mutual funds based on the new model. Furthermore, we will distinguish between fund managers who are able to outperform the market persistently due to skills and those who are able to gain abnormal returns out of pure luck.

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1.0 Introduction

Most of the funds at the Norwegian stock market are actively managed, which means that the fund managers try to exploit mispricing and gain returns in excess of the market return. This is often referred as "beating the market". Passive management on the other hand means replicating a benchmark index, such as S&P 500 by mirroring the components of the benchmark (Sørensen, 2009). The strategy of active management will only be successful if the markets are not efficient (Fama, 1970). This implies that active fund managers cannot gain abnormal returns if the markets are fully efficient (Sørensen, 2009). However, the markets cannot be perfectly efficient, which is pointed out by Grossmann and Stiglitz (1980). Findings from previous and recent research on the subject seem to be ambiguous. On one hand, papers suggest that active fund managers are not able to outperform the market; hence, investors are better off with investing in passive index funds. On the other hand, some papers suggest the opposite; active fund managers are able to beat the market after accounting for managing fees. Kosowski et al. (2006) conducted the first examination of mutual fund performance with a bootstrapping technique, which explicitly controls for luck in performance outcomes. Their findings support prior evidence of skills among active fund managers (Chen et. al., 1999). Kosowski et al.'s (2006) findings indicate that a group of managers actually managed to pick stocks that were able to beat the market persistently.

In this paper, we will examine the performance of Norwegian mutual funds that invest primarily in Norwegian equities. Sørensen (2009) conducted recent study on the Oslo Stock Exchange (OSE) where he measured returns on OSE in the period 1982-2008. He used the same bootstrapping approach as introduced by Kosowski et al. (2006), with modifications suggested by Fama and French (2010). Sørensen (2009) used a dataset free of survivorship bias, and concluded that active fund managers were unable to gain abnormal returns in the long-term.

In 2013, Fama and French presented a draft of a new asset-pricing model for the first time, which consists of two new explanatory variables, namely investment and profitability. The 5-factor model is an extension of the previous 3-factor model developed by Fama and French in 1993. The new model performs better than the 3-factor model when tested on U.S. data and international markets except for Japan (Fama and French, 2015a,b). Fama and French's first draft of the 5-factor model is the motivating paper to our thesis. Their findings imply that the new model performs better than previous models, and hence it is more reasonable to examine mutual fund performance based on the new model developed by Fama and French.

We will apply the same bootstrapping simulation technique as Sørensen (2009) in our study in order to distinguish between managers with superior skills and those who are able to gain abnormal returns out of pure luck. Furthermore, we will use a dataset free of survivorship bias in order to get realistic and accurate measurements of fund performance. International evidence suggests that addressing survivorship bias is important since funds do not exit the sample randomly; most often they become defunct (Sørensen, 2009).

To our knowledge, there are no papers, which have conducted a study of the 5-factor model explicitly on the Norwegian stock market. However, based on tests conducted in U.S and internationally, we assume that the 5-factor model is superior to previous models when applied to the Norwegian data as well.

Hence, our research question is following; *can Norwegian mutual funds outperform a passive benchmark based on the 5-factor model developed by Fama and French?*

2.0 Literature review

2.1 Mutual fund performance

Mutual fund performance has been a debated topic for a long time in the field of finance. Both investors and academics have had a great interest in this topic for several reasons. For academics, it is important since the existence, and persistence of managerial skills would support the rejection of efficient market hypothesis of the semi-strong form as described by Fama (1970). While for investors, it is interesting to know whether investing in active mutual funds is worth the extra costs compared to passive funds, and if so, which sort of funds they should invest in (Gallefoss et al.,2012).

Sharpe (1964), Lintner (1965) and Mossin (1966) laid the foundation of modern finance theory. They introduced the capital asset pricing model (CAPM), which is a single-factor model that explains the relationship between risk and average return.

Jensen (1968) made one of the first interesting researches on this topic. He argues that past research has relied too much on relative measures of fund performance, when what we really need is an absolute measure. Jensen (1968) used the CAPM to introduce Jensen's alpha, which he defined as an absolute measure of manager's skill to outperform the market index. He concludes that active funds are not able to gain abnormal returns compared to the market after accounting for managing costs. Later research conducted by Malkiel (1995), Gruber (1996) and Busse (2001) support Jensen's (1968) results. Malkiel (1995) argues that in the aggregate, mutual funds have underperformed compared to benchmark portfolios, both after management costs and gross of management expenses. He also emphasizes the importance of using a dataset free of survivorship bias in order to get precise results. Furthermore, Malkiel's (1995) findings indicate that it does not exist any consistent strategy in which investors can gain abnormal returns in the long-term. Fortin and Michelson (2002) concluded in a more recent study that most active funds were actually outperformed by index funds. However, funds investing in less efficient markets were better able to utilize mispricing and earn returns in excess of the market return. Later studies do not support these results. According to Henriksson (1984), Chang and Lewellen (1984) managers possess enough skills and private information to offset their expenses, thereby implying that investors' returns lie along the capital market line. This is supported by Ippolito's (1989) findings, which indicate that return before loads lie above the capital market line. Wermers (2000) argues that active mutual fund management do add value to investors.

Furthermore, past research performed by Hendricks, Patel and Zeckhauser (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995) and Wermers (2000) suggest that investors could earn abnormal returns by purchasing past winners and selling past loser. This strategy or behavior of managers is often referred as *hot hands*. Furthermore, they find evidence of persistence in mutual fund performance over short-term period of one to three years. There are several studies on persistence of mutual fund performance. Grinblatt and Titman (1992) find evidence that differences in mutual fund performance persist over time. Furthermore, their findings indicate that this persistence is consistent with the ability of fund managers to earn abnormal returns. These results are supported by Elton et al. (1993) and Elton, Gruber and Blake (1996). Brown et al. (1992) analyzes the relationship between volatility and returns by using a sample with survivorship bias. Their findings indicate that this relationship gives rise to the appearance of predictability. Brown and Goetzmann (1995) use a dataset free of survivorship bias in order to test persistence in mutual fund performance, and their findings indicate the existence of persistence. However, persistence is mostly due to funds that lag the S&P 500. The latter results imply that persistence is a helpful indicator of which funds to avoid, but rather useless for selecting funds that will persistently deliver abnormal returns (Brown and Goetzmann, 1995). Berk and Green (2004) argue that abnormal returns persist in the short-term. However, active funds are not able to outperform the market over a longer time horizon. Furthermore, funds with positive alphas will attract new money flows to the funds until their expected alphas are driven down to zero due to competitive market of capital provision. Hence, investors cannot expect to gain abnormal returns (Berk and Green, 2004).

Researchers have tried to explain the cross section of returns both domestic and internationally, however, as the asset pricing models improve, new discoveries happen. In 1993, well-known American professors, Fama and French, did a study where they introduced two new factors additional to the market-factor developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The new variables, size (SMB) and book-to-market (HML), combined with the market-factor forms what is called Fama and French 3-factor model. The new asset-pricing model developed by Fama and French (1993) predicts expected stock market returns better than the classical CAPM model, thus more precise measurement of Jensen's alpha. This alpha tries to explain if mutual fund managers can outperform the market. Research argues that the 3-factor model did not capture Jegadeesh and Titman's (1993) momentum effect or explained the phenomenon of *hot hands* described by Hendricks, Patel and Zeckhauser (1993). Four years after Fama and French’s groundbreaking studies, in 1997, Carhart suggested a new explanatory variable to their 3-factor model. Hence, inclusion of momentum-factor would better encounter the issues discussed by Jagadeesh and Titman in their studies from 1993. Furthermore, Carhart 4-factor model is broadly used for measuring mutual fund performance. The fourth factor, momentum, is established by going short for the stocks with lowest one-year and going long on the stocks with the highest one-year lagged returns. However, the Carhart model (1997), or any other capital asset pricing models, do not provide any evidence of the existence of skilled mutual funds managers.

Kosowski et al. (2006) developed a statistical technique to examine how the different mutual funds in U.S. performed. The bootstrapping technique is widely used to distinguish between whether managers possess skill or if they are lucky when picking stocks. Kosowski argues that bootstrapping analysis is necessary because the cross-section of mutual fund alphas has a complex non-normal distribution due to heterogeneous risk-taking by funds as well as non-normalities in individual fund alpha distributions (Kosowski et al., 2006). Kosowski et al. in their research found that the mutual fund managers possessed enough knowledge to pick the right stocks in order to gain returns net of costs. Cuthbertson et al. (2008) implemented a similar methodology for limited numbers of top performing U.K. mutual funds, where they came to the same conclusion. However, they also concluded that not all poor performing funds were due to unluckiness, but bad skills performed. In 2010, Fama and French refined Kosowski et al.´s approach in their research paper, where the authors take into consideration the potential correlation between estimated alphas for the mutual funds. The issue arises since benchmark model does not capture fund returns´ common variation. The results support previous research; there exist evidence of skills in the extreme right tail, and lack of skills in the extreme left tail of the mutual fund alpha estimates. Sharpe (1991) argues that passive investors achieve a passive return before accounting for costs. Hence, active mutual funds must also be a zero-sum game, with other words, managers experiencing positive significant alphas before taking costs into account has to be of the expense of other active investors. Furthermore, this indicates that after accounting for costs, active mutual funds have to be a negative sum game. Moreover, Fama (1970) argued that if fund managers were able to beat the market, it proves that market was no longer efficient in the semi-strong sense. Additional, Grossman and Stiglitz (1980) pointed out in their paper that markets cannot always be perfectly efficient, and managers who are able to obtain new information do get compensation. This illustrates the existence of equilibrium degree of disequilibrium.

Most of the research done on the field of mutual fund performance has been conducted in the U.S. stock market. This is no surprise as the U.S. stock market is the largest and most active one in the world.

2.2 Fama French 5-factor model

As mentioned earlier, Fama and French presented a draft of the 5-factor model for the first time in 2013. Two year later, they published the paper regarding the 5-factor model that includes two new factors. Available evidence suggests that a significant part of the volatility in returns related to investment and profitability is left unexplained by the 3-factor model. Hence, it is reasonable to include investment and profitability as factors in a new model (Fama and French, 2015a). Fama and French use the dividend discount model to explain why these variables are related to average returns, and thus justify their inclusion of the variables in a new model.

Fama and French (2015a) analyze whether the 5-factor model explain average returns on portfolios formed to produce large spread in the factors except the market return. The tests are conducted on U.S. data. They argue that a 5-factor model directed at capturing patterns in the average stock returns performs better than the 3-factor model of Fama and French (Fama and French, 2015a). However, the GRS-test conducted by Fama and French (2015a) rejects the 5-factor model. Hence, the 5-factor model is imperfect, but it this still able to explain between 71% and 94% of the volatility of expected returns for the portfolios they examine (Fama and French, 2015a). The authors conclude that the 5-factor models main problem is its failure to capture the low average returns on small stocks whose returns behave like those of firms that invest a lot despite low profitability (Fama and French 2015a).

Fama and French (2015c) conduct the same research on international markets. The paper's main goal is to examine whether the patterns in U.S. average stock returns related to the 5-factor model show up in other markets. Furthermore, the authors want to test whether the 5-factor model captures the patterns in average returns better than the 3-factor model (Fama and French, 2015c). Fama and French (2015c) conclude that the first goal is fulfilled internationally except for in Japan. The reason is that average returns show little relation to profitability or investment. Regarding the second goal, 3- and 5-factor model performs poorly in tests on regional portfolios. The 3-factor model does not perform well when using local versions either. However, local versions of the 5-factor model are better able to describe the patterns in average returns (Fama and French, 2015c).

In a recent unpublished study, Fama and French (2015b) use portfolios formed on anomaly variables that are not directly targeted by the 5-factor model in their tests on U.S. data. Their findings indicate that the list of anomalies shrink when applying the 5-factor model, since the anomaly returns become less anomalous and because the returns for different anomalies have similar 5-factor exposures (Fama and French, 2015b).

2.3 Research on Norwegian Data

As mentioned earlier, little research has been done on Norwegian mutual fund performance. Gjerde and Sættem (1991) conducted the earliest research, where they evaluated performance in the period 1982-1990. Their conclusion was that managers demonstrated market-timing skills, however, managers´ ability to pick the right stocks were somewhat limited.

Næs, Skjeltorp and Ødegaard (2008) tried to uncover the returns’ pattern on the Oslo Stock Exchange (OSE) for the period 1980-2006. The purpose of the research was to analyze the factors driving these patterns on the stock market. Their findings indicate that oil price and liquidity are significant factor affecting OSE. Furthermore, the authors conclude that changes in oil prices only influence domestic firm's expected cash flows, and not the underlying risk factors.

Che, Norli and Priestley (2008) conducted a study on persistence of mutual fund performance of individual investors. They argue that a significant amount of individual investors possess persistence in performance. Furthermore, their findings indicate that investors can gain abnormal returns by holding stocks previously favored by top performing investors.

Sørensen´s unpublished research is arguably the nearest paper to ours. He analyzes mutual fund performance and persistence based on Fama French 3-factor model on all Norwegian equity funds listed on the Oslo Stock Exchange in the period 1982-2008. Using a dataset free of survivorship bias, he concludes that there are no statistically significant evidence of abnormal performance among active funds. Sørensen uses a bootstrapping technique to distinguish skill from pure luck, and he finds only weak signs of skill in the right tail and lack of skills in the left tail of the distribution of alphas. He does not find any persistence in either winners or losers. The study indicates that funds with high exposure to beta-risk earned high returns. However, as pointed out in the Economist on March 22nd 2007, even though it is beta risk, active fund managers does add value to investors, since they could not have constructed the portfolios themselves: "This type of analysis give managers no credit for choosing the systematic factors the betas that drive their portfolios. Yes, these betas could often have been bought for very low fees. But would an investor have been able to put them together in the right combination?"[6] This means that a negative alpha does not necessarily mean value destruction (Sørensen, 2009).

3.0 Data

3.1 Mutual fund data

We have not collected the mutual fund data needed yet, but we are confident that this will not be an issue. To our knowledge, Bernt Arne Ødegaard provides Norwegian factor returns online. However, we will need to create factor returns for the two new variables. We do also know that earlier students at BI Norwegian Business School have created a dataset free of survivorship bias for the period 2002-2012. On the other hand, Sørensen (2009) created a dataset free of survivorship bias, which consists of the period 1982-2008. Hopefully, one of them will be willing to share their dataset.

3.2 Benchmark

In our study, we will be using data on Norwegian Mutual Funds listed on the Oslo Stock Exchange that invest primarily in Norwegian equities. We are unsure about the period in our study, since it depends on which dataset we are able to gather. However, we do know that we will use the Oslo Stock Exchange Mutual Fund Index (OSEFX) as a benchmark in our research. OSEFX is adjusted to meet particular diversification requirements and to comply with the EU directives set forth in UCITS, which regulate investments in mutual funds (Sørensen, 2009). By

[6] http://www.economist.com/node/8892422

the Norwegian law, Norwegian mutual funds most hold at least 16 different stocks, and the weight in any particular company cannot exceed 10% (Sørensen, 2009). We do also need information about managing fees in order to assess returns net of all costs.

3.3 Interest rates

Since we are going to use the 5-factor model to evaluate the funds, we require a proxy for the risk-free rate. As a proxy, we will be using the three-month treasury bills, which is the most common rate to use when applying asset-pricing models. However, it depends on what is available for our data set period. If not, the one-month interbank rate is best available substitute for the three-month treasury bills.

4.0 Methodology

Our research paper will primarily focus on the time-series regression of Fama and French's 5-factor model. We will also apply the bootstrapping method used by Sørensen (2009) in order to evaluate the financial performance of the funds. Furthermore, the Carhart-model is more applicable when running bootstrapping method (Sørensen, 2009). However, Sørensen (2009) concluded that the Carhart-model is insignificant when testing for Norwegian mutual funds and find it more reasonable to apply Fama and French's 3-factor model. We will in our research add two new explanatory variables to the model, profitability factor RMW_t and investment factor CMA_t. As mentioned earlier, the findings in Fama and French's articles from 2015 indicate that the 5-factor model are superior to all previous asset-pricing models. Hence, we want to test if the Norwegian mutual funds can outperform a passive benchmark based on the new model developed by Fama and French. Finally, we will compare our results with the findings in Sørensen´s studies (2009), in order to examine whether the funds performs greater based on the 5-factor model. We will mainly be using the statistical package EViews to gather relevant econometric analyses.

4.1 Factor models

In our paper, we will measure mutual fund performance based on the Norwegian fund returns compared to the 5-factor model. However, we will start by presenting CAPM, 3-factor model and finally describe the 5-factor model. We will evaluate the performance based on the measured alpha (the intercept from the time-series regression) and corresponding t-values. We believe it may be better to rank funds based on the t-statistic rather than the alpha value since the precision of the alpha estimate varies across funds (Sørensen, 2009).

The CAPM is a single-factor model developed by Sharpe (1964), Lintner (1965) and Mossin (1966). According to the model, the market return is the only factor that determines expected return, which you can see in the model below:

$$E(R_{i,t}) = R_{f,t} + \beta_{i,m}(E(R_{m,t}) - R_{f,t}) + e_{i,t} \qquad e_{i,t} = 0 \; when \; diversified$$

The components in the model are as following: R_f is the risk-free rate and the β_i represents the covariance risk (systematic risk) for the fund. The $E(R_m)$ shows the expected return on the market. Furthermore, the error-term,$e_{i,t}$, is believed to go towards zero as the fund get well diversified. In order to rank funds based on whether they beat a passive benchmark or not, is tested by an extension of the classical CAPM model, developed by Jensen (1967):

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

The only difference between the classical CAPM model and the model above is α_i(alpha). The alpha represents the excess return of a portfolio that is not explained by the factor(s) in the model. This excess return can stem from either luck or skills. This implies that a significant positive or negative α_i indicates either positive or negative excess return.

In 1993, Fama and French introduced two new stock-market factors additional to the overall market factor. These two new variables are related to firm size (SMB_t) and book-to-market equity (HML_t). The motivation for the 3-factor model was to better explain the volatility in returns; they argued that the single-factor model CAPM did not do well in capturing the differences in returns (Fama and French, 1993). Carhart (1997) in his research added another explanatory variable to the 3-factor model in order to evaluate fund performance. The momentum factor ($PR1YR_t$) is described as the trend for stock prices to continue to rise or fall depending if the stock is going up or down. The model presented below includes Fama and French´s 3 factors as well as Carhart´s momentum-factor, which is referred as Carhart's 4-factor model:

$$E(R_{i,t}) = \alpha_i + \beta_{i,m}(E(R_{m,t}) - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,PR1YR}PR1YR_t + e_{i,t}$$

Sørensen suggest that we should not test with Carhart´s momentum factor, as the factor is insignificant when measuring Norwegian mutual fund performances. However, the factor has been highly relevant when testing for US funds (Sørensen, 2009).

As mentioned earlier, Fama and French presented a draft of the 5-factor model for the first time in 2013. It includes two new variables, namely profitability (RMW_t) and investment (CMA_t). According to Fama and French (2015a,b), the 5-factor model is superior to previous factor models.

$$E(R_{i,t}) = \alpha_i + \beta_{i,m}(E(R_{m,t}) - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + e_{i,t}$$

4.2 Bootstrapping method

In our research we will be using bootstrapping method introduced by Kosowski et al. (2006), however we will be sampling fund and explanatory returns jointly, which was suggested by Fama and French (2010). The reason for this is to avoid the correlation of α ("alphas") estimates for the funds, which occurs as a consequence of benchmark model not capturing all the variation in fund returns (Fama and French, 2010).

The bootstrapping approach is determined by the following stages. Firstly, estimating the alpha and its corresponding t-statistics for each fund, and then measuring the t_α-distribution. Secondly, we obtain the true alpha of zero by subtracting the estimated actual alpha of a fund from its monthly returns. For each simulation, we will draw a vector from the distribution and multiply the vector by the number of observations in the sample. After constructing time series of excess returns for the different funds, we can run the time-series factor model regression on the constructed excess returns. We then attain the alphas and matching t-statistics for the clones. Whether the simulated alpha is greater than the actual alpha, and whether the simulated t-statistic is greater than the actual t-statistic, determine if managers possess stock picking skills or not (Sørensen, 2009).

4.3 Survivorship bias

When we remove the returns from non-functioning funds from a sample, it will lead to unrealistic high estimate of mutual fund performance in general, since non-functioning funds normally underperformed relative to the market. This is what we call ***survivorship bias***. By neglecting the effect of *dead* funds it will consequently lead to inaccurate measurements as several studies has shown (Brown et al., 1992; Brown and Goetzmann 1995). We can simply encounter this problem by subtracting funds return and the market return for the same sample period (Sørensen 2009):

$$R_{it}^{x} = R_{it} - R_{Mt}.$$

Based on the results we are able to either keep or reject the null hypothesis that the funds return of the functioning funds are equal to the dead funds. If we are able to reject the test, we can conclude that there is evidence of survivorship bias in the sample.

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