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A Contrarian Investment Strategy for Equity Fund Selection

Master Thesis in Financial Economics (FIE)

Lars Patrick Eriksson

&

Uman Ilyas

Supervisor: Professor Svein-Arne Persson

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The following thesis examines the existence of contrarian profits in the Norwegian equity fund market. Three different pricing models are used to determine if a contrarian strategy is able to create abnormal returns in the Norwegian equity fund market from 1995-2014[1]. Firstly, we apply a similar approach as De Bondt and Thaler (1985) by using a single-index CAPM model. Our results initially support the work of De Bondt and Thaler, as we find significant reversals in fund returns with a two-year ranking and two-year holding strategy. Secondly, we expand the CAPM model by adding size- and value risk factors as suggested by Fama and French (1993), which results in a statistically *insignificant* alpha, suggesting that the strategy significantly loads on size and value. Finally, we extend the model even further, by adding Carhart's momentum factor, which also yields an insignificant alpha. Our research suggests that the single-index CAPM model, initially tested by De Bondt and Thaler, is an inferior model compared to the three-factor model introduced by Fama and French. The results indicate that contrarian investors do not obtain abnormal returns as they are simply compensated for the inherent risk of their portfolios, mainly suggested by the size effect literature by Banz (1981).

[1] Abnormal returns, refers to returns in excess of a relevant benchmark. Excess returns, refers to returns in excess of the risk-free rate.

Acknowledgements

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I. Introduction

This thesis is based on a specific request from Gabler AS to perform a quantitative analysis on contrarian strategies in the Norwegian equity fund market over the last two decades. We find this research to be particularly interesting and relevant for a couple of different reasons. Firstly, interest rates are at a historical low level in many parts of the world, mostly because of the global financial crisis in 2008-2009. The recent decline in oil prices has also played a crucial a role in pushing interest rates down, especially for oil exporting countries such as Norway (Aarø, 2015). Low interest rates imply low returns for investors that are currently invested in bank deposits, especially in Norway, where interest rates are lower than inflation (Statistics Norway, 2015). The Norwegian Fund and Asset Management Association (Verdipapirfondenes forening) reports that small private investors are investing more in mutual funds than ever before (Verdipapirfondenes forening, 2015). This might be seen in relation to the negative real returns for Norwegian bank deposit holders, which should provide reasonable incentives to invest in the mutual fund market. Furthermore, this low interest rate regime is predicted to persist as Norges Bank's third quarter Monetary Policy Report (Pengepolitisk rapport) projects interest rates below one percent at least until 2018 (Olsen, 2015, p. 21). Secondly, in recent decades, plenty of research papers have been written on stock selection strategies such as contrarian strategies. However, to our knowledge, there is little research to be found on contrarian strategies regarding mutual funds. Research available on fund investment strategies mostly revolve around momentum strategies. For this reason, our thesis is not only relevant due to the current macroeconomic outlook, but also because of the modest amount of research on this specific mutual fund selection strategy. Although the latter remark makes our research more interesting, unfortunately, it also limits our basis of comparison to contrarian strategies performed on stocks. Finally, to our knowledge, this is the first paper to examine the existence of contrarian profits in the Norwegian equity fund market, and hopefully both academics and investors alike will appreciate this contribution.

Our research is inspired by Svalestad (2015), who questions the value of quantitative analysis in regards to fund selection. Specifically, the relationship between Information Ratio (IR) based fund ratings and subsequent performance is scrutinized. His findings suggest that fund selection strategies based on IR ratings could in fact generate significant abnormal returns in the short run, meaning that the highest rated funds generate higher levels of annualized abnormal returns than lower rated funds. Although these findings are somewhat unreliable as they are based on a simplistic approach, they do provoke some interesting questions, especially as the analysis also indicates a long run reversal effect in fund performance. The long run reversal effect indicates that the lowest rated funds generate the highest annualized average abnormal returns, while the highest rated funds experience diminishing abnormal returns over time, however, this effect is statistically insignificant (Svalestad, 2015, p. 44). Despite an insignificant long run reversal effect, Svalestad's research begs the question; is there a way of generating abnormal returns by constructing a portfolio consisting only of the lowest rated funds?

In the following thesis, we are going to examine a variety of contrarian strategies in the Norwegian equity fund market over the last 20 years. However, we will mostly focus on the optimal two-year ranking and two-year holding strategy, which gives both maximum performance and statistical significance with a single-index CAPM model. Three different pricing models will be utilized to perform the analysis, and the goal is to examine returns in excess of relevant benchmarks over the last 20 years. Previous critique such as disregard to risk changes in ranking periods, beta estimation biases, size effect implications and the potential impact of the January effect, will also be addressed. Finally, the formal hypothesis testing will be based on the theory of efficient markets, specifically at a semi-strong level of market efficiency.

I.I Contrarian strategies

Chan (1988) briefly explains the theoretical basis of a contrarian strategy, and suggests that equity markets often overreact to news, both good and bad, which often leads to winners being overvalued and loser being undervalued. In financial theory, this idea or assumption is commonly known as the Overreaction Hypothesis (Chan, 1988, p. 147). Contrarian investors exploit this tendency by going long in stocks in period *n* that have performed relatively poorly (loser stocks) in period (*n-1*), and by short-selling stocks in period *n* that have performed relatively well (winner stocks) in period (*n-1*). However, the purpose of this thesis is not to verify or debunk the Overreaction Hypothesis, as it is only presented as a theoretical justification for contrarian strategies. In previous research, such as De Bondt and Thaler (1985) and Chan (1988), the Overreaction Hypothesis is tested by creating winner and loser portfolios. In the following thesis, we are only interested in the applicability of a contrarian strategy on loser funds in the Norwegian equity fund market. This is mostly due to practical considerations as short-selling of funds is rarely an option for small private investors.

According to the Overreaction Hypothesis, an over- or undervaluation of an asset is usually followed by a reversal effect, which is illustrated in figure 1. The curved orange lines illustrate possible overreactions to unexpected news on a certain asset, both good and bad, and the straight green lines illustrate changes in fundamental value of that particular asset. Figure 1 shows that an overreaction is usually followed by a reversal in the opposite direction towards the fundamental value of the asset.

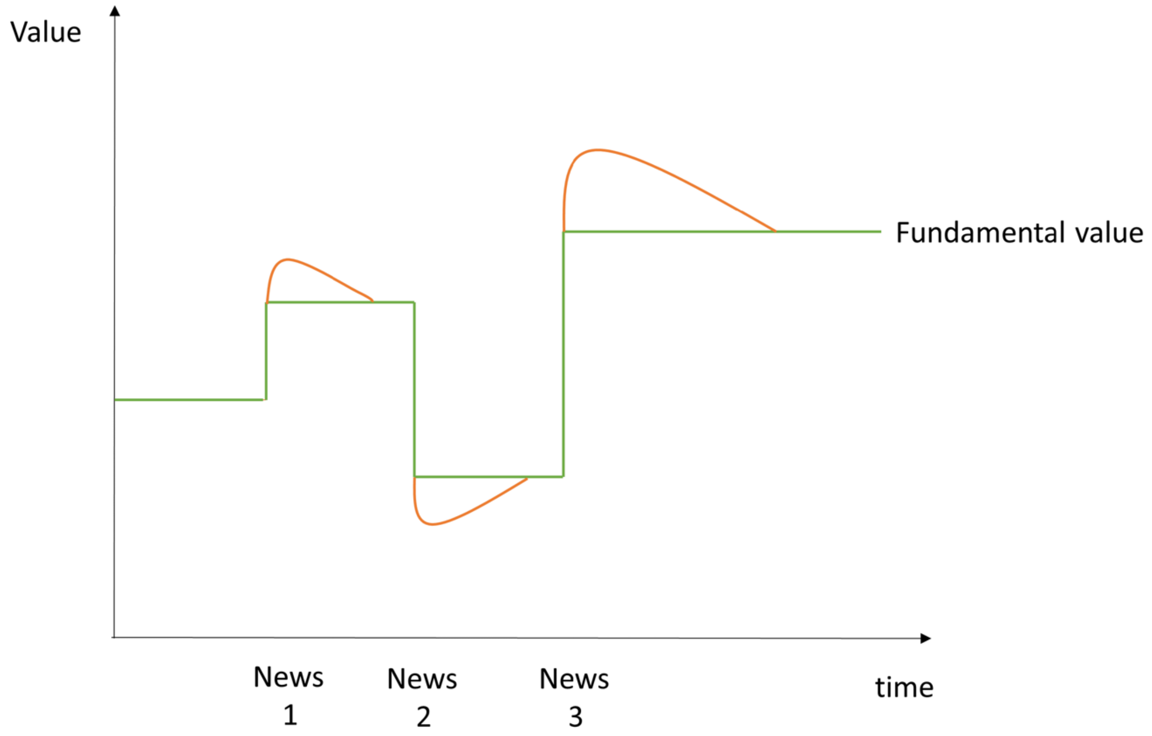

Figure 1: Overreaction in capital markets

II. Literature review

II.I An influential contribution to contrarian strategies

In general, contrarian strategies are well documented and frequently applied by investors, however, they have their share of critics among theorists. Chan (1998) reminds us that any trading strategy that relies on historical performance might violate the weakest form of market efficiency. According to the theory of efficient markets at the semi-strong level, all news, expected or unexpected, should immediately be priced in all relevant assets. Thus, a reversion over time as illustrated in figure 1 should not take place (Brealey et al., 2011, p. 345). However, famous research papers such as De Bondt and Thaler (1985, 1987) present convincing evidence, not only consistent with an *inefficient* market at the semi-strong level, but also with the Overreaction Hypothesis. According to themselves, this was the first attempt at using a behavioral principle, i.e. the Overreaction Hypothesis, to examine the existence of a contrarian investment anomaly (De Bondt & Thaler, 1985, p. 795). Most, if not all research papers on contrarian strategies refer to De Bondt and Thaler's (1985) work.

By making use of a single-index CAPM model, De Bondt and Thaler (1985) report large abnormal returns when applying a contrarian strategy on stocks traded on the New York Stock Exchange (NYSE) from 1926-1982. Maximum performance is found with a three-year ranking and three-year holding strategy, with a portfolio consisting of 35 stocks. 16 ranking periods are created to isolate the top and bottom 35 stock performers by computing cumulative residual returns (CU), each over the previous 36 months, and 16 holding periods are created to track performance, each over the following 36 months[2]. For the loser portfolio, the average cumulative residual returns (CAR) in month 36 (CAR_{36}) over all 16 holding periods is 19.6%, and the CAR in month 36 (CAR_{36}) over all 16 holding periods for the winner portfolio is -5%. This implies that the loser portfolio outperforms the winner portfolio by 24.6%, with a t-statistic of 2.20[3] (De Bondt & Thaler, 1985, p. 800).

[2] Residual returns, refers to returns beyond a relevant benchmark: $(R_i - R_M)$.
[3] CAR is the average of the cumulative residual return (CU) of each month (month = 1,..., N; N = 36) in each of the 16 holding periods.

II.II Conflicting empirical results

Generally, empirical evidence of the Overreaction Hypothesis in stock returns is a controversial topic in the international finance community (Maheshwari & Dhankar, 2014). Empirical results seems to be highly dependent on variations in methodology, meaning length of ranking and holding periods, market of interest, choice of pricing models and assumptions.

In UK's stock market for instance, the conclusion is unclear. At first, Campbell and Limmack (1997) provide evidence against the Overreaction Hypothesis with a one-year ranking and one-year holding strategy. However, when they extend the analysis with both a two-year ranking and two-year holding and a four-year ranking and four-year holding strategy and restrict the sample exclusively to smaller companies, they find evidence in support of the Overreaction Hypothesis with a sample from 1979-1990. In contrast, Clare and Thomas (1995) examine UK's stock market from 1955-1990, but they find little evidence in favor of the overreaction effect. They suggest that an appropriate inclusion of the size effect leads to lower abnormal returns, thus undermining the overreaction effect in UK's stock market. Evidence from the Spanish stock market is also divided. Alonso and Rubio (1990) and Forner and Marhuenda (2000) both contradict each other's findings. The former pair are in support of a strong overreaction from 1967-1984, as they observe that losers outperform winners with a one-year ranking and one-year holding strategy. They also find that longer ranking and holding periods generate stronger overreactions than shorter ranking and holding periods. Furthermore, they suggest that their results are robust even after correcting for size. In complete contrast, the latter pair of researchers provide evidence against the Overreaction Hypothesis from 1963-1997. Kryzanowsko and Zhang (1992) test the Canadian stock market from 1950-1988, and they find little evidence consistent with the Overreaction Hypothesis, even after testing both shorter and longer ranking and holding periods. The same result is evident in Brailsford's (1992) research of the Australian stock market, as he finds little evidence of a mean reversion in winner and loser portfolios from 1958-1987. Finally, Baytas and Cakici (1999) test the overreaction effect in seven developed stock markets, specifically in USA, Canada, Japan, France, Italy, Germany and the United Kingdom. Generally, the results support the overreaction effect and significant long-term reversal are found in all stock markets except for the US and Canadian (Baytas and Cakici, 1999).

Previous research is most certainly divided, and support can be found on either side of the overreaction anomaly, thus the applicability of contrarian strategies is questioned. However, based on previous research, Dissanaike (1994) finds the performance of contrarian portfolios to be quite sensitive to methodological approach, specifically in regards to computing returns in both ranking and holding periods. Therefore, we use several different models and consider previous criticism in regards to methodology and approach, especially in terms of considering risk changes in ranking periods, beta estimation biases, the size effect, and the January effect.

II.III Quantifying contrarian strategies

A validation of the Overreaction Hypothesis implies that well performing funds in period *n* usually perform poorly in period (*n+1*), and that poorly performing funds in period *n* usually perform well in period (*n+1*). In fact, we see a clear tendency of this behavior in our two-year ranking and two-year holding strategy, in which funds are ranked based on geometric average return over a two-year ranking period. We observe that highly ranked funds in period *n*, often perform poorly in period (*n+1*), and eventually revert back to being highly ranked in period (*n+2*). This behavior is illustrated in figure 2 with a fictive example of a successful contrarian portfolio.

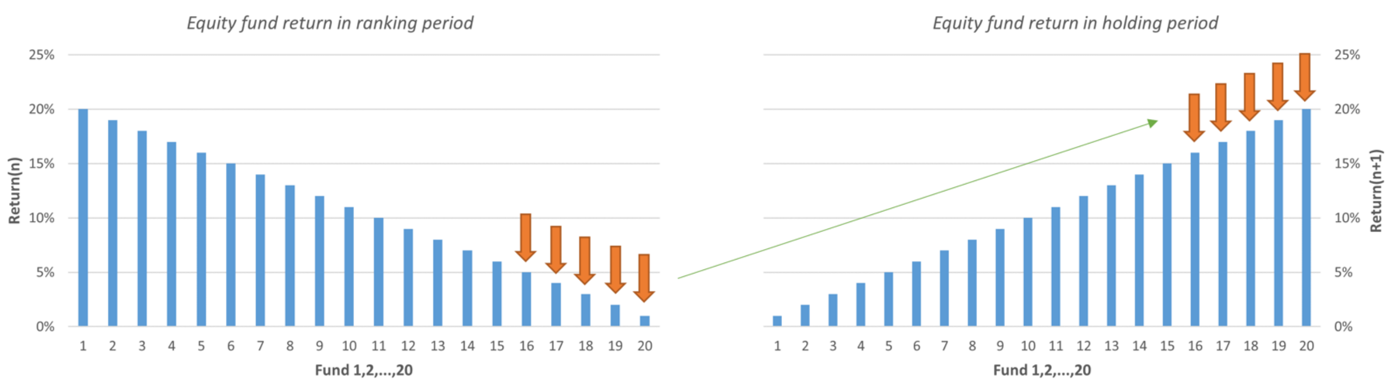

Figure 2: Performance reversal from period n to period (n+1)

This "bouncing" pattern in fund performance has to be repeated systematically over the sample period in order to create a successful contrarian portfolio. De Bondt and Thaler (1985, 1987) contribute this type of behavior in stock performance to the Overreaction Hypothesis, which actually is nothing but a psychological phenomenon where market participants overreact to unexpected news, both good and bad. However, there have been attempts to translate this behavior into more quantifiable explanations, where researchers examine the mechanics behind mutual fund reversals.

Morey's (2003) research suggests a negative relationship between 5-star Morningstar mutual fund ratings and subsequent three-year fund performance, which is also supported by Jain and Wu (2000)[4]. His research suggest that highly rated funds generate relatively lower future three-year returns than lower rated funds. In addition, he finds that funds experience greater risk three years after receiving 5-star ratings, compared to the prior three years, where risk is measured by both the standard deviation of monthly returns and the systematic risk from a single-index model (Morey, 2003, p. 9). If contrarian investors believe this to be true, they can exploit this tendency by short-selling highly ranked assets. As one can see, Morey's research sheds some light on the underlying dynamics of the Overreaction Hypothesis, especially for the potential overvaluation of winner assets. However, his research does not provide a conclusive explanation behind the relationship between 5-star Morningstar ratings and subsequent performance. More importantly, for us at least, his research does not try to explain if or why lower rated funds experience relatively higher average returns than higher rated funds.

Guercio and Tkac's (2002, p. 920) research suggests that an initial 5-star rating, on average, generates a seven-month abnormal capital inflow of 53% in excess of expected capital inflows. Morey (2003) also refers to their research and argues that excess capital inflows over normal levels may lead to poor investment decisions and cause a subsequent fall in performance. However, he does not provide any explanations behind his claim. Hauge (2011) on the other hand explains this by suggesting that large funds (relative to their

[4] Morningstar ratings range from 1-5, where 5 is the highest rating and 1 is the lowest rating. Mutual funds are rated based on previous performance, where performance is adjusted for both risk and costs. Funds that rank among the top 10% receive a 5-star rating while the bottom 10% receive a 1-star rating (Morningstar, 2015).

investment mandate, i.e. Norway, Scandinavia, Asia etc.) might find it challenging to find good investment alternatives. The rationale behind this suggestion is that large funds are reluctant to take large position in any single company's outstanding shares, because if they buy (sell) such large positions they might drive the price up (down) to unsustainable levels. Therefore, Hauge claims that equity funds managers are cautious when buying or selling stocks, and that they typically are comfortable with holding 5% or less of any single company's outstanding shares. Given a maximum stake of 5% in any single company, funds with large capital bases only generate small gains on their investments in absolute terms, especially relative to their size. Thus, he summarizes by suggesting that the larger the funds, the harder it becomes to increase total returns. Other possible explanations might be that fund managers see excess inflows as an opportunity to invest in assets that they previously considered too risky given available resources at that particular time, thus are more willing to increase their downside risk by investing in relatively riskier assets after receiving abnormal inflows. Again, this is just a suggestion, and it is not based on any hard evidence. On the contrary, several researches disagree with Morey and Hauge by suggesting the opposite, such as Warther (1995) who finds a positive relationship between capital inflows and subsequent performance.

Frazzini and Lamont (2008) substantiate Morey's research, at least to a certain degree, as they discuss the "dumb money effect", which refers to small private investors' tendency to invest in funds that perform poorly in subsequent periods. This effect is measured through inflows and outflows in the fund market, and suggests that investors reallocate poorly. In our opinion, there is an obvious connection between Frazzini and Lamont's "dumb money" argument, Morey's abnormal inflows argument and the Overreaction Hypothesis. If small private investors are "dumb money" and follow a sentiment-orientated herd-like behavior as suggested by Frazzini and Lamont, they will most likely invest in highly rated funds, thus contribute to abnormal inflows. In turn, this might lead to a drop in performance, as suggested by Morey and Hauge. Alternatively, highly ranked funds that experience abnormal inflows, thus considered equivalent to overvalued funds, might experience downward revisions towards their true values, as suggested by the Overreaction Hypothesis. These examples are mostly suggested explanations as to why highly ranked funds perform poorly in subsequent periods, but they are vague in terms of explaining why poorly ranked funds perform well in subsequent periods. In any case, these examples are attempts at providing quantifiable explanations behind contrarian strategies.

Literature on contrarian strategies is quite extensive and surprisingly unclear in terms of acknowledging abnormal returns as a result of contrarian strategies. However, it is even more unclear in terms of identifying the underlying causes that might or might not lead to contrarian profits. Antoniou et al. (2005, p. 73) brilliantly summarizes some of the more formal literature on contrarian strategies, which goes to show just how divided literature is on the explanations behind contrarian profits: i) overreaction and/or underreaction to firm specific information, ii) seasonality effects, iii) size effects, iv) lead-lag explanations, v) changes in risk and microstructure biases within an efficient market context and vi) behavioral aspects[5]. Our research however, is primarily consistent with the size effect as an explanation to why significant abnormal returns in a CAPM framework does not hold in a Fama and French framework, thus resulting in insignificant abnormal returns.

III. Approach and modelling of abnormal returns

III.I Risk changes, size effect and January effect

De Bondt and Thaler's publication in 1985 has not gone unnoticed in the finance literature, and as all important contributions, it is both praised and criticized. Several researchers have replicated their work by slightly modifying some of the methods and underlying assumption. One of them is Chan (1988) who criticizes De Bondt and Thaler's (1985) use of rank period betas, and their lack of regard to risk changes in ranking periods. Further suggesting that rank period betas in their research might be biased. Chan argues that betas are assumed to vary with changes in market value, which he in turn relates to the size effect literature by Banz (1981). In fact, he finds that in De Bondt and Thaler's sample, the average value of loser stocks from the beginning to the end of ranking periods, on average, changes by -45%,

[5] Antoniou et al. (2005) refers to the following literature: i) Pettengill & Jordan (1990), De Bondt & Thaler (1985, 1987), Lehman (1988), Mendenhall (1991) and Abarbanell & Bernard (1992), ii) Chopra, Lakanishok & Ritter (1992) iii) Clare & Thomas (1995), iv) Lo & Mackinley (1990), v) Chan (1988), Ball & Kothari (1989), Kaul & Nimalendran (1990) and Kaul, Conrad & Gultekin (1997) and vi) Barberis, Shleifer & Vishny (1997) and Amir & Ganzach (1998).

and the value of the winner stocks changes by 365% (Chan, 1988, p. 149). Considering the size effect, these results indicate that loser stocks become much riskier at the end, compared to the start of ranking periods, and that winner stocks become much safer at the end, compared to the start of ranking periods, therefore, rank period betas might be biased. He suggests that holding period betas should be estimated directly in order to perform the correct risk-adjustment. Chan (1988) uses the same sample as De Bondt and Thaler in his own research, however, when accounting for risk changes in ranking periods, only small differences are found between winner and loser portfolios. In addition, he assumes these small differences to be economically insignificant after transaction costs. Therefore, he claims weak support for the Overreaction Hypothesis and contrarian strategies. In order to avoid the issue of risk changes in ranking periods completely, we estimate betas directly from holding periods, as suggested Chan (1988).

Zarowin (1990) documents the size effect by recreating De Bondt and Thaler's (1985) research. Similar to our research, he finds initial support for De Bondt and Thaler research, however, when controlling for size by comparing winners and losers of somewhat equal size, he finds that losers outperform winners only in the month of January. In addition, he finds that when losers are smaller than winners, losers outperform winners, but also that when winners are smaller than loser, winners outperform losers. He contributes these results to the size effect, and concludes that De Bondt and Thaler's research is nothing but a further strengthening of the already established literature on the size effect (Zarowin, 1990, p. 124). Clare and Thomas (1995) support this conclusion, as they also find no significant reversals when adjusting for the size effect in UK's stock market. However, there is literature that contradicts both their research, as Alonso and Rubio (1990) find significant reversals with a one-year ranking and one-year hold strategy in the Spanish stock market, even after adjusting for size. Furthermore, they suggest that longer ranking and holding periods generate higher level of abnormal returns. Due to practical considerations, we do not create winner portfolios as shorting of funds is usually not an option. In any case, our research adjusts for the size effect by extending the single-index CAPM model with the SMB risk factor.

De Bondt and Thaler's (1985) research clearly indicates that most of their returns are generated in the month of January. This phenomenon is well known in finance, and Thaler (1987) refers to this effect as the January effect. Several researchers have addressed this effect, for instance, Pettengill and Jordan´s (1990) research shows that close to half of their yearly CAR in their 90-day portfolio is created in January. Chopra, Lakonishok and Ritter (1992) also support this finding as they criticize De Bondt and Thaler (1985) by pointing out that most of their overreaction effect is realized in the month of January. Due to this effect and its ability to misrepresent actual contrarian profits, we also perform tests to examine the significance of the January effect. However, tests performed with the Fama and French three-factor model and the Carhart four-factor model on the optimal two-year ranking and two-year holding strategy indicate a statistically *insignificant* January effect. Therefore, the January effect is not displayed in the regression model specifications in the methodology section[6].

III.II Efficient Market Hypothesis

An efficient market is a market where new information regarding different securities is priced instantaneously (Brealey et al., 2011 p. 916). Maurice Kendall (1953), a British statistician, is considered the first to present a theory on efficient markets. His studies of stock prices indicate that stock prices are highly random from one week to the next, meaning that prices follow a so-called "random walk" (Brealey et al., 2011, p. 342). Furthermore, he adds, if capital markets were predictable, investors would easily make superior profits. Actually, any trading strategy that relies on historical performance might violate the weakest form of market efficiency (Chan, 1988). If markets are efficient, there should never be an overreaction, as new information on a particular asset should be priced instantly.

The efficient market hypothesis proposes three levels of market efficiency; weak, semi-strong and strong market efficiency (Brealey et al., 2011 p. 345). In the weak market efficiency assumption, it is believed that prices only reflect information that can be found in

[6] Regression specifications with a dummy variable for January (not displayed in methodology);
i) Three-factor: $R_i - r_f = \alpha_i + \beta_{iM}\big(E(R_{mt}) - r_{ft}\big) + \beta_{iS}E(SMB_t) + \beta_{iH}E(HML_t) + \gamma_{iJ}\theta_t + \epsilon_i$ and
ii) Four-factor: $R_i - r_f = \alpha_i + \beta_{iM}\big(E(R_{mt}) - r_{ft}\big) + \beta_{iS}E(SMB_t) + \beta_{iH}E(HML_t) + \beta_{iP}E(PR1YR_t) + \gamma_{iJ}\theta_t + \epsilon_i$.

historical price data. The validity of this level of market efficiency implies that it is impossible to earn superior profits by taking advantage of historical returns, which is what we are trying to do with a contrarian strategy. If an exploitation of historical data results in abnormal returns, it will most certainly also imply weak form *inefficiency*. In the semi-strong market efficiency assumption, pricing of an asset reflects both historical prices and all other publicly available information. At this level of market efficiency, prices should immediately adjust to changes in public information. The strong market efficiency assumption implies that prices should reflect all available information, including inside information. Thus, no superior investment strategy should exist, and no strategy should consistently outperform the market (Brealey et al., 2011 p. 346).

Fama (1970, p. 387) argues that capital markets that fully reflect all available information have the following characteristics; i) there are no transaction costs involved in trading securities, ii) all available information is available to all investors without costs associated and iii) all market participants agree on how current information affects current prices, and the distribution of future prices of all securities.

III.II.I Hypotheses

The relevant hypothesis for this thesis is derived from the theory of efficient markets. Much like De Bondt and Thaler (1985), we are interesting in testing the semi-strong level of market efficiency. The rationale behind the testing of this level of market efficiency is based on the idea that historical prices are used to rank funds in ranking periods, given that the Overreaction Hypothesis is assumed to be the theoretical justification behind contrarian strategies, the potential overreaction to unexpected news should occur in holding periods. In turn, this implies that any positive, statistically significant deviation from zero will indicate a semi-strong market *inefficiency*. Tests are conducted on the performance in all holding periods. Although individual holding periods are not sufficient to conclude efficiency or inefficiency, the whole sample of all holding periods is assumed sufficient.

The empirical testing will be performed on a single-index CAPM model, in which statistical significance will be determined by the intercept, commonly known as Jensen's alpha (Berk

& DeMarzo, 2014, p. 410). The following equation will be used to model returns in holding periods,

(1) $$(R_i - r_f) = \alpha_i + \beta_i(R_m - r_f) + \epsilon_i \ .$$

Here, $(R_i - r_f)$ is the excess return of an equity fund i, r_f is the risk-free rate, β_i is the beta of an equity fund i, $(R_m - r_f)$ is the excess return of the market index (e.g. OSEFX) and ϵ_i is the error term (Fama & French, 2004).

If a loser portfolio ranked on historical performance is unable to predict abnormal returns in subsequent holding periods, the estimated excess return of the loser portfolios relative to the market index should be below or equal to zero, indicating semi-strong market *efficiency*,

$$H_0 \colon \alpha \ \leq \ 0.$$

If historical performance can help a contrarian investor in consistently predicting a reversal in performance of loser funds from ranking to holding periods, the estimated excess return of the resulting loser portfolio relative to the estimated excess return of the market index should be greater than zero, indicating semi-strong market *inefficiency*,

$$H_1 \colon \alpha > 0.$$

However, it is important to note that several aspects of this testing procedure might potentially lead to spurious results. The cause might be a misspecification of the CAPM, meaning possible misestimations of alphas and betas, or simply because the inefficiency exists at a weak level instead of a semi-strong level of market efficiency (De Bondt & Thaler 1985, p. 795). It would be careless to simply assume that these potential problems will not bias our results, therefore we introduce two additional models to challenge the robustness of the single-index CAPM model.

III.III Capital Asset Pricing Model

The theoretical basis of this thesis relies mostly on the Capital Asset Pricing Model (CAPM), a framework developed by Sharpe (1964), Lintner (1965) and Mossin (1966) (Fama & French, 2004, p. 26). It is one of the first models to predict the relationship between risk and return in a single security. Several decades later, CAPM is still widely recognized as a simple and intuitive, yet powerful model in regards to determining the relationship between risk and expected return. For that reason, it is still used as a tool for cost of capital estimations and evaluations of actively managed portfolios (Fama & French, 2004).

III.III.I Mean-variance framework

The CAPM itself builds on Markowitz's (1959) mean-variance framework, where risk-averse investors only care about the relationship between expected return and the variance of return. Furthermore, The CAPM builds on three key assumptions; i) investors incur no transaction costs, and they may borrow and lend unlimited amounts at the risk-free interest rate, ii) investors are assumed to be mean-variance optimizers, and they may buy and sell securities without incurring taxes, and iii) investors have homogenous expectations regarding volatilities, correlations and expected returns of securities (Berk & DeMarzo, 2014, p. 379)[7].

Figure 3 provides an easy and intuitive interpretation of the idea behind the CAPM by illustrating different portfolio combinations. The horizontal axis shows portfolio risk, and the vertical axis shows expected return. The curve *abc* illustrates the minimum-variance frontier, which shows the lowest attainable risk for any given level of expected return (Santos, 2015). The tradeoff between risk and expected return is obvious, e.g. if an investor desires high expected return as illustrated by point *a*, he must accept greater risk. In addition, the global minimum is given by point *b*, which gives the lowest possible portfolio risk. Note

[7] Investors construct a portfolio at (n-1) which gives a random return at time (n). As risk averse investors, they will strive to construct a "mean-variance-efficient" portfolio, meaning that they will, i) minimize the variance of the portfolio, given expected returns, and ii) maximize expected return, given variance (Fama & French, 2004).

that only portfolio combinations above point *b* along the *abc* curve are mean-variance-efficient, meaning that all portfolio combination above point *b* dominate all other combinations below point *b*, given the same level of risk. This is often called the efficient frontier (Fama & French, 2004, p. 26).

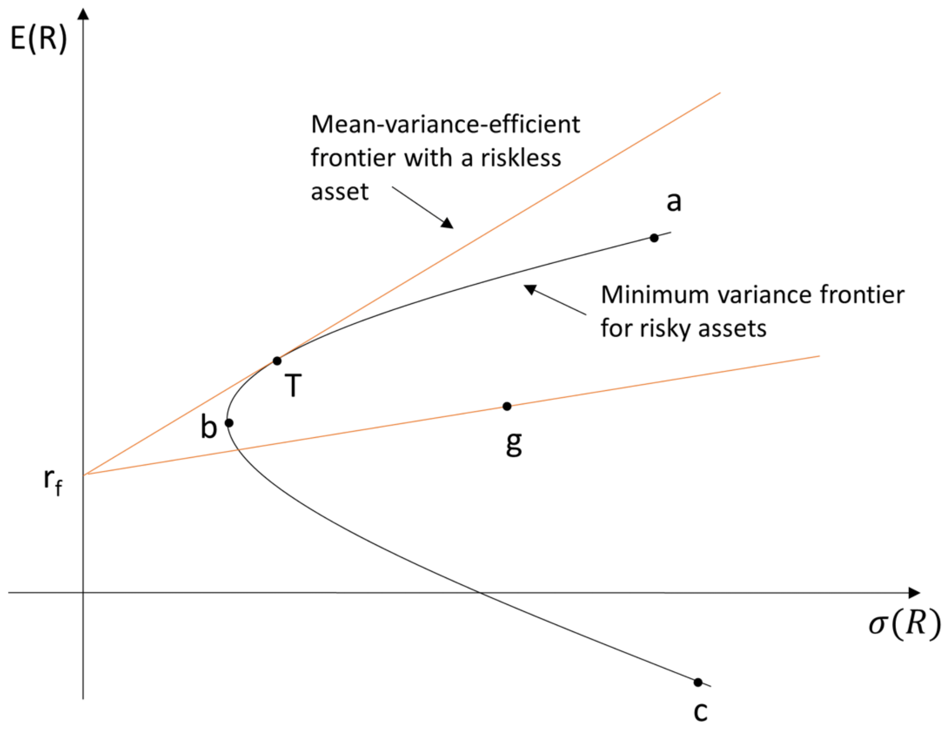

Figure 3: Investment opportunities (Fama & French, 2004, p. 27)

By introducing risk-free borrowing and lending, the efficiency with a risk-free asset can be illustrated in a straight line. Assume a portfolio that invests a proportion *x* in a risk-free security (r_f) and (*1-x*) in a risky portfolio, *g*. If *x* equals 1, everything will be invested in the risk-free security at the risk-free interest rate. The portfolio will carry no risk, and it will yield a return equivalent to the risk-free rate. Movements towards *g* along the straight line indicates lower proportion invested in the risk-free security and higher proportion invested in the risky portfolio, *g*. Movements to the right of *g* indicates borrowing at the risk-free rate, where the borrowed capital is used to increase investments in the risky portfolio (Fama & French, 2004, p. 27).

The mean-variance-efficient portfolio combinations with risk-free borrowing and lending can be found by drawing a straight line from the point (r_f) to the point of tangency at point T. Now, all efficient portfolios are combinations of the risk-free security, and a single risky tangency portfolio, T[8]. This result is commonly known as Tobin's (1958) "separation theorem" (Fama & French, 2004, p. 28)[9].

III.III.II Systematic risk, beta and SML

The general risk associated with investing in securities can be divided in two types, firm-specific risk and systematic risk. Securities fluctuate because of firm-specific news, e.g. lower earnings, which is called firm-specific risk. This risk however, can be diversified by holding a larger portfolio, hence investors with this type of risk will not be compensated with higher returns. Systematic risk on the other hand is not diversifiable because it occurs as a result of market-wide events, which in turn affects the whole economy. Thus, investors are compensated for this type of risk through higher returns (Berk & DeMarzo, 2014, p. 332). The measure of systematic risk is denoted by beta (β_{iM}),

$$(2) \qquad \beta_{iM} = \frac{cov(R_i,R_m)}{\sigma^2(R_M)}$$

Systematic risk or beta is calculated by dividing the covariance between a certain security *i* and the market portfolio, with the variance of the market portfolio (Berk & DeMarzo, 2014 p. 382). The interpretation of a security's beta is that it measures the sensitivity of its returns to fluctuations in market returns, essentially how much that particular security on average moves up (down) when the market portfolio goes up (down). When the market goes up, a high beta (>1) indicates returns higher than the market, and a low beta (<1) indicates returns lower than the market. Thus, the CAPM model prices expected returns of any security using

[8] This set of opportunities apply to all investors, and they all agree on this set of opportunities. This means that all investors hold the same risky tangency portfolio *T*, and combine it with the risk-free security according to their level of risk-aversion. The tangency portfolio is often referred to as the market portfolio, since all investors hold the same risky portfolio. The tangency portfolio should be a value-weighted portfolio of all risky assets (Fama & French, 2004).

[9] The total return is a function of the weight in the risk-free asset (r_f) and the risky asset (R_a): $\mathrm{E}(R_p) = x(r_f) + (1-x)R_a$(Fama & French, 2004).

the market portfolio as a benchmark. The Sharpe-Lintner-Mossin CAPM equation is therefore formulated as,

(3) $E(R_i) = r_f + \beta_i(E(R_m) - r_f)$.

Here, $E(R_i)$ is the expected return of a security i, r_f is the risk-free rate, β_i is the beta of security i and $(E(R_m) - r_f)$ is the return of the market (e.g. S&P 500 index) less the risk-free rate (Fama & French, 2004, p. 29). The CAPM equation is assumed to price any security i, where the expected return is the risk-free interest rate (r_f) plus a risk premium, which is a security's sensitivity to the market, β_i, multiplied by the premium per unit of beta risk, $(E(R_m) - r_f)$ (Fama and French, 2004). As equation (3) implies, a linear relationship is found between a security's systematic risk and its expected return. This linear relationship is usually illustrated with a straight line called the security market line (SML) (Berk & DeMarzo, 2014, p. 384). The intuition behind the SML is illustrated in figure 4.

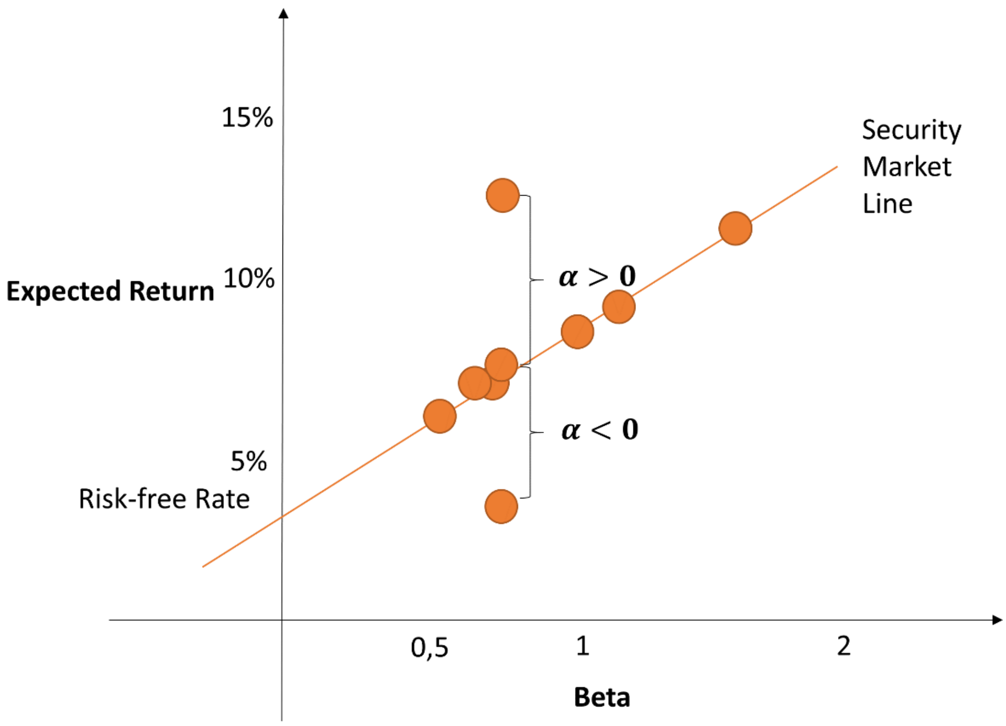

Figure 4: The SML (Berk & DeMarzo, 2014, p. 384)

According to the CAPM theory, all securities should lie on the SML. Securities above or below the SML (orange dots in figure 4) generate abnormal return, commonly known and measured by *Jensen's alpha* (Berk & DeMarzo, 2014, p. 410). Abnormal returns in a CAPM framework are by definition unexplained returns, as abnormal returns are either higher or lower than what CAPM predicts.

A linear regression can be used to determine the alpha and the beta of any security, i. This specific technique is used to identify the best-fitting line in a scatter plot, between a security and a relevant market index. The relationship is linear, and the intercept is used to estimate the alpha, while the slope is used to estimate the beta. The alpha can be interpreted as the "risk-adjusted measure of a stock's historical performance" (Berk & DeMarzo, 2014, p. 410). However, according to the CAPM and the efficient market hypothesis, the alpha of any given security should not significantly depart from zero because CAPM is assumed to price all securities. The CAPM equation is now formulated as a regression model,

$$(4) \qquad (R_i - r_f) = \alpha_i + \beta_i(R_m - r_f) + \epsilon_i \, .$$

According to the CAPM model, the beta of a security is assumed sufficient to determine the expected return of any security. However, Fama and French (1992) famously criticized the CAPM's applicability in empirical testing as they pointed towards convincing evidence of the fact that size, earnings-price, debt-to-equity and book-to-market ratios contribute to some of the expected return implied by the market beta (Fama and French, 2004, p. 37). For this reason, we cannot rely solely on the CAPM model, and we will introduce additional risk factors to adjust the return estimated by the single-index CAPM.

III.IV Fama-French three-factor model

In light of their critique towards the CAPM, Fama and French developed the Fama-French three-factor model in 1992. This model extends the CAPM framework with additional risk factors such as SMB (small-minus-big) and HML (high-minus-low) (Fama & French, 1992). Banz (1981) delivers one of the first significant blows to the CAPM framework by documenting the size effect, as he finds that the average returns of small stocks, on average, generate higher returns than predicted by the CAPM. The procedure of creating the SMB involves dividing companies in a single market into two portfolios based on their market value of equity. Companies that are below the median size cut-off are defined as, S, and companies above the median cut-off are defined as, B. Thus, the small-minus-big (SMB) risk factor is added to the CAPM to account for the fact that buying a portfolio of stocks with small market capitalization (price multiplied by shares outstanding) and short-selling a portfolio of stocks with large market capitalization, historically has proven to generate positive risk-adjusted returns (Berk & DeMarzo, 2011, p. 437). Stattman (1980) and Rosenberg, Reid and Lanstein (1985) also find that stocks with high book-to-market equity ratios, on average, generate higher returns than what is captured by their respective CAPM betas (Fama and French, 2004, p. 36). The procedure involves creating a portfolio of companies with book-to-market ratios lower than the 30th percentile in a single market, defined as, L. Furthermore, a portfolio of companies with book-to-market ratios higher than the 70th percentile in the market is created, and defined as, H. Therefore, the high-minus-low (HML) risk factor is added to the CAPM to adjust for the anomaly, where buying a portfolio of stocks with high book-to-market ratios and short-selling a portfolio of stocks with low book-to-market ratios, historically has proven to generate positive risk-adjusted returns (Berk & DeMarzo, 2011, p. 437). Thus, the Fama-French model assumes to explain expected returns to a greater degree than the single-index CAPM (Fama & French, 2004, p.38),

$$(5) \qquad E(R_i) - r_f = \beta_{iM}(E(R_m) - r_f) + \beta_{iS}E(SMB) + \beta_{iS}E(SMB) + \beta_{iH}E(HML).$$

The additional factors included has their own respective betas, which estimate the degree of contribution to the expected return of a security, i. The resulting linear regression model determines both alpha and beta values,

$$(6) \qquad (R_{it} - r_{ft}) = \alpha_i + \beta_{iM}(E(R_{m,t}) - r_{ft}) + \beta_{iS}E(SMB_t) + \beta_{iH}E(HML_t) + \epsilon_i.$$

III.V Carhart four-factor model

Carhart's four-factor model (1997) is a challenger to the famous CAPM and Fama-French three-factor model. Carhart (1997) extends the latter by incorporating Jegadeesh and Titman's (1993) one-year momentum anomaly as a fourth factor, denoted PR1YR. Jegadeesh & Titman (1993) find that buying a portfolio of stocks that ranked among the top 30% in the previous year and selling short a portfolio of stocks that ranked among the bottom 30% in the previous year, yields a positive risk-adjusted return in the following year. Therefore, Carhart (1997) adds this momentum factor as a fourth explanatory variable in his research,

(7) $$E(R_i) - r_f = \beta_{iM}(E(R_m) - r_f) + \beta_{iS}E(SMB) + \beta_{iH}E(HML) + \beta_{iP}E(PR1YR)\ .$$

Actually, this multifactor model is considered the most popular choice among asset pricing models in recent times (Berk & DeMarzo, 2011, p. 347). The extended alternative linear regression model that determines alpha and beta values is now formulated as,

(8) $$(R_{it} - r_{ft}) = \alpha_i + \beta_{iM}(E(R_{m,t}) - r_{ft}) + \beta_{iS}E(SMB_t) + \beta_{iH}E(HML_t) + \beta_{iP}E(PR1YR) + \epsilon_i\ .$$

IV. Data and methodology

IV.I Data retrieval

The task of gathering and sorting return data for Norwegian equity funds has at times been a difficult and time-consuming process. We mostly ended up using the database administered by the Norwegian School of Economics (NHH), called Børsprosjektet/Amadeus. This database is a great source of information on end-month return data, especially in regards to relatively old data. However, it has limited tools in terms of isolating specific data. In our case, we are only interested in Norwegian equity funds and their end-of-month return data, but Amadeus does not differentiate between equity funds and other types of funds such as bond funds, therefore, a lot of work has been done in Microsoft Excel. Keep in mind that whenever one is forced to sort data manually, there is always a risk of including or excluding the wrong funds, but at the same time, one would be naive to blindly trust pre-completed lists from any database. For the purpose of including and excluding the right funds, we use both Morningstar Direct and Børsprosjektet to collect vital information about the funds, such as investment mandate, region of sale etc. Furthermore, we use Bernt Arne Ødegaard's data (Ødegaard, 2015) to collect the following factors; SMB, HML, Carhart's momentum factor PR1YR and monthly risk free interest rates. Although Ødegaard (2015) creates these factors to perform regression analysis on stock returns in the Norwegian stock market, we have no reason to believe that these factors will be insufficient for running regressions on equity fund returns in the Norwegian fund market. The main justification is that our sample of funds is restricted to the Norwegian equity funds, meaning that the investment mandate for funds in our sample is mostly limited to the Norwegian equity market. Thus, we believe that it is unnecessary to create our own risk factors in the Norwegian equity fund market, as they most likely would be negligibly different from Ødegaard's risk factors. In regards to the construction of risk factors, Ødegaard creates the SMB, HML and PR1YR by using the same approach as Fama & French (1992) and Carhart (1997). Furthermore, we use the monthly NIBOR (Norwegian Interbank Offered Rate) as the risk-free rate, which retrieved from Ødegaard (2015). Return data for Oslo Stock Exchange Fund Index (OSEFX) is retrieved from Morningstar Direct. According to the UCITS directives for mutual funds, OSEFX is a value-weighted index, but it is also considered as another version of the Oslo Stock Exchange Benchmark Index (OSEBX) (Oslo Børs, 2015).

In our experience, Bloomberg and Datastream are relatively poor sources in terms of collecting fund returns, mostly because their databases do not display "dead" (liquidated) funds prior to the year of 2000. Børsprosjektet is much better at including dead funds, but is has its own drawbacks as previously mentioned. Therefore, we have to limit ourselves to a 20-year horizon, specifically from 1995-2015. Ideally, a longer time frame is preferred, however, given that is difficult enough to find reliable information regarding funds from the previous 20 years, we conclude that we would much rather have accurate data with a 20-year time frame instead of unreliable data with a longer time frame. Fortunately, there are several research papers on stock selection strategies that have found contrarian profits with a similar time frame as our own, such as Mun et al. (1999). However, from a statistical point of view, a longer sample period is not exclusively positive. Firstly, in order to limit survivorship bias it is important to include dead funds in the sample. This becomes more problematic with longer sample period, because the number of dead funds, in absolute terms, increase over time. Secondly, there are few databases except for Børsprosjektet/Amadeus, at least to our knowledge, which have reliable return data for much longer than 20 years back. Lastly, gathering return data is obviously important, but given our objective, it is even more important to only include Norwegian equity funds. Considering this last remark, we would not have been able to guarantee reliable data for a longer sample period, especially since we use Bloomberg and Morningstar Direct to manually verify which of the mutual funds that can be characterized as Norwegian equity funds. In our experience, these two databases are relatively poor sources for old equity fund data, thus we consider our time frame to be optimal given available data.

After a coarse selection process, a set of requirements are established with the purpose of collecting data on all Norwegian equity funds from 1995-2015, both “dead” and “living”. Each fund has to pass these requirements in order to be included in the fund sample, and every single fund is manually verified through information collected from Bloomberg, Datastream, Morningstar Direct or Børsprosjektet. Again, there is always a possibility of making mistakes when performing such procedures manually, but we have no reason to believe that our sample does not sufficiently represent the Norwegian equity fund market, and we proceed with the assumption that it does. We also believe that we have managed to suppress survivorship bias to a level that will not alter any of the results in the analysis.

Requirements for being included in the fund sample:

- At least 80% is invested in stocks
- “Region of sale” is Norway
- “Base currency” is NOK
- The investment market is Oslo Stock Exchange
- Sector funds are not included unless they only invest in Norway
- Only actively managed funds are included

The purpose of these restrictions is to limit ourselves to the Norwegian equity fund market. As previously mentioned, contrarian strategies have already proven to generate abnormal returns in France, Germany, UK, Spain, Italy and USA. Therefore, we do not find it necessary to test other markets than the Norwegian market. Furthermore, in comparison to the markets mentioned above, the Norwegian market is much smaller, which in turn makes the analysis a bit different, if not more interesting (Quandl, 2015). Finally, at least to our knowledge, this is the first paper on contrarian strategies in the Norwegian equity fund market, which in itself is interesting.

A couple of remarks have to be made in regards to the requirements. Firstly, given that we only include actively managed funds, the active share in our fund sample, measured by long or short positions relative to the positions of the OSEFX index, might not always be ideal (Petajisto, 2013). This remark is related to Petajisto's research on closet indexers. He points out that some mutual funds carry high management fees due to their active management, however, in reality their positions are highly correlated to the indices they are trying to outperform. In our research, we do not distinguish between "very active" funds and "slightly active" funds, we only distinguish between actively managed funds and index funds. In any case, if closet indexers prove to be a problem, they will probably bias towards our null hypothesis and lower abnormal returns, which is easier to justify than the opposite. Secondly, some fund managers might distribute two (or more) seemingly different funds, however, in reality they contain almost exactly the same positions, with the only difference being management fees or minimum capital barriers (Dagens Næringsliv, 2008). Often, this type of price discriminations is used to appeal to both small private investors and institutional investors. As a result, our sample might include two (or more) almost identical funds in a given holding period, meaning that they take very similar positions in the market. In turn, this might lead to an overrepresentation of a certain type of fund in a given holding period. Unfortunately, it is both difficult and time-consuming to address this problem, let alone solve it by conducting yet another selection process in a reliable fashion. Luckily, since our portfolios at most consist of five funds, it is relatively easy to identify funds managed by the same institution, however, we find this to be a rare occurrence in our strategies, and therefore we do not consider closet indexers to affect our results in any significant way.

The final sample consists of 82 equity funds with end-of-month return data from 1995-2015, which is comprised of 37 "dead" and 45 "living" equity funds[10].

IV.II Methodology

We define a strategy based on ranking and holding periods, for instance, a two-year ranking and two-year holding strategy implies ranking funds based on each funds geometric mean over the past two years, and then measuring performance by holding a loser portfolio over the next two years[11]. In regards to funds disappearing, we use the same approach as Wermers (1997), where each fund is assigned a specific number, and the number stays with the fund as long as it exists. The implications of this approach is that funds will not be dropped even if their names or investment objectives change. They will continue to be a part of the portfolio over the entire holding period unless the funds merge into other funds or until they are liquidated. In the case of a fund disappearing in a portfolio of five funds, the portfolio will be *explicitly rebalanced*, and replaced with the sixth worst ranked fund in the previous ranking period. If more than one fund disappears, five plus *n* funds that immediately rank as the worst funds will replace the liquidated funds in the portfolio. Sometimes, rebalancing is not possible due to the absence of replacement funds. In those cases, the portfolio will be *implicitly rebalanced* by averaging the remaining funds (*n* minus liquidated funds). In addition, the portfolio is held for entire holding periods only, e.g. in the case of a two-year ranking and two-year holding strategy, all ranking and holding periods are exactly two years. Furthermore, the performance in holding periods is measured by monthly returns, which are calculated from changes in adjusted net asset value (adjusted NAV). In general, NAV is calculated by taking the value of all stocks and other securities in a fund, subtracting management fees and operating expenses, and then dividing the net value by the total number of outstanding shares (Morningstar, 2005). Adjusted NAV is NAV adjusted for dividend payouts, where dividend payouts are collected from Børsprosjektet. Furthermore, the justification for using monthly data is the same as for De Bondt and Thaler

[10] For an overview of the number of living funds through the sample period, see figure 12 in appendix.
[11] In our sample, loser funds are characterized as the bottom five performers over a certain ranking period, based on geometric mean returns. In other words, a portfolio will consist of five loser funds, unless a fund disappears, and it is not possible to replace it with another, in which case a portfolio will consist *n* minus liquidated funds.

(1985) as they suggest that daily or weekly returns may lead to problems with both risk and return variables, which includes bid-ask spreads and effects of infrequent trading. Pagan and Schwert (1990) support this decision, as they suggest that daily data comes with significant amounts of white noise, which in turn might disturb the analysis.

In regards to the ranking procedure, we choose to calculate geometric mean returns instead of arithmetic mean returns. This decision is based on both Mun et al. (1999) and Chan's (1988) critique of De Bondt and Thaler (1987) in which arithmetic mean returns are used. De Bondt and Thaler (1985, 1987) have been great sources of information to our research, as they have produced several key research papers on contrarian strategies. However, in this matter we choose to trust the critique directed toward the pair. Mun et al. (1999) explain that geometric average returns are more suited for time series data if one assumes an underlying growth rate, which we do. Furthermore, they explain that the squared value of an arithmetic mean is equal to the squared value of a geometric mean plus the variance of an underlying variable. This in turn implies that an arithmetic mean return will be equal to a geometric mean return, only if the variance of the underlying assets is assumed equal to zero (Mun et al., 1999, p. 219). However, fund returns can be both positive and negative, in addition, they often carry some degree of variance or risk. Given the fact that funds are risky assets and therefore will carry some risk, we comfortably proceed with geometric mean returns, as they are assumed to be more reliable and conservative compared to arithmetic mean returns. The formula used to calculate the geometric means is as follows,

$$(9) \qquad \sqrt[n]{(1+R_1)*(1+R_2)*\ldots*(1+R_5)}-1.$$

Obviously, one has a lot of freedom when constructing loser portfolios as there is no golden rule as to how large or small a contrarian portfolio should be. In empirical testing of investment strategies, it is common to examine more than one portfolio size, however, we choose to stick to one approach only, which is to construct a portfolio of the bottom five funds in any given ranking period. The justification for this singular approach is simply that by having too many variables, we might complicate the analysis more than necessary, but also because it might restrict our ability to expose important patterns. For that reason, some variables are kept constant, such as portfolio size. Another reason, perhaps more important, for applying the strict bottom five approach is that we impose a strict criterion that restricts the sample from which we can construct loser portfolios. In order to avoid funds that systematically perform worse than the majority of funds, we only construct loser portfolios consisting of funds that previously have been ranked in the top 30% in at least one out of two years prior to any given ranking period. This criterion proves effective in isolating the reversal effect, as it shuts out funds that do not display the characteristic bouncing pattern of a typical “contrarian-friendly” equity fund, as previously illustrated in figure 2. Unfortunately, this criterion also has a restricting impact on the size of the sample from which we can construct loser portfolios. Given our relatively small sample, due to the very nature of mutual fund markets in small countries such as Norway, this approach seems to be optimal. Therefore, a greater portfolio size would not adequately serve its purpose of selecting loser funds, given this strict criterion. In comparison, previous research on contrarian strategy is mostly performed on stock markets, which obviously allows for a greater sample size compared to fund markets, thus provides greater freedom when examining the optimal portfolio size.

Figure 5 provides a visual illustration of the construction of the two-year ranking and two-year holding strategy. Criterion periods C1 and C2 are used to sort the top 30% funds in 1995 and 1996. The first ranking period stretches from 1997-1998, where a loser portfolio of the bottom five performing funds is created. Note that each and every fund in the loser portfolio must have performed among the top 30% funds in either C1, C2 or both C1 and C2. Furthermore, the portfolio’s performance is tracked from 1999-2000 before it is rebalanced. Finally, all 8 two-year holding period returns proxy the returns of the two-year ranking and two-year holding portfolio from 1999-2014.

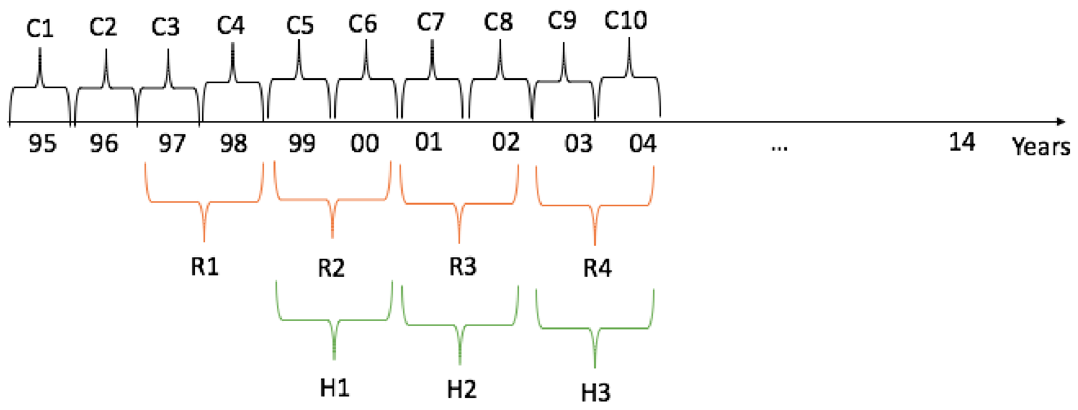

Figure 5: The construction of the two-year ranking and two-year holding strategy[12]

Similar to De Bondt and Thaler's (1985) approach, each of the five funds in the loser portfolio are given equal weight, and the performance is measured by monthly returns. Obviously, value weighting our portfolios in an option, which perhaps will have an impact, as it might be distinctive differences between small capitalization funds and large capitalizations funds in terms of contrarian movements, as suggested by Chan's (1998) risk argument. However, we are only interested in identifying funds that pass our requirements and we do not differentiate between small cap funds and large cap funds. In any case, differences and/or changes in size, and the resulting implication of risk, will be adjusted with the SMB factor in the Fama and French three-factor model and the Carhart four-factor model. The return of an equally weighted portfolio is calculated as,

(10) $$\frac{1}{5} * r_1 + \frac{1}{5} * r_2 + \cdots + \frac{1}{5} * r_5 = r_{EW} \ .$$

A regression analysis is conducted based on the equally weighted return of the two-year ranking and two-year holding portfolio, with respect to different models and their respective risk factors. Firstly, we use the same approach as De Bondt and Thaler (1985), by using the single-index CAPM model to measure the performance of the contrarian strategy. Secondly, we use the Fama and French three-factor model and finally, we use Carhart's four-factor

[12] C = criterion period(s), R = ranking period(s), H = holding period(s)

model with Jegadeesh and Titman´s one-year momentum factor. Abnormal return is measured while controlling for premiums in the market, and it is formally defined as Jensen's alpha (Hendricks, 1993). The respective regression model specifications are listed below:

(11) $$r_{pt} = \alpha_p + \beta_{OP} F_{OSEFX} + \varepsilon_i \ ,$$

(12) $$r_{pt} = \alpha_p + \beta_{OP} F_{OSEFX} + \beta_{SP} F_{SMB} + \beta_{HP} F_{HML} + \varepsilon_i \ ,$$

(13) $$r_{pt} = \alpha_p + \beta_{OP} F_{OSEFX} + \beta_{SP} F_{SMB} + \beta_{HP} F_{HML} + \beta_{PP} F_{PR1YR} + \varepsilon_i \ .$$

The single-index CAPM (11) uses OSEFX as the benchmark instead of the commonly used OSEBX. The justification is that we consider OSEFX to be a more relevant benchmark than OSEBX when adjusting returns of an equity fund portfolio against market returns. Nonetheless, we perform tests with both OSEFX and OSEBX and find that the differences in results are negligibly small, therefore, we proceed with OSEFX as the benchmark. The Fama and French three-factor model (12) simply adds two factors, SMB and HML, to respectively adjust for size and value. Lastly, Carhart's four-factor model additionally includes PR1YR.

Table 1 lists different variations of the contrarian strategy, where all of the strategies are put through each of the three introduced models.

Table 1: Different ranking- and holding periods

3 months ranking	**6 months ranking**
· 3 months holding	· 6 months holding
1 year ranking	**3 years ranking**
· 1 year holding · 2 years holding · 3 years holding · 4 years holding · 5 years holding	· 1 year holding · 2 years holding · 3 years holding · 4 years holding · 5 years holding
2 years ranking	**4 years ranking**
· 1 year holding · 2 years holding · 3 years holding · 4 years holding · 5 years holding	· 1 year holding · 2 years holding · 3 years holding · 4 years holding · 5 years holding

IV.II.I Diagnostic tests

Several diagnostic tests are run, specifically on the two-year ranking and two-year holding strategy, but also on other variations of the strategy. Results are presented in table 2, respectively for the two-year ranking and two-year holding strategy, and the mean of all other variations. The optimal two-year ranking and two-year holding strategy is specifically scrutinized, not only because it is the most profitable and statistically significant strategy, but also because it is in agreement with Benjamin Graham's prediction that "the interval required for a substantial undervaluation to correct itself averages approximately 1½ to 2½ years" (De Bondt and Thaler, 1985, p. 799). Furthermore, tests are performed in STATA, approach and the selection of tests are based on diagnostic tests performed by Mun et al.

(1999) and the theoretical basis of all econometric procedures are mainly based on Wooldridge (2009).

Dickey-Fuller tests for unit root are run with MacKinnon simulated critical values, and the results indicate stationary processes (Wooldridge, 2009, p. 631). In fact, we find all of the factors used in our analysis to be stationary processes, hence we are able to run regressions without the concern of spurious regression results. Furthermore, we perform a test for AR(1) serial correlation without strictly exogenous regressors, and find that the two-year ranking and two-year holding strategy indicates some degree of positive autocorrelation when testing with the CAPM (Wooldridge, 2009, p. 416). Due to the possibility of autocorrelation, we are neither able to fully trust standard errors nor t-statistics in the resulting regressions, which is a major concern in any empirical analysis (Wooldridge, 2009, p. 416). However, when examining the sample mean of all strategies, as well as the strategies individually, the problem of autocorrelation seems less severe, as most of the strategies do not display autocorrelation. Nevertheless, whenever autocorrelation is detected, it should be taken seriously, and adjusted for in order to obtain reliable results (Wooldridge, 2009, p. 419). Autocorrelation is adjusted by using a Prais-Winsten estimation (Wooldridge, 2009, p. 422). This method will probably lower t-statistics, hence significance levels, but at the same time it will also mitigate most of the problem of autocorrelation and provide more reliable results. Interestingly, an AR(1) serial correlation test on the Fama-French three-factor model does not suggest any problem of autocorrelation in any of the strategies. This might suggest that the problem lies with CAPM model, not with the data, since the Fama and French three-factor model shows no signs of autocorrelation. It might just be that the CAPM model is insufficient in explaining the variations in returns of a security (Wooldridge, 2009, p. 411). A possible explanation to this might be that the SMB and HML risk factors are included in the CAPM model’s error term, thus causing autocorrelation. Furthermore, the same test is performed on the Carhart four-factor model, which also shows no sign of autocorrelation, thus further strengthening the suspicion towards CAPM´s inability to explain variations in returns of a security. Therefore, the Prais-Winsten estimation is used to adjust for autocorrelation in the CAPM model, which mostly lowered t-statistics. Several of the strategies that were significant at a 5% level are now only significant at a 10% level, due to the Prais-Winsten estimation adjustment. It might be that the autocorrelation detected in the

CAPM model prior to the Prais-Winsten estimation is an exception to typical autocorrelation results for the CAPM model. However, if that is not the case, one can wonder if autocorrelation is properly adjusted in papers written on contrarian strategies where CAPM is the main model.

A Breusch-Pagan heteroscedasticity test is run to determine if the variance of the error terms is constant or non-constant (Wooldridge, 2009, p. 272). The test results indicate that our data has heteroscedastic features, however, it is quite easy to mitigate the problem of heteroscedasticity, which is done by simply running heteroscedastic-robust regressions (Wooldridge, 2009. p. 267). We also perform a normality test in accordance with Mun et al. (1999), but also because normality is one of the underlying assumption behind the OLS method (Wooldridge, 2009, p. 351). The residuals of the two-year ranking and two-year holding strategy do not seem to pass the criteria of a univariate skewness and kurtosis test for normality, hence these residuals appear to be non-normally distributed. However, the mean of all the strategies suggests otherwise. Generally, non-normality in empirical testing is not considered a crucial issue to deal with. Firstly, Wooldridge (2009, p. 173) explains that normality does not affect the unbiasedness of the OLS, and considers OLS to be the best linear estimator. He continues to explain that when a sample size gets sufficiently large, the central limit theorem leads to an approximate normal distribution (Wooldridge, 2009, p. 174). Secondly, some researches such as Zuur et al. (2010) claim that linear regressions are fairly robust against non-normality. Other researches, such as Thode Jr (2002) question the accuracy of normality tests, thus their validity. Based on Woolridge's explanation and the critique towards the importance of normality in applied finance, e.g. by Zuur et al. (2010), we proceed with the analysis and assume that non-normality will not affect any of our results.

A Ramsey RESET test for functional form is also run in order to detect possible model misspecification. However, the RESET test only detects possible functional form problems, it does not provide nor does it suggest any other models that might be more suitable (Wooldridge, 2009, p.305). In order to avoid model misspecification, a Davidson-MacKinnon test is performed on the three-factor model to examine the fit of a linear-log model specification instead of a linear specification (Wooldridge, 2009, p. 305). Also in this test, it is important to note that it does not suggest any alternative model specification, it is only presumed to have the ability to detect functional form misspecifications (Wooldridge, 2009, p. 306). The test results however, do not suggest a linear-log specification, thus we continue with linearly specified models, however, we remain cautious in claiming that our models are correctly specified.

Table 2: Diagnostic tests

Results from the Diagnostic Tests			
Models	p-value (two-year/two-year)	p-value (mean)	Implications
Breusch-Pagan to test for heteroscedasticity			
• CAPM	0,001*	0,22	Heteroscedastic/Homoscedastic
• three-factor model	0,001*	0,22	Heteroscedastic/Homoscedastic
• four-factor model	0,001*	0,23	Heteroscedastic/Homoscedastic
Augmented Dickey-Fuller test: Random Walk			
• Strategy	0,001*	0,001*	Stationary
• (OSEFX-R_f)	0,001*		Stationary
• SMB	0,001*		Stationary
• HML	0,001*		Stationary
• PR1YR	0,001*		Stationary
AR(1) test for serial correlation without strictly exogenous regressors			
• CAPM	0,001*	0,25	Autocorrelation/ No autocorrelation
• three-factor model	0,058	0,463	No serial correlation
• four-factor model	0,058	0,511	No serial correlation

Ramsey RESET test for misspecification			
• CAPM	0,009*	0,2491	Misspecification/No misspecification
• three-factor model	0,001*	0,0814	Misspecification/No misspecification
• four-factor model	0,001*	0,0784	Misspecification/No misspecification
Davidson-MacKinnon test for model specification			
• three-factor model	0,48	0,58	Linear model
Skewness & Kurtosis test for Normality			
• CAPM	0,001*	0,10	Non-normal/normal
• three-factor model	0,001*	0,055	Non-normal/normal
• four-factor model	0,001*	0,059	Non-normal/normal

**Significance level at 5%*
-Breusch-Pagan test for heteroscedasticity. Ho: homoscedasticity, H_1: heteroscedasticity
-Augmented Dickey-Fuller test: Ho: Unit root, H_1: Stationary process
- AR(1) test for serial correlation: Ho: Autocorrelation, H_1: No autocorrelation
-DM-test for model specification: Ho: Linear model, H_1: Not linear model
-Ramsey RESET test for misspecification: Ho: no omitted variables, H_1: omitted variables(misspecification)
-Skewness/Kurtosis test for normality: Ho: Normally distributed, H_1: Non-normally distributed.

We also examine the existence of cross correlation between different risk factors in our analysis, which is assumed to detect multicollinearity (Carhart, 1997). The problem of multicollinearity in econometrics is not completely clear, but in general, one should have as little multicollinearity as possible (Wooldridge, 2009, p. 98). Carhart (1997. p. 62) argues that “low cross-correlation implies that multicollinearity does not substantially affect the estimated four-factor model loadings”. The correlation matrix below indicates acceptable levels of cross-correlations, therefore, it does not indicate a problem of multicollinearity. We proceed with the regression analysis with the assumption that our sample is not substantially affected by multicollinearity.

Table 3: Cross-correlation

	OSEFX-R_f	HML	SMB	PR1YR
OSEFX-R_f	1.0000			
HML	-0.2158	1.0000		
SMB	-0.5036	0.0029	1.0000	
PR1YR	-0.2653	0.0096	0.1662	1.0000

V. Empirical Results

V.I Initial results

Figure 6 displays the actual development of both the two-year ranking and two-year holding strategy and the OSEFX index. The optimal two-year ranking and two-year holding strategy yields an accumulated return of 800% from 1999-2014, while the OSEFX index yields an accumulated return of around 450% over the same time period. Note also that the global financial crisis in 2008 is a potential outlier, however, since we measure the performance of the portfolio relative to the OSEFX index, the impact is considered relatively small.

Figure 6: Accumulated returns of the two-year ranking and two-year holding strategy versus the OSEFX Index

V.II Findings with the Capital Asset Pricing Model

Figure 7 displays the development of CAR's (CAR = 1,..., N; N = 24) over all 8 holding periods for the two-year ranking and two-year holding strategy from 1999-2014. The loser portfolio outperforms the OSEFX index by a CAR of 7%, 24 months into the holding period (CAR_{24}). Other than the obvious outperformance of the market index, a couple of analytical remarks can be made on the basis of figure 7. Firstly, the strategy seems to perform relatively poorly around 9 and 10 months into the average holding period. Secondly, the strategy seems to experience a bounce-back at 12 and 13 months into the average holding period, which substantially improves CAR from approximately 1% in month 10 and 11, to around 3% in month 12 and 5.5% in month 13.

Figure 8 displays abnormal returns for all variations of the contrarian strategy, and it clearly indicates that medium term strategies outperform both short and long term strategies. This pattern is interesting for a couple of reason. Firstly, several researchers point towards short term persistence i.e. momentum in stock returns rather than a reversion, such as Brown and Goetzmann (1995), Elton, Gruber and Blake (1996), Jegadeesh and Titman (1993), Carhart (1997) and Davidson and Dutia (1989). Therefore, it is not surprising that short-term contrarian strategies on equity funds also perform poorly in the short term. Secondly, the two-year ranking and two-year holding strategy is categorized as a medium term strategy, and it is in agreement with Benjamin Graham's prediction that reversal effects are especially noteworthy between 1½ and 2½ years (De Bondt and Thaler, 1985). This prediction further strengthens the notion that medium term strategies outperform both short and long term strategies[13]. A further discussion on the timing of investment will be conducted under "timing of investment and implications for general investors".

In figure 9, other variations of the contrarian strategy are compared to the two-year ranking and two-year holding strategy. The purpose of this illustration is to analyze apparent turn-of-the-year changes (the January effect), as pointed out earlier in the thesis. De Bondt and

[13] In our paper, we categorize strategies as short, medium and long term strategies. As mentioned previously, several researchers find significant long term reversal, therefore, it is worth mentioning that their long term strategies are equivalent to our medium term strategies. Thus, we generally agree with previous research in terms of the optimal timing of contrarian investments.

Thaler (1985) report that much of the abnormal return in their sample is realized in the month of January, and contribute this finding to the January effect. This effect refers to a tendency of substantial upturns in returns during the month of January (Thaler, 1987). Thaler suggests that tax-loss selling might be a contributing factor to this phenomenon. The argument behind tax-loss selling is that investors sell out of "bad" stock at the end of the year with the purpose of realizing tax benefits as a result of capital losses. In the beginning of the following year, as selling pressure dampens, prices tend to bounce back. Thus, holding poorly performing stocks at the turn-of-the-year might generate abnormal returns, but at the same time, he also points out that researchers are far from unanimous in support of the January effect (Thaler, 1987, p. 199). Figure 9 shows that a bounce-back occurs at the turn-of-the-year almost simultaneously in all of the four strategies. In figure 10, a four-year ranking and four-year holding strategy illustrates this effect even more clearly. However, when running a more formal test by creating a January dummy in the extended three-factor and four factor models, the optimal two-year ranking and two-year holding strategy, as in most of the other strategies, indicate a statistically *insignificant* January effect[14].

All of the strategies tested on the CAPM model are summarized in table 4. The output shows that 9 out of 22 strategies generate positive abnormal returns, while 13 strategies generate negative abnormal returns. However, only two strategies generate statistically significant positive abnormal returns at a 10% significance level. Besides the already mentioned two-year ranking and two-year holding strategy, which generates monthly abnormal returns close to 0.43% with a t-statistic of 1.90, the two-year ranking and one-year holding strategy generates monthly abnormal returns close to 0.37% with a t-statistic of 1.79. In regards to the Overreaction Hypothesis, and the formal hypothesis testing procedure formulated earlier in the thesis, the single-index CAPM model indicates that a two-year ranking and two-year holding contrarian strategy does in fact generate abnormal returns, which by definition, is a violation of the semi-strong market efficiency. Thus, a single-index CAPM model indicates a semi-strong market *inefficiency*.

[14] The significance of the January effect is displayed in table 8 in appendix

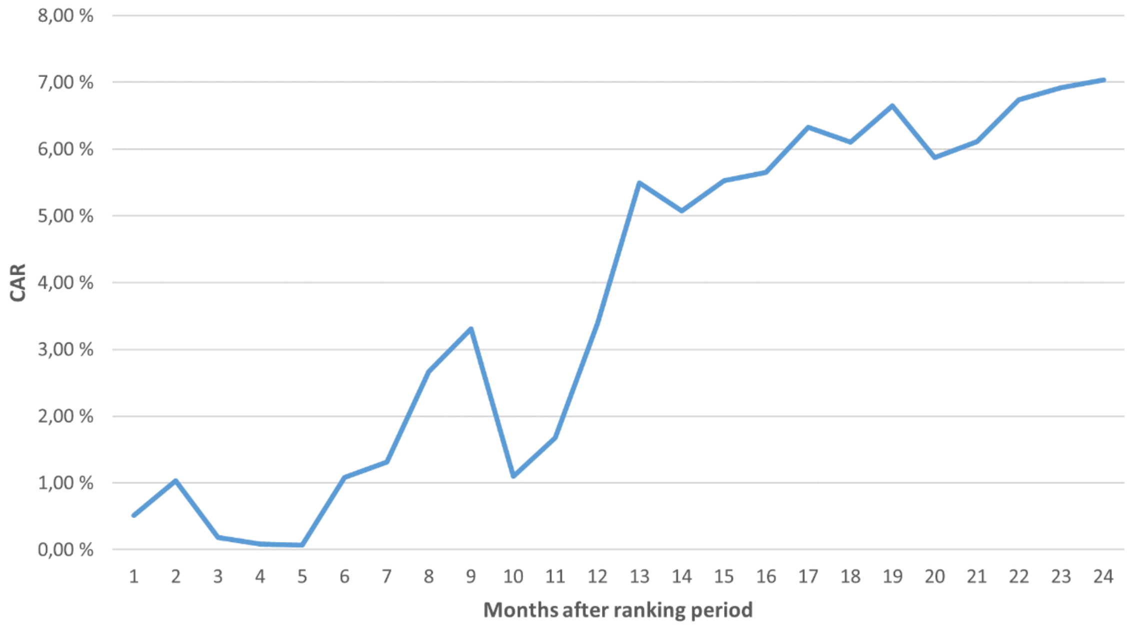

Figure 7: CAR's of the two-year ranking and two-year holding strategy

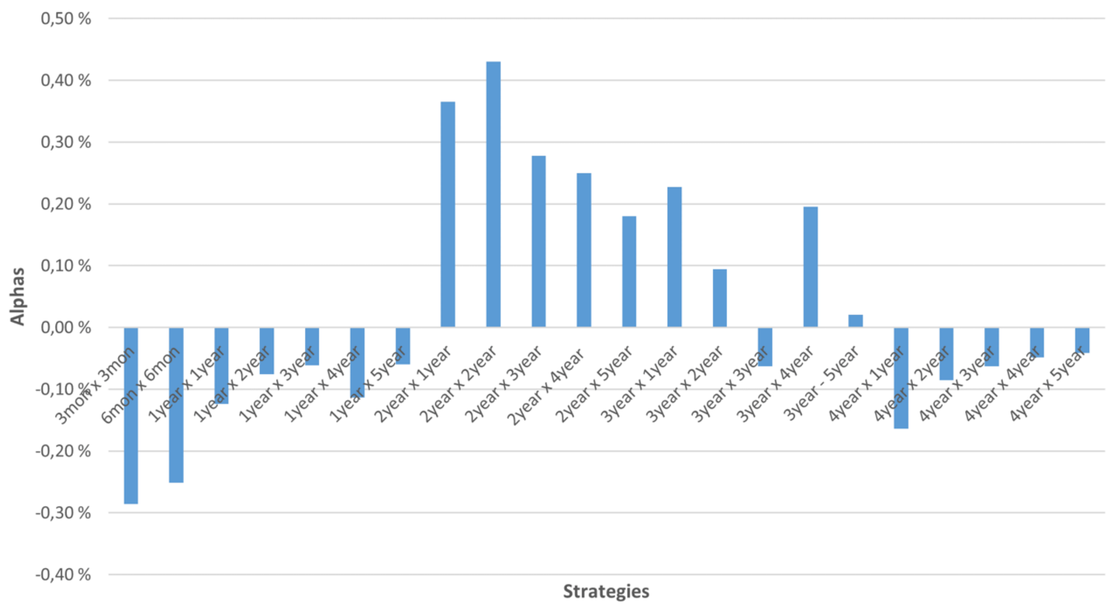

Figure 8: Abnormal returns with the single-index CAPM model

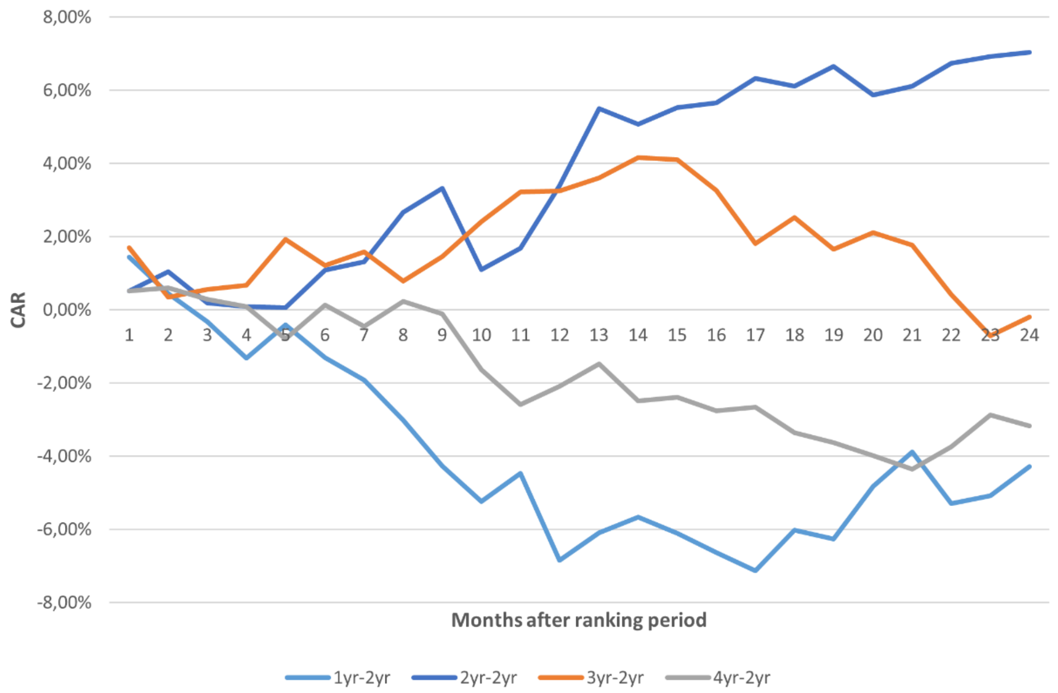

Figure 9: A comparison of strategies with different ranking periods

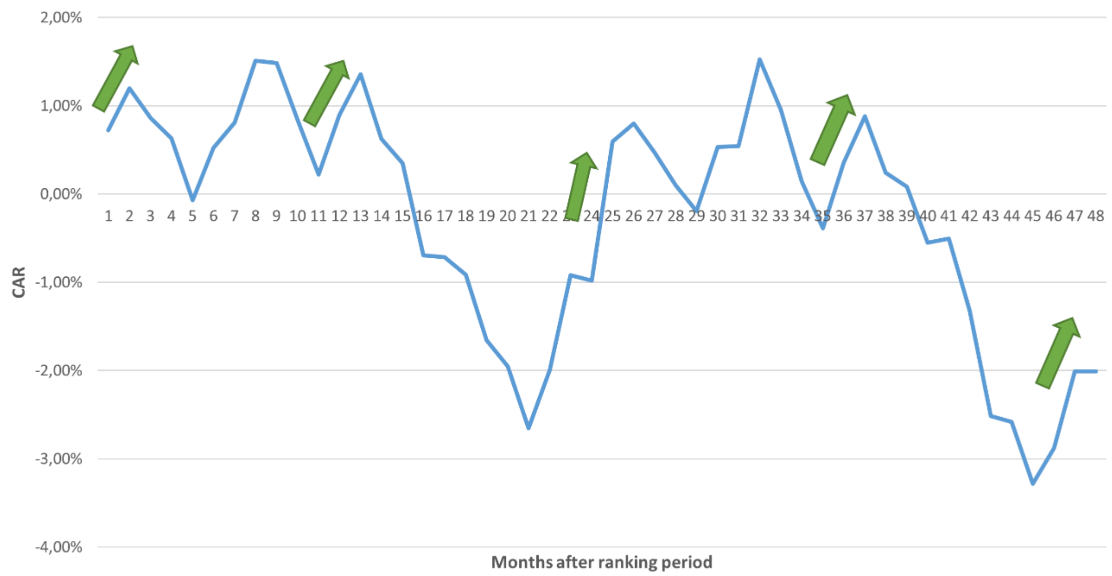

Figure 10: CAR's of the four-year ranking and four-year holding strategy

Table 4: Output from the CAPM

Portfolio Selection Period in Months (Ranking)	Average Number of Funds	Alpha values in CAPM (t-statistic)						
		Months After Portfolio Ranking Period						
		3	*6*	*12*	*24*	*36*	*48*	*60*
3	5	- 0.286% (-1,93*)	-	-	-	-	-	-
6	5	-	-0.251% (-1,68*)	-	-	-	-	-
12	5	-	-	-0.124% (-0,70)	-0.076% (-0,48)	0.061% (-0,29)	-0.113% (-0,66)	0.060% (0,34)
24	5	-	-	0.365% (1,79*)	0.430% (1,90*)	0.278% (1,12)	0.250% (1,04)	0.180% (0,85)
36	5	-	-	0.227% (1,53)	0.094% (0,67)	-0.063% (-0,59)	0.195% (1,06)	0.020% (0,17)
48	5	-	-	-0.164% (-1,53)	-0.085% (-0,79)	-0.063% (-0,56)	-0.048% (-0,46)	-0.041% (-0,32)

* =Significant at a 10% level
** =Significant at a 5% level
- =not applicable

V.III Findings with the three-factor and four-factor model

The extended models are primarily included to test the robustness of the single-index CAPM model, as they adjust for risk factors that are believed to affect our analysis, such as SMB, HML and PR1YR. SMB is considered to be particularly important as Chan (1988, p. 151) argues that, “since loser stocks are smaller than winner stock at the beginning of the test periods, the reversal effect may be related to the size effect”. Zarowin (1990) and Clare and Thomas (1995) also advocate the importance of size as both find no significant reversals when adjusting for size. Therefore, the alpha estimates should become more accurate by making this adjustment. The most noteworthy discovery from the Fama and French three-factor model is that the SMB risk factor is always positive and significant in all of the strategies, thus further strengthening its explanatory power. The HML risk factor is always negative, suggesting that the contrarian portfolios loads on growth fund, however, it is not always significant[15]. PR1YR is rarely significant, which perhaps is not surprising, as it is an adjustment for a one-year momentum effect, but also because we find that short term strategies perform poorly. Nevertheless, we choose to include this risk factor, as it is well documented in previous research e.g. Fama and French (1992).

The output from the Fama and French three-factor model turns out substantially different from the single-index CAPM model. Now, most of the strategies generate negative abnormal returns. Only 4 of the 22 strategies still generate positive abnormal returns, while 18 generate negative excess returns. Figure 11 displays abnormal returns for all strategies. Furthermore, table 5 shows that statistical significance is only accompanied by negative abnormal returns. The successful two-year ranking and two-year hold strategy is still the best strategy, but now, it only generates monthly abnormal returns of 0.19%, with a t-statistic of 1.28. Our main finding is that the size effect seems to explain much of the returns previously contributed to the CAPM beta. Obviously, the Fama and French three-factor model cannot reject the null hypothesis of an *efficiency* at a semi-strong level. The results of the four-factor model did not add any value to the analysis, therefore, they are excluded in regards to illustrations and discussions[16].

[15] Risk factor loadings are displayed in table 8 in appendix.
[16] Illustrations of the four-factor model are presented in appendix.

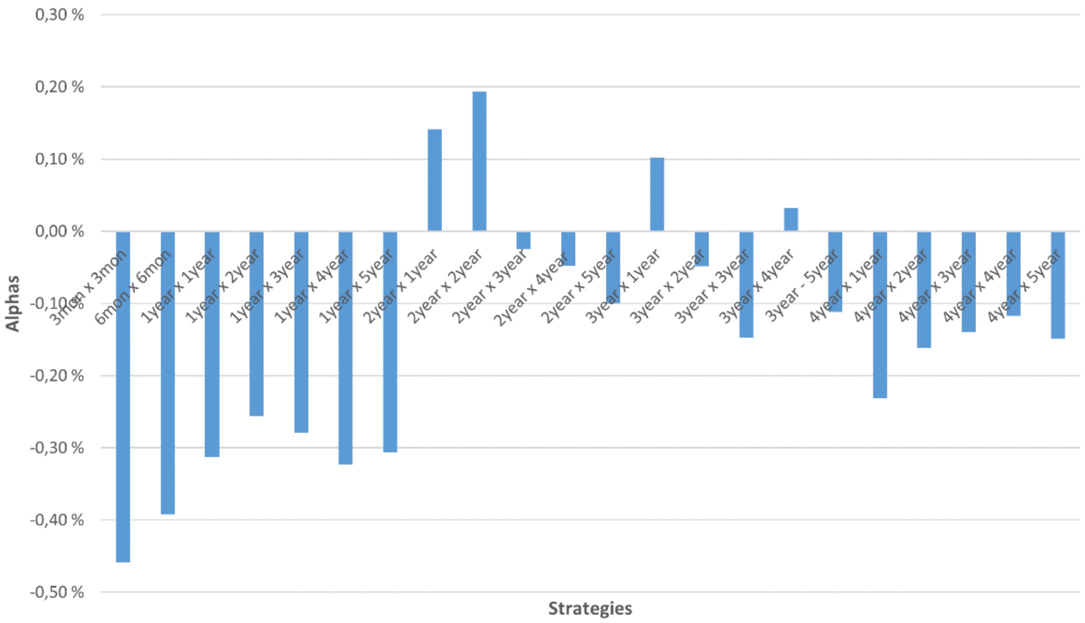

Figure 11: Abnormal returns with the Fama and French three-factor model

Table 5: Output from the Fama-French three-factor model

Portfolio Selection Period in Months (Ranking)	Average Number of Funds	Alpha values in three-factor model (t-statistic)						
		Months After Portfolio Ranking Period						
		3	*6*	*12*	*24*	*36*	*48*	*60*
3	5	-0.459% (-3,33**)	-	-	-	-	-	-
6	5	-	0.392% (-2,75**)	-	-	-	-	-
12	5	-	-	-0.313% (-1,94*)	-0.256% (-1,76*)	-0.279% (-1,9*)	-0.323% (-2,2**)	-0.306% (-2,2**)
24	5	-	-	0.141% (0,89)	0.193% (1,28)	-0.025% (-0,15)	-0.048% (-0,30)	-0.1% (-0,81)
36	5	-	-	0.102% (0,80)	-0.048% (-0,37)	-0.147% (-1,41)	0.032% (0,22)	-0.112% (-1,22)
48	5	-	-	-0.231% (-2,23**)	-0.162% (-1,55)	-0.140% (-1,3)	-0.117% (-1,18)	-0,149% (-1,24)

* =Significant at a 10% level
** =Significant at a 5% level
\- = not applicable

V.IV Timing of investment and implications for general investors

Even though most of the results from the Fama and French three-factor model indicate negative abnormal returns, our analysis still adds value in terms of understanding the optimal timing of contrarian investment strategies. Our results indicate that betting on short term reversal of funds is unwise, as reversal strategies shorter than one year clearly generate negative abnormal returns. This is also supported in literature, as both Campbell and Limmack (1997) and De Bondt and Thaler (1985) find no evidence consistent with the Overreaction Hypothesis with a one-year ranking and one-year holding strategy. In addition, and perhaps more interestingly, short-term persistence in stocks is well documented, as mentioned previously, thus betting on short term reversal is not recommended. The best bet would be to aim for a medium term investment horizon, for instance with a two-year ranking and two-year holding strategy. This is supported by De Bondt and Thaler (1985) with a three-year ranking and three-year holding strategy, Campbell and Limmack (1997) with a two-year ranking and two-year holding strategy and finally by Alonso and Rubi (1990) who find stronger overreactions for strategies longer than a one-year ranking and one-year holding strategy.

The final decision to invest depends on which asset pricing models the investor believes to be true. On one hand, our research suggests that a two-year ranking and two-year holding strategy is highly profitable within a CAPM framework, but on the other hand, at least from a theoretical or statistical point of view, it fails in a Fama and French framework. Our understanding is that investors rarely care about the origin of profits or where they come from. For instance, we explain that the CAPM model generates a significant alpha for the optimal strategy, which by definition is unexplained abnormal returns. By adjusting for SMB and HML risk factors and by verifying their significance we effectively reduce some of the previously unexplained alpha, implying that some of the abnormal returns are explained by a loading on these risk factors. This discovery might not be as important to an investor who is actively trying to outperform the market, as he only cares about beating the market index. Our results indicate that, yes, the optimal strategy generate abnormal returns, but not as a results of a contrarian profits, rather as a results of added risk through loading on risk factors such as SMB and HML, however, SMB seems to be the dominant risk factor.

Nevertheless, a couple of important remarks have to be highlighted. Firstly, the fact that one finds abnormal returns in historical data does not necessarily imply abnormal returns in the future. Secondly, some funds require high levels of minimum capital, such as Storebrand Norge I, which might not be optimal for small private investors (Netfonds Bank, 2015). Thirdly, the costs of trading on a contrarian strategy might be excessive. Sometimes, investors are charged fees both when buying and selling funds, as well as being charged for management fees. Needless to say, fees vary between funds, for instance, DNB Norge has management fees of 1.4% annually, however, buying and selling is free of charge (DNB, 2015). Nordea Avkastning on the other hand, has annual management fees of 1.5%, but also buying and selling fees of respectively 0.5% and 0.05% (Nordea, 2015). Obviously, management fees and transaction cost have a direct negative impact on performance, and high costs of trading will therefore result in negative effects on returns.

VI. Conclusion

Data suggests that several different time lags generate positive abnormal returns when based on a single-index CAPM model, however, almost all abnormal returns become negative when SMB and HML is added. As for the two-year ranking and two-year holding strategy, it consistently generates the highest return across all models, and it remains positive with both the single-index CAPM model and the Fama and French three-factor model, with average monthly abnormal returns of respectively 0.430% and 0.193%. The general indication is that contrarian strategies perform relatively poorly in the short and long term, and perform best in the medium term. Furthermore, the single-index CAPM model initially indicates a rejection of the null hypothesis as the alpha of our optimal strategy is significantly larger than zero. However, an inclusion of additional risk factors leads to insufficient evidence to reject the null hypothesis. Overall, data suggests that the single-index CAPM model alone is insufficient in explaining abnormal returns of contrarian strategies, as it seems that investors are compensated for their inherent portfolio risk, where risk is mainly reflected by SMB, thus we are not able reject the null hypothesis.

In terms of further analysis, it would be interesting to replicate Zarowin's (1990) exercise of creating and comparing loser and winner portfolios of equal size in the Norwegian market.

Due to practical considerations of short-selling financial assets, this exercise should be performed on stocks, not on equity funds. In addition, the task of exclusively comparing funds of equal size might lead to an insufficient fund sample, therefore stock markets are preferred as they will provide more data than fund markets.

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VIII. Appendix

Attachment 1: Information about the fund sample

Table 7: Final equity fund sample

1	*Avanse 2020*	*22*	*OF Enter Mobile Internet*	*43*	*ABN AMRO Optimal*	*64*	*DnB NOR SMB*
2	*Avanse 2030*	*23*	*Pareto Aksje Norge*	*44*	*Avanse Norge I*	*65*	*Postbanken Fremtid*
3	*Gjensidige Invest*	*24*	*Pareto Aktiv*	*45*	*DnB NOR Norge Selektiv II*	*66*	*WarrenWicklund Norge*
4	*Globus Norge*	*25*	*Pareto Verdi*	*46*	*Avanse Norge II*	*67*	*Fokus Barnespar*
5	*Handelsbanken Norge*	*26*	*Postbanken Norge*	*47*	*DnB NOR Norge Selektiv III*	*68*	*Danske Fund NorgeII*
6	*Holberg Norge*	*27*	*Storebrand Norge Institusjon*	*48*	*ABN AMRO Aktiv*	*69*	*Danske Fund NorgeI*
7	*KLP Aksje Norge*	*28*	*Danske Fund Norge Aksj Inst1*	*49*	*ABN AMRO Norge*	*70*	*Danske Fund Norge Vekst*
8	*NB Aksjefond*	*29*	*Storebrand Norge*	*50*	*ABN AMRO Norge +*	*71*	*First Generator*
9	*NB Plussfond*	*30*	*Storebrand Norge I*	*51*	*ABIF Norge*	*72*	*Fondsfinans Spar*
10	*Nordea Norge Verdi*	*31*	*Storebrand Norge H*	*52*	*Banco Humanfond*	*73*	*FORTE Trønder*
11	*Nordea Avkastning*	*32*	*Storebrand Vekst*	*53*	*Carnegie Aksje Norge*	*74*	*GAMBAK*
12	*Nordea Kapital*	*33*	*Storebrand Verdi*	*54*	*Carnegie Teknologi*	*75*	*ABN AMRO Kapital*
13	*Nordea Norge Pluss*	*34*	*Terra Norge*	*55*	*Danske Fund Norge Aksj Inst2*	*76*	*Avanse 2010*
14	*Nordea SMB*	*35*	*RF Aksjefond*	*56*	*Delphi Vekst*	*77*	*Landkreditt Norge*
15	*Nordea Vekst*	*36*	*RF Plussfond*	*57*	*DNB Norge Selektiv*	*78*	*Landkreditt Utbytte*
16	*Atlas Norge*	*37*	*Storebrand Norge A Inc*	*58*	*DNB Barnefond*	*79*	*Globus Aktiv*
17	*ODIN Norge*	*38*	*Gjensidige Aksje Spar*	*59*	*Postbanken Folkefond*	*80*	*Storebrand Optima Norge A*
18	*ODIN Norge II*	*39*	*Banco Norge*	*60*	*DnB NOR Kompass*	*81*	*Storebrand Aksje Innland*
19	*Omega Investment Fund B*	*40*	*Alfred Berg Aksje fNorge*	*61*	*DNB Norge IV*	*82*	*Delphi Norge*
20	*Omega Investment Fund C*	*41*	*Danske Fund Aktiv Formuesf A*	*62*	*DNB Norge III*		
21	*Orkla Finans Inv Fund*	*42*	*Alfred Berg Aksjespar*	*63*	*DnB NOR Norge I*		

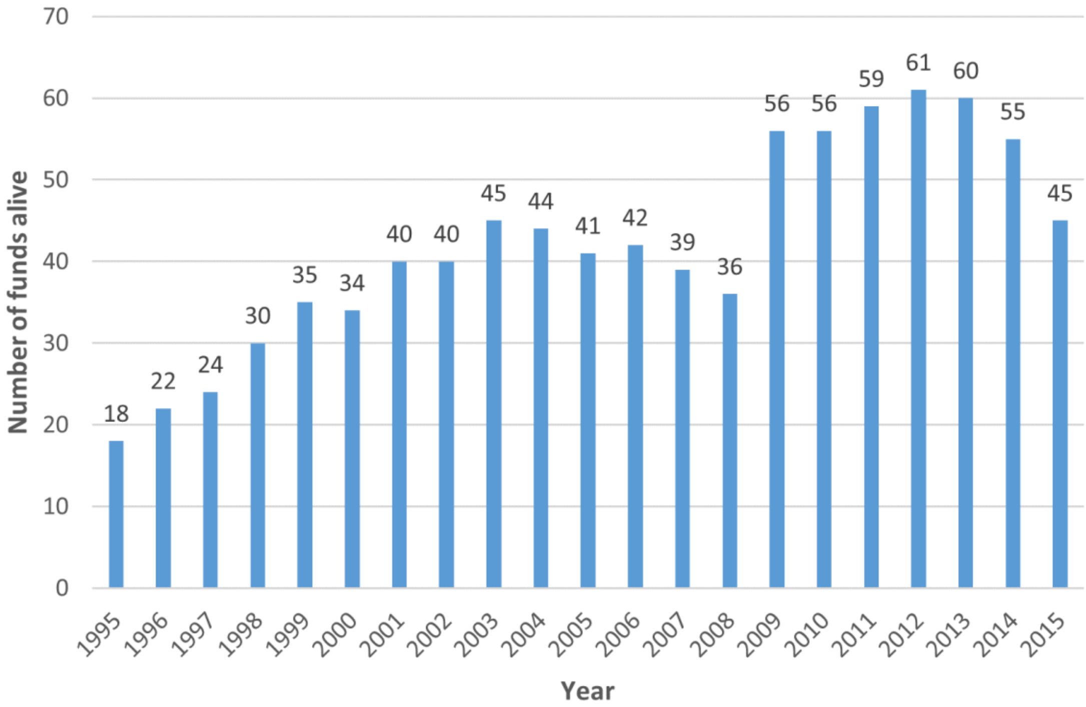

Figure 12: Number of "living" funds from 1995-2015

Attachment 2: The results from the Carhart four-factor model

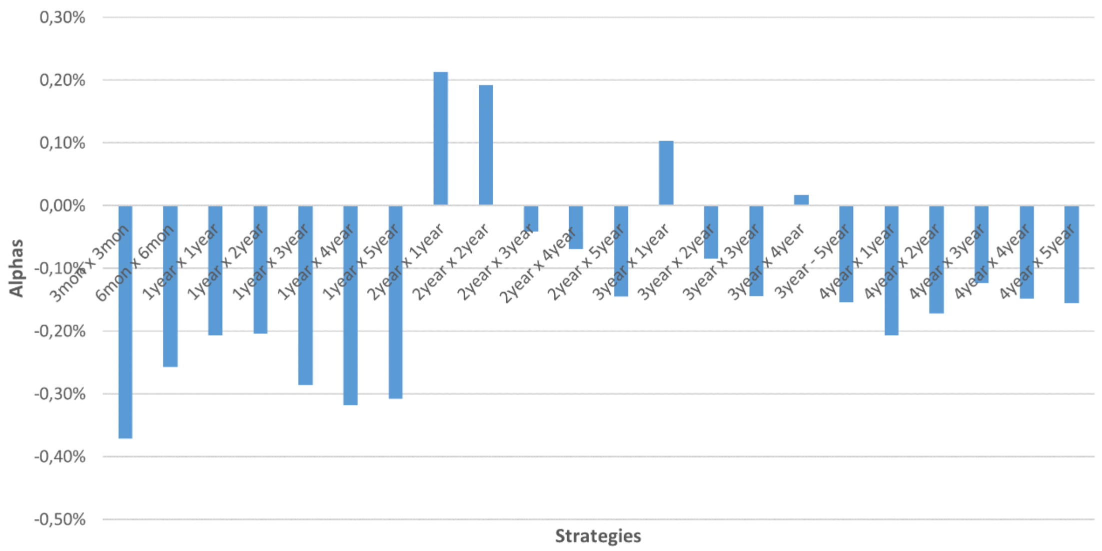

Figure 13: Abnormal returns with the Carhart four-factor model

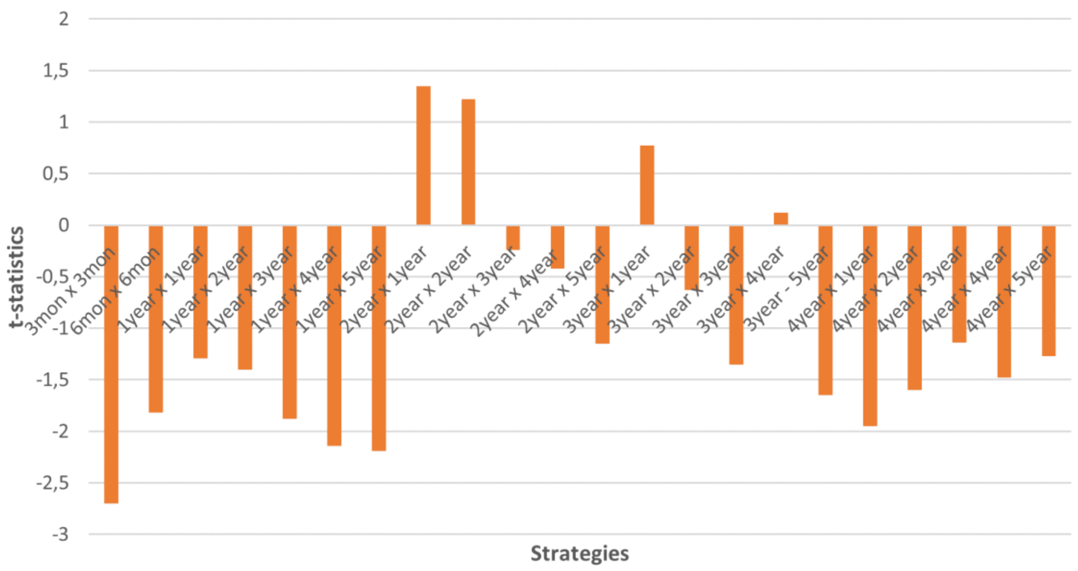

Figure 14: T-statistics with the Carhart four-factor model

Attachment 3: Different risk factor loadings

Table 8: Risk factor loadings for all strategies

Strategy	Beta*	HML	SMB*	PR1YR	January dummy (three-factor)	January dummy (four-factor)
3x3’	0.861 (39.38)	-0.0558 (-1.85)	0.246 (6.28)	-0.096 (-3.29*)	0.010 (1.44)	0.009 (1.34)
6x6’	0.874 (29.25)	-0,0941 (-2.62*)	0.189 (4.11)	-0.149 (-4.57*)	0.013 (1.75)	0.011 (1.67)
1x1	0.800 (22.89)	-0.118 (-1.87)	0.263 (4.79)	-0.119 (-3.47*)	0.005 (0.86)	0.003 (0.66)
1x2	0.787 (35.46)	-0,0703 (-2.23*)	0.234 (5,86)	-0,0692 (-2.27*)	0.008 (1.64)	0.007 (1.53)
1x3	0.726 (30.23)	-0.139 (-3.33*)	0.291 (7.40)	0.0116 (0.42)	-0.001 (-0.18)	-0.001 (-0.16)
1x4	0.863 (35.66)	-0.176 (-5.55*)	0.258 (6.40)	-0.0059 (-0.19)	0.004 (0.80)	0.004 (0.79)
1x5	0.894 (37.32)	-0.134 (-4.49*)	0.338 (8.94)	0.00379 (0.13)	0.011 (1.97*)	0.011 (2.00*)
2x1	0.810 (31.61)	-0.105 (-3.14*)	0.263 (5.76)	-0.0782 (-2.39*)	0.007 (1.28)	0.006 (1.21)
2x2	0.801 (27.35)	-0.128 (-2.21*)	0.269 (5.50)	0.0007 (0.02)	0.004 (0.66)	0.004 (0.67)
2x3	0.793 (28.36)	-0.157 (-4.43*)	0.329 (6.88)	0.0218 (0.62)	0.005 (0.86)	0.006 (0.91)
2x4	0.823 (23.67)	-0.162 (-2.86*)	0.350 (6.73)	0.0232 (0.65)	0.005 (0.74)	0.005 (0.78)
2x5	0.950 (39.88)	-0.138 (-2.57*)	0.296 (7.40)	0.0588 (1.87)	0.011 (2.29*)	0.011 (2.46*)
3x1	0.834 (29.62)	-0.0264 (-0.95)	0.173 (5.17)	-0.0003 (-0.01)	0.005 (0.97)	0.005 (0.97)
3x2	0.806 (28.82)	-0.0208 (-0.77)	0.190 (5.44)	0.0438 (1.64)	0.006 (1.02)	0.006 (1.10)
3x3	0.923 (58.43)	-0.0278 (-1.21)	0.123 (4.01)	-0.0025 (-0.11)	0.001 (0.29)	0.001 (0.28)

3x4	0.834 (27.63)	-0.0289 (-0.95)	0.231 (5.82)	0.0200 (0.63)	0.009 (1.52)	0.009 (1.53)
3x5	0.932 (62.76)	-0.0140 (-0.69)	0.172 (6.38)	0.0414 (2.09*)	0.005 (1.13)	0.005 (1.24)
4x1	0.940 (59.86)	-0.0557 (-2.30*)	0.128 (3.97)	-0.0234 (-1.02)	0.008 (1.87)	0.007 (1.78)
4x2	0.918 (58.26)	-0.0300 (-1.23)	0.137 (4.20)	0.00957 (0.41)	0.005 (1.16)	0.005 (1.19)
4x3	0.927 (60.12)	-0.0254 (-1.02)	0.144 (4.42)	-0.0214 (-0.92)	0.007 (1.95)	0.007 (1.80)
4x4	0.947 (51.84)	-0.0427 (-2.00*)	0.133 (5.07)	0.0410 (1.83)	0.004 (1.04)	0.005 (1.18)
4x5	0.924 (41.99)	-0.0414 (-1.77)	0.176 (6.61)	0.00800 (0.27)	0.002 (0.47)	0.002 (0.48)

** =significance at a 5 % level*

‘ =months not years

Attachment 4: Further description of the econometric analysis

OLS assumptions for time series

An Ordinary Least Squares (OLS) method is used to perform regression analysis on all of the different strategies. The OLS method has several underlying assumptions that should be addressed for the purpose of obtaining reliable results (Wooldridge, 2009, p. 345).

1. *A stochastic time series process is linear in parameters. Where, u, is the error term, representing the variations in y which is not explained by the explanatory variable(s),* ***x****.* (Wooldridge, 2009, p. 346)

2. *The sample has no perfect collinearity, meaning, no explanatory variable is constant or a perfect combination of another explanatory variable* (Wooldridge, 2009, p. 346).

3. *The sample has a zero conditional mean, indicating that the expected value of the error term is zero for all periods* (Wooldridge, 2009, p. 348).

4. *The error term is homoscedastic, where the variance of the error term remains constant for all periods* (Wooldridge, 2009, p. 349).

5. *There is no serial correlation in the sample, meaning, that the error terms in different periods are uncorrelated* (Wooldridge, 2009, p. 350).

6. *The errors are independent for every* **x***, and are identically normally distributed* (Wooldridge, 2009, p. 351).

Breusch-Pagan test for heteroscedasticity

Heteroscedasticity is observed when the variance of the error term is non-constant, which is a violation of the fourth OLS assumption. Often, heteroscedasticity is observed through trends in the error term, either positive or negative (Wooldridge, 2009, p. 413). In statistical terms, the following is a description of heteroscedasticity

(14) $$Var(u|x_1, x_2, .., x_n) \neq \sigma^2$$ (Wooldridge, 2009, p. 413).

In order to detect heteroscedasticity, a Breusch-Pagan test is used to test for heteroscedasticity (Wooldridge, 2009, p. 432). This is done by regressing residuals on explanatory variables, furthermore, using the F-test on the resulting coefficients to test for heteroscedasticity. This is usually done by the *hettest* command in Stata. The null hypothesis indicates constant variance, which represents an insignificant F-statistic, while the alternative hypothesis, represents a significant F-statistic, indicating non-constant variance, hence heteroscedasticity (Wooldridge, 2009, p. 273),

H_0: Constant variance,

H_1: Non-constant variance.

A rejection of the null hypothesis indicates heteroscedasticity. A common way of dealing with the issue of heteroscedasticity is to run robust regressions, to obtain robust standard errors, which will adjust for the heteroscedasticity in all series (Wooldridge, 2009, p. 267).

Dickey-Fuller test for unit root processes

The assumption of stationarity in time series analysis requires a transformation of non-stationary processes into stationary processes. The problem of running regressions on non-stationary time series, is that one may find relationships where there are not supposed to be any, which in turn might lead to unreliable conclusions, also called spurious regressions (Wooldridge, 2009, p. 636). Assets prices such as fund prices often display non-stationary processes through a random walk with an upward drift, or in econometric terms, a unit root process. This issue is resolved by using the percentage differences (i.e. returns) instead of raw price data. A simple explanation of a unit root process is that a variable y is affected and correlated with it previous observation of itself y_{t-1}.

One of the ways to test a sample for unit root properties is to run the augmented Dickey-Fuller test with Davidson and MacKinnon (1993) critical values (Wooldridge, 2009, p. 633). A Dickey-Fuller test examines the relationship between different observations in the same variable y, across time. If p-values are smaller (read: more negative), than previously determined Davidson and Mackinnon critical values, stationary processes are evident. The hypothesis tests are formulated below (Wooldridge, 2009, p. 632),

H_0: A unit root process,

H_1: A stationary process.

<u>AR (1) t test for serial correlation</u>

Serial correlation occurs when error terms are correlated across time, also called autocorrelation (Wooldridge, 2009, 413). This serves as a problem in time series analysis, as standard errors and t-statistics might be wrongly estimated due to serial correlation. This may lead to unreliable conclusions in regards to hypothesis testing (Wooldridge, 2009, p. 409). A "t-test for AR (1) serial correlation with strictly exogenous regressors" is used to test for autocorrelation in the sample (Wooldridge, 2009, p. 412). This is done by regressing the predicted residual û on a lagged version of itself $\hat{u}_{t+1}$. Furthermore, the significance level of the lagged version is used to determine the degree of autocorrelation (Wooldridge, 2009, p. 413). The null hypothesis says that the lagged coefficient is insignificantly different from zero, indicating no autocorrelation, while the alternative hypothesis says that the lagged coefficient is significant, indicating a problem of autocorrelation,

H_0: No autocorrelation,

H_1: Autocorrelation.

One way of adjusting for autocorrelation is to perform a Prais-Winston estimation (Wooldridge, 2009, p. 422). This estimation transforms data and adjusts the significant lagged error coefficient. Furthermore, it estimates a new OLS model with adjusted variables.

Ramsey's regression specification error test (RESET)

A regression specification error test (RESET) is a general specification-test for functional form (Wooldridge, 2009, p. 303). The RESET test is performed by including quadratic terms of the dependent variable and testing their joint significance by using an F-test. This test will reveal if the model suffers from misspecification, but it does not provide any advice on how to correctly specify a given model. The null hypothesis represents an insignificant F-statistic, while the alternative hypothesis indicates a significant F-statistic, thus suggesting some sort of functional form misspecification (Wooldridge, 2009),

H_0: The model is correctly specified,

H_1: Some sort of functional form problem.

MWD test for model specification

A Davidson-MacKinnon test is used to find the best fit for our data in regards to model specifications (Wooldridge, 2009, p. 305). We primarily focus on the best fit between a linear-log model and a simple linear model. The Davidson-MacKinnon test uses fitted values of one model specification (linear-log), and test the significance of these fitted values in the other model specification (linear). Significant fitted values imply that the model specification might be wrong (Wooldridge, 2009). The hypothesis test is formulated below,

H_0: Linear model,

H_1: Linear-log model.

Skewness and kurtosis test for normality

The OLS method assumes normally distributed error terms, therefore, a normality test should be performed. One may perform a skewness and kurtosis test for normality, but there are also other known tests that might be used (Ghasemi & Zahediasl, 2012). The null hypothesis indicates normally distributed residuals, hence high p-values indicate normal distribution. Small p-values indicate a rejection of the null hypothesis, hence non-normally distributed error terms (Ghasemi & Zahediasl, 2012),

H_0: Normal,

H_1: Non-normal.