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Time-series and cross-sectional price momentum: Applying the Dual Momentum strategy from a Norwegian perspective

AUTHOR(S)		SUPERVISOR:
Student number:	Name:	KJELL JØRGENSEN
235918	JOAKIM OPSAHL TØNNESSEN	

Abstract

Time-series and cross-sectional price momentum have been observed in the majority of asset classes around the globe. This thesis investigates and replicates the Dual Momentum strategy created by Antonacci (2014) from a Norwegian perspective. The Dual Momentum strategy combines both time-series and cross-sectional price momentum and applies the price momentum to indexes. Using indexes simplifies and reduces the transaction cost compared to momentum strategies that involve large stock portfolios. The Dual Momentum strategy uses the current price and the historical price less the risk-free rate to determine if an asset's momentum is positive over the last twelve months. The asset with the highest momentum is held, unless the momentum is negative, then high-quality bonds are held until the momentum returns to positive. In this thesis OBX and ST5X serve as the Norwegian assets, and 39 different foreign indexes have been tested as the third asset of the Dual Momentum strategy. The results show impressive risk-adjusted returns, lower standard deviations, higher sharpe ratio and lower maximum drawdowns than holding OBX as a passive index investment in the same period. The vast majority of the Dual Momentum portfolios return significant positive alphas after the CAPM model, Fama-French and Carhart factors are applied in regression analysis. The thesis validates the Dual Momentum strategy from the Norwegian perspective in the tested sample period of 21 years. The strategy produces higher risk-adjusted returns in the sample period than the benchmark, and the findings are in line with the current price momentum literature.

Acknowledgements

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Content

List of Tables

List of Figures

1 Introduction

1.1 Background

It has been suggesting that the most rational strategy for the majority of investors for maximising their risk-adjusted returns is to buy and hold a passively managed low-cost index fund or an exchange-traded fund (Ang, Goetzmann and Schaefer, 2016). This strategy is prominently promoted by such individuals like Warren Buffett and a range of academics. The debate over active versus passive investing is an ongoing and exciting debate bringing up a range of problems such as holding period, transaction cost, the efficient market hypothesis, timing and performance measures to name a few topics, several of which will be explored in the thesis.

In the 2014 book "Dual Momentum Investing – an innovative strategy for higher returns with lower risk" Antonacci (2014) outlines a rather simple active trading strategy to use the price momentum effect to generate a significantly higher risk-adjusted return compared to holding the market index. Antonacc's (2014) book builds on the research papers "Risk Premia Harvesting Through Dual Momentum" from 2012 and "Absolute Momentum: a simple Rule-based strategy and Universal Trend-Following Overlay" from 2013. Antonacci (2012, 2013) investigate the price momentum effect of multiple asset classes, multiple indexes and demonstrate easy ways to implement momentum strategies. In the book, Antonacci (2014) outlines the Dual Momentum strategy and apply it to indexes like S&P500, ACWI ex-U.S. and U.S. Aggregate bonds.[1] The results are presented in the table below and they are pretty impressive. Are they too good to be true?

Table 1.1 - Antonacci's GEM portfolio - Dual Momentum vs S&P500 - 1974-2013

Metrics, measurements and ratios	GEM[2]	S&P500
Annual return	17.43	12.34
Annual standard deviation	12.64	15.59
Annual Sharpe ratio	0.87	0.42
Maximum drawdown	-22.72 %	-50.95 %
Months with profit (%)	68	62

[1] The Dual Momentum strategy will be explained and detailed in section 3.
[2] The Portfolio is called GEM, Global Equities Momentum.

1.2 Research questions

The purpose of the paper is to replicate the Dual Momentum strategy of Antonacci (2014), from the viewpoint of a Norwegian investor. [3] A Norwegian investor will naturally benchmark his or her return against the OBX Total Return Index, and count profits in Norwegian Krone (NOK).[4] By applying the strategy from a non-American point of view and in another sample period, we will be able to draw some conclusions about the validity of the Dual Momentum strategy. The results will either discredit or validate the Dual Momentum strategy. The tests will also explore the persistence of the price momentum anomaly in the markets used and sample periods. Furthermore, we will also be able to draw some conclusions regarding the practicality of the strategy and add to the growing literature of momentum research. Exploring the price momentum effect is important because the price momentum effect has not been fully explained by the current models used in finance and has been credited as a source of abnormal profits and contradicting the efficient market hypothesis. Investors long for abnormal profits and systems to harvest them, will the Dual Momentum strategy prove to be such a system? This thesis will investigate the following questions:

1.2.1 Research question 1

Review the relevant literature of market momentum in light of the efficient market hypothesis and modern portfolio theory. Do the findings in this thesis support the current momentum literature?

1.2.2 Research question 2

Replicate and test the Dual Momentum strategy from a Norwegian investors perspective. Can the Dual Momentum strategy can provide higher risk-adjusted returns than OBX in the sample period?

[3] The Dual Momentum strategy Garry Antonacci outlines in his book and paper are in USD and have the American perspective.
[4] The OBX Total Return Index consists of the 25 most traded securities on Oslo Børs, based on six months turnover rating.

1.3 Paper organization

The thesis is organised into the following sections; section 2 will give an overview of the relevant academic literature. Starting in section 2.1 with the efficient market theory. Following up with section 2.2 on the inefficiency of the markets and moving on to the price momentum research in section 2.3. In section 2.3 the price momentum research is reviewed, and several proposed explanations are explored. Section 2.4 gives a short summary of the modern portfolio theory and section 2.5 the performance measurement, which will be used to test the Dual Momentum strategy from the Norwegian perspective. Section 3 walks though the Dual Momentum method, and in section 4 an overview of the data used in the thesis are given. Results are presented in section 5 and followed up with discussion in section 6, before conclusions are drawn in section 7. References are found in section 8 and the section 9 hold the appendix, including all the portfolio data.

2 Literature review

2.1 Efficient markets

The markets primary function is arguable to price assets correct at any time. Adam Smith argued that free markets would tend to balance supply and demand into the equilibrium state. In financial markets the participants use a vast range of pricing models to price assets correct. In the markets this pricing is done more and more automatically with algorithms that does the calculations and trading in microseconds or less. From a theoretical perspective, it is crucial that we look at the efficient market hypothesis to understand the relationship between the market theories, current pricing models and the anomalies like the price momentum.

2.1.1 The efficient market hypothesis

Academics have traced the history of the efficient market theory back to the French mathematician Louis Bechelier and his 1900s paper "Theory de la Speculation" where he outlines the assumption that if a market is in an equilibrium state, the current price is the best estimate of the price in the following period. By studying the French stock market, he observed that price jumps are a result of new information becoming available. He went on to conclude that price changes are random and impossible to predict. This conclusion implies that historical prices cannot be used to predict the future prices, as they retain "no memory". Prices was thought to follow a Brownian motion with a drift. The name Brownian Motion comes from the Scottish botanist Robert Brown, who in 1826 noted random movements of pollen grain when suspended in water. It was, however, Albert Einstein, who got the credit for mathematically explaining the Browninan motion in 1905. Becheliers work describing the randomness in 1900 was not rediscovered before in the late 1950s. The rediscovery laid the foundations for the efficient market theory with Samuelson (1965) using ideas from Bachelier and his data to support it.

It is, however, the Chicago based Professor Eugene Fama that is the modern academic father of the market efficiency hypothesis. In 1965 Eugene Fama published the article "Random Walks in Stock Market Prices". In the article Eugene Fama defined the market efficiency as:

"In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now,

the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value" (Fama, 1965, 56).

Fama (1970) argued that in a market of well-informed, rational investors the price of the assets would reflect all available information at any point in time and the present market price would always be the best estimate of the real price of the asset. The implications are that if the market is, in fact, efficient, no information or analysis can give profits above the expected returns of the market.

The theory has several assumptions:

- Investors act rationally. If some investors act irrationally, their actions will be random and cancel each other out.
- If many investors act irrationally in a group. Arbitrage opportunities are presented and are exploited by a rational investor. The rational investor will drive the price back to its correct price.
- There are no transaction costs
- Information is available to all market participants

Fama (1970) gave the three forms of the efficient market hypothesis:

I. Weak Form Efficient; future prices cannot be predicted by technical analysing prices from the past. Excess returns cannot be earned in the long run by using investment strategies based on historical asset prices or other historical data.

II. Semi-strong form Efficient; no fundamental or technical analysis can be used to produce excess returns over time. Meaning no public information can be used to beat the market.

III. Strong Form Efficient; all the relevant information is reflected in the market prices. Not even insider or "private" information can be used systematically used to beat the market.

The theory explains how free and efficient markets operate. The theory rests heavy on the assumption that information is available to all investors and they act on the information instantly to price the assets accordingly. All the available information is “baked” into the asset prices and when new information becomes available the prices changes in a flash to reflect the new information. No investor can have advantages if all the participants in the market have the same access to information. The implications for investors operating in an efficient market is that they cannot over time, systematically expect to outperform the market without taking on higher risk than the market. The competition between the participants will drive the price into its equilibrium state. The price momentum effect challenges the weak form of market efficiency, as the price momentum effect is identified by using historical prices. Then the price momentum effect is applied to predict future prices.

2.1.2 Random walk

Maurice Kendall (1953) discovered by the use of computer power that stock prices he analysed was moving randomly and was unpredictable. They followed a random walk. The mathematical formula for a random walk is as follows:

$$Y_t = Y_{t-1} + \varepsilon_t \tag{1}$$

Where Y_t is the value of the time series at the time t. Y_{t-1} is the value of the time series at a previous time. ε_t is an unpredictable event. Stock prices have been observed to grow over time, so by adding β_0 representing the trend in the random walk. This gives us the random walk with a drift:

$$Y_t = \beta_0 + Y_{t-1} + \varepsilon_t \tag{2}$$

The random walk model does not imply that prices are irrational. They can be set rationally, but changes are unpredictable because no one can predict the news. The news is per definition unpredictable, and both rational and irrational reactions to news can form the random movements. The random walk theory gives a strong reason to consider buy and hold strategies as no one is thought to be able to systematically predict the randomness coming from new information.

2.2 The inefficiency of markets

We will now take a look at some of the challenges facing the efficient market theory. Among them are the assumption about rationality that will be problematized from the view of behaviour finance. Several of the known anomalies will be briefly mentioned before focusing on the main anomaly of this thesis, the price momentum effect. The price momentum effect will be discussed, and several proposed explanations will be offered.

2.2.1 Cost of information

Grossman and Stiglitz (1980) argued that in a world where there are cost of gathering information, the investors must be compensated for the cost of information. If all the information is already priced into the assets, the incentives to look for more or new information would be gone, and it would not be rational to look for new information. This would result in situations where the price does not reflect all available information. Grossman and Stiglitz (1980) introduced a model where the price is explained by the information held by the informed investor. The model also has a noise factor. The Noise factor will over time be equal to zero, this would mean that the price on average would be a product of the information of the informed investors, but also that the asset could be over- or underpriced. The size of the pricing error could depend on several factors such as the number of informed investors. The number of informed investors would be expected to rise until the marginal profit equals the cost of being informed. This implication would suggest that it is profitable to look for new information because there will be arbitrage opportunities and wrongly priced assets that the rational investor could exploit by looking for new information and in the process drive the market back into efficiency. We know information has its costs, Reuters, Bloomberg and other providers of information can charge high fees for access to the information.[5] The paradox following the cost of information is that the more investors believe that the market is not efficient, the more they will look for information and drive the market towards the efficient state. Moreover, the more the market is efficient, the fewer opportunities can be found looking for news, resulting in the market becoming less efficient because participants would think there was no point in looking for the information. A question arises about the newschaisers, can they over time find news that will systematically help them generate higher risk-adjusted returns? Grossman and Stiglitz (1980) showed that an equilibrium state might be approached, but not necessarily reached.

2.2.2 Behaviour finance

In the 1990s the field of behaviour finance started to gain attraction with its questioning of the rationality and efficient market hypothesis. In his book “Irrational Exuberance” Shiller (2000) describe the hypothesis that investors are not only not rational, but irrational in a predictable way, moving in herds, prone to cognitive biases and overreacting on the news. Prominent psychologists and economists in the field of behavioural finance such as Daniel

[5] An interesting research question could be to investigate if investors with costly Bloomberg subscriptions do better than the average investor that uses free information.

Kahneman, Amos Tversky, Richard Thaler, and Paul Slovic have supplied research suggesting that the rational assumptions do not hold up. The findings in the behavioural finance field include; trading of irrelevant information (noise trading), investors not being optimally diversified, buying into assets with an unreasonable transaction- and administration costs, tendency to value last information the highest, acting different on the same information and loss aversion to naming a few. The behavioural finance field has seriously questioned the rationality assumption of efficient markets. Behavioural finance and some of the findings mentioned above will be further explored in section 2.3 when focusing on momentum.

2.2.3 Investors that beat the market

There are several examples of investors with different strategies that beat the market constantly over long periods. One of them, George Soros is on record calling the efficient market hypothesis “market fundamentalism”, as it grew to be a religion like belief in the 1970s and 1980s (Soros, 2003). Warren Buffett, another investor that systematically has beaten the market for decades, described the market as frequently efficient in his 1988 Berkshire Hathaway chairman’s letter. But he goes on to point out that many market participants have been concluding from their observations that it was always efficient and that the difference between these propositions is night and day. Some academics regard these investors as statistical out layers and argue that in a large market you will find investors with “many strikes in a row”, just by chance or luck. The question remains, if they do use systematic approaches to beat the market, their actions do question the efficient market hypothesis.

2.2.4 A look at different market anomalies

Academics and market participants have discovered a range of anomalies in the market that may question the theory of market efficiency. We will now look at some of them before moving on with the anomaly in question in this thesis, the price momentum effect.

2.2.4.1 The January effect and the tax-loss selling.

Rozeff and Kinney (1976) documented the stock market return was higher in January than other months. This effect has been seen in relations to the tax-loss selling effect found December and around the turn of the year and has been observed by Dai (2003) on Oslo stock exchange.

2.2.4.2 Sell in May and go away.

Several researchers like Bouman and Jacobsen (2002) and Andrade, Chhaochharia and Fuerst (2012) have observed and the found patterns that show stocks tend to perform worse in May-October than the period between November-April.

2.2.4.3 Reversal effect and overreaction.

De Bondt and Thaler (1985) observed the reversal effect. They found that when stocks are ranked on 3-5-year past returns, past winners tend to be future losers, and the past losers tend to be the winners over the 3-5-year period. They attribute these long-term return reversals to investor overreaction. Jagadeesh (1990) found the reversal effect on short-term and concluded that investors overreacted on information. Shiller (1981) found that stocks tended to overreact to changes in the dividend.

2.2.4.4 The size and value effect

Banz (1981) and Reinganum (1981) documented that small stocks gave a higher return than what would be expected by the CAPM model. According to the Chicago Center for Research in Security Prices, \$ 100 invested at the end of 1925 in small stocks would grow to \$ 8 244 228 and \$ 100 invested in S&P500 over the same period would grow to \$ 234 705 by the year 2005.[6] Basu (1977, 1983) documented the value effect by observing that stocks with high earnings-to-price ratio performed better than stocks with low earnings-to-price ratio. It is worth mentioning that Warren Buffet, who was mentioned before is a value investor. Rosenberg, Reid and Lanstein (1985) documented that stocks with high book-to-market ratio performed better than stocks with a low book-to-market ratio. Both of these findings were included in the Fama-French three-factor model that will be described in section 2.4.4.

2.3 Price momentum

Price momentum is a form of trend following and has been around for very long. Kaminski and Greyserman (2014) documented time-series momentum going back 800 years. The legendary trader Jesse Livermore is depicted in the 2010 book *Reminiscences of a Stock Operator* by Edwin Lefère where he has stated that *"Prices are never too high to begin buying or too low to begin selling"*. This is a very accurate description of price momentum speculation. The earlier mentioned investor George Soros have also used the momentum effect, although he names it

[6] Assuming all returns and dividends are reinvested without transaction cost and tax.

“reflexivity”, where buying brings about, even more buying in a self-reinforcing process (Soros, 2003).

Modern momentum research is mostly built out from the publication “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency” by Jagadeesh and Titman (1993). They found that buying the stocks that had outperformed over the past 3-12 months and selling the stocks that had underperformed over the same look-back periods gave significant positive returns over the next 3-12 months. A rather simple rule-based system using relative strength, where stocks are ranked by performance over a 3-12-month look-back period. Then portfolios with the strongest performing stocks are created and hold and the weakest shorted. Researchers have tested the different holding periods extensively and the consensus is that 12 months works best to minimize transaction costs (Antonacci, 2014). Jagadeesh and Titman (1993) have been criticised for data mining so they did a follow-up study in 2001 to meet this accusation, by expanding their dataset. Jagadeesh and Titman (2001) found the same momentum effect as in their 1993 study, with a new sample. The findings have been replicated several times, in many different markets, including the Norwegian market by Rouwenhorst (1998) and Griffin, Ji and Martin (2003, 2005). Rouwenhorst (1998) tested 12 different markets in the period of 1978 to 1995 where only Sweden did not show significant momentum effect in the sample period.

2.3.1 Momentum definitions

Before moving on it is about time to clear up some of the many definitions in the momentum research. Momentum refers to positive auto-correlations. We expect winners to continue to be winners and losers to continue to be losers.

2.3.1.1 Cross-sectional momentum

Ranking assets performance, usually to its peers over the last 3-12 months. Then buying and holding the best performing asset(s) until the next evaluation period usually 1-12 months. But the strategy is also used by traders and investors with all timeframes, from intraday to years. It can also be used to find the worst performance and short them. The method is the same as “relative-strength” used by Jagadeesh and Titman (1993) and in the Carhart 4 factor model.

2.3.1.2 Time-series momentum

Time-series momentum looks at an assets own return over a period to determine the momentum of the asset. This method is used to find the assets own trend, positive or negative and buy or short it. Using the assets own past price to predict its future. This is also known as trend following.

2.3.1.3 Relative and absolute momentum

Antonacci (2014) uses time-series momentum to create what he calls absolute momentum. Absolute momentum is an assets own return, less the risk-free rate over a given look-back period. If the assets excess return is above zero, then the asset has positive absolute momentum. If the assets excess return is below zero, then the asset has negative absolute momentum. By introducing the cross-sectional momentum (relative strength), which Antonacci (2014) calls relative momentum. It is possible for an asset to have positive relative momentum if its performing strong relative to its peers and to have negative absolute momentum if its own trend has been performing worse than zero. The asset can also have positive absolute momentum if its trend has been positive and negative relative momentum if compared to another asset that has performed better.

2.3.2 Price momentum is present in asset classes all over the world

Momentum researchers have found that price momentum is present and work well across over a dozen asset classes and in more than 40 countries (Accantonacci, 2012; Asness, Moskowitz and Pedersen, 2013; King, Silver and Guo, 2002). The research includes U.S. equities by Fama and French (2008). Foreign equities by Rouwenhorst (1998), Chan, Hameed and Tong (2000) and Griffin, Ji and Martin (2005). Momentum findings in industries by Moskowitz and Grinblatt (1999), and Asness, Porter and Stevens (2004). Research of equity indexes by Asness, Liew and Stevens (1997). Momentum in global government bonds by Asness, Moskowitz and Pedersen (2013). Commodities momentum findings by Pirrong (2005) and Miffre and Rallis (2007). Okunev and White (2003) find profitability of momentum strategies in the foreign exchange markets. Moreover, real estate momentum by Beracha and Skiba (2011). Furthermore, Geczy and Samonov (2012) has found that momentum worked with out-of-sample testing on U.S. equities all the way back to 1801. Lillelien (2013) detected significant momentum in some of the countries where Rouwenhorst (1998) did not. Rouwenhorst (1998) did, however, use a cross-sectional momentum strategy and Lillelien (2013) used time-series momentum. Technics and sample periods vary, but these findings suggest that the momentum effect can be found in most markets tested, but it is not present at all times, making it harder to exploit and explain.

2.3.3 Price momentum in the Norwegian market

Næs, Skjeltorp and Ødegaard (2009) observed the price momentum effect for stocks on Oslo stock exchange in periods between 1980-2006. They found substantial momentum effect from one year to the next in the 80s, negative effects in the 90s and the momentum effect were back between 2000 to 2006. Kloster-Jensen (2006) replicated the Jagadeesh and Titman (1993) findings in Norway and found significate positive alpha in sample period tested. Nygaard (2016) also show significant potential for abnormal returns applying momentum trading strategies with stock portfolios on the Oslo stock exchange in the period 1985 to 2015. Reiersrud (2013) has shown the momentum effect to be present in the period of 2004 to 2012. However, when the period is split into before and after the financial crisis of 2008, she finds significant results before the crisis, but not after. These findings in the Norwegian market also support the observation from section 2.3.2 that the price momentum is not always present in all of the sample periods.

2.3.4 Proposed explanations to the momentum effect

To this date, the momentum effect has not been satisfactorily explained by academics, in contrast to some of the other anomalies described in section 2.2.4, which has been explained and, in some cases, partly eliminated. We will now take a look at some of the possible explanations for the price momentum effect.

2.3.4.1 Behavioural explanations for momentum

A proposed explanation for the price momentum effect is that investors behave irrationally in systemic and predictable ways. Momentum strategies are largely based on buying high to sell even higher or sell low to buy lower. This might be very counterintuitive to the value investment where investors buy cheap to sell higher. Momentum might be a product of greed, that often is associated with money and speculation.

Kahneman and Tversky (1979) laid the some of the modern foundations for behavioural economics with their seminal paper “Prospect Theory: An analysis of Decision Under Risk”. Earning the Nobel Prize in economics for the work. The paper demonstrated that investors were more sensitive to losses, than to gains and act irrationally based on the bias known as loss aversion. Demonstrating irrationality was a big deal since the assumptions of the efficient market theory lean heavy on the rationality of investors. The effect could, however, not explain the price momentum effect, so many other behavioural explanations were introduced. Tversky and Kahneman (1974) also demonstrated that people anchor their views in past data and are slow to adjust to new data. Anchoring can lead to under reaction to the news. Barberis, Shleifer and Vishney (1998) argue that price momentum comes from investors underreacting because they have a limited ability to gather, process and conclude from information. Underreaction would in this context point to the conservative, slow way people adopt new information and embrace it fully. Hong and Stein (1999, 2000) also argue that price momentum can be explained by underreactions and that the underreactions are a result of the gradual way people absorb information, because of the anchoring effect. On the other side Daniel, Hirscleifer and Subrahmayan (1998) argue that the price momentum effect can be explained by the overreaction and point to the investors too high confidence in their ability to analyse information. Cooper, Gutierrez and Hameed (2004) find that the momentum profit only is present in bull markets and not bear markets which support the overreacting hypothesis. Tversky and Khaneman (1974) also demonstrated how people looked for information confirming their beliefs and disregarding information that challenges their beliefs. This could mean that investors correctly identify the momentum when observing the performance of stocks. The confirmation bias would then make them look for evidence of the momentum continuing. The disposition effect may be another explanation for the momentum effect: investors sell their winners too early to lock gains and hold on to the losses too long in the hope of making back the loss. Odean (1998) analysed thousands of investor trades and found substantial losses from more frequently selling winners and holding on to losses. Herding may also be a bias that leads to a price momentum effect, herding is found in analyst recommendations by Welch (2000) and among institutional investors by Grinblatt, Titman and Wermers (1995). It can be easy to jump on the bandwagon; the trend is your friend. Behavioural finance does give a lot compelling of reasons for the momentum anomaly and tie the explanations to human irrational behaviours and biases. Modelling or removing the effect may be hard. Maybe the effects of computer trading and algorithms will decrease the momentum effect if the human aspects are removed and not programmed into the algorithms?

2.3.4.2 *Risk*

One of the proposed explanations are the rational explanation that momentum profits are compensation for taking on higher risks, this view is in line with the efficient market theory. Many of risk-based factors were introduced to try to explain the momentum effect. Liu and Zhang (2008) proposed a link between momentum profits and the industrial production growth rates. Johnson (2002) introduced episodic growth stocks. A range of risk factors like aggregate liquidity, high revenue volatility and low cost of goods sold were introduced without any impressive results. There was a legit concern of data mining to find the perfect risk factor. None of the introduced risk factors explained the price momentum with any satisfaction. Griffin, Ji, and Martin (2003) showed that macroeconomic risk factors could not explain the price momentum effect. Jagadeesh and Titman (1993) used the CAPM model to account for the relationship between risk and return. Their findings showed that the systematic risk (Beta) could not account for the momentum effect. As mentioned in section 2.2.4.4 Fama and French (1993) developed the Fama-French three-factor model which adjust the market's risk for the size and value. The model will be explored further in section 2.4.4.

2.3.4.3 *Transaction costs and liquidity risk*

The cost of transactions can be split into three parts. The first is the bid-ask spread in the market. The second is the cost applied by the broker. The third is the taxes. The liquidity risk is the risk stemming from the lack of marketability of an asset that cannot be sold or bought quickly enough to prevent or minimize losses (big spread between bid and ask and low transaction volume). Liquidity is a major reason for large bid-ask spreads.

Most of the momentum research has been conducted without realistic transaction costs. Pastor and Stambaugh (2003) and Sadka (2006) point to the liquidity risk as significant factor explaining the abnormal profit from momentum strategies. Ball, Kothari and Shanken (1995) conclude that the bid-ask spreads significantly reduce the momentum profits. In small stocks, the spreads can be large and inflict investors with double-digit transaction costs. Researchers have responded to this by removing the smallest, illiquid stocks from the test samples to deal with the issues of large price spreads and liquidity risk. Korajcyk and Sadka (2004) conclude that the transaction cost in the form of bid-ask spreads cannot account for all of the momentum profits. They also point out that the momentum effect is largest with small and illiquid stocks and strategies will not be profitable trading stocks in this category because of the transaction costs. Carhart (1997) estimated that the transaction costs eliminated the profit from momentum strategies. In section 2.5.5 we will look at the Carhart addition to the Fama-French three-factor model. Carhart (1997) findings are supported by other researchers like Lesmond, Schill and Zhou (2004) who took a look at the Jagadeesh and Titman (1993) findings and find no significant profits after adjusting for transaction costs.

It is clear that the transaction costs can account for at least parts, if not all of the momentum profit. However, most of the criticised studies use portfolios consisting of the ten percent best-performing momentum stocks in a given stock exchange, this creates a high number of transaction, and some of the stocks suffer from large spreads and illiquidity. Antonacci (2014) does, however, uses large indexes with low costs, high liquidity and very tiny spreads. Furthermore, Antonacci (2014) demonstrate that his strategy averages 1,35 trades per year over 40 years. Comparing this to the momentum stock trading strategies with monthly or yearly rebalancing of a broad stock portfolio, the costs structure will be significantly different.

2.3.5 Summary of the price momentum section

There is to this day no satisfactory single explanation or model to explain the price momentum. It is likely that all the reasons explored in section 2.3.4 and undiscovered explanations contribute to the price momentum effect. The most compelling explanations are found in the field of behavioural finance and the psychology of human interactions in the markets. If the behavioural finance is accepted as the basis for price momentum, the effect will be present in the future, as long as humans with their biases participate in the markets or our human biases are programmed into algorithms. It is, however, important to point out that Jegadeesh and Titman (1993) and the momentum research building on their work has shown weak links in the weak form efficient market hypothesis. Demonstrating that past prices can be used to predict future prices, but there is a serious question whether the findings can be systematically exploited after transaction costs.

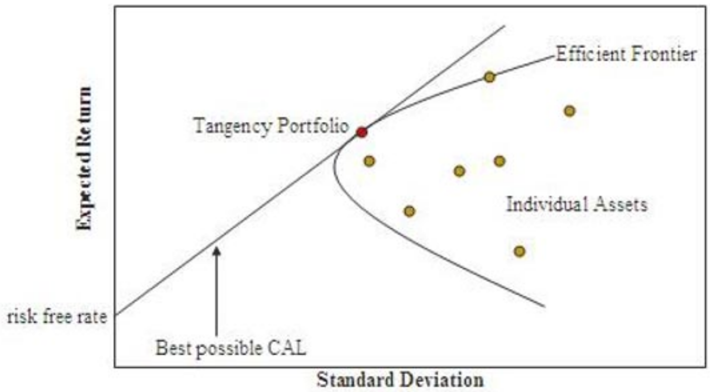
2.4 Modern portfolio theory

The basis for the modern portfolio theory was laid by Harry Markowitz in 1952. Over the following years, names such as Eugene Fama, Kenneth French and William Sharpe has contributed significantly to the evolution of the theories. The theories are today the basis of the modern portfolio management and have helped guide the allocation of capital to maximize profits and at the same time minimize the risk.

2.4.1 Markowitz mean-variance optimization

The Nobel Prize-winning economist Harry Markowitz (1952) demonstrated mathematically how to construct portfolios with the highest risk-adjusted return with a given set of assets.[7] The algorithm used by Markowitz, maps out the frontier of the efficient portfolios, by using expected return, standard deviation (square root of the variance) and correlations. The method Markowitz used is called mean-variance optimisation. The market portfolio includes all stocks with their representative weight proportion to the market. This market portfolio is the tangency portfolio to the optimal capital allocation line (CAL). The slope of the capital allocation line is equal to the incremental return of the portfolio to the incremental increase of risk, because the expected return increases continually with the increase of risk as measured by the standard deviation.

Figure 2.1 - The Tangency Portfolio on the Capital Market line



Markowitz demonstrated the effectiveness of diversification by showing how the individual risk of the assets (unsystematic risk) can be diversified away, by holding several assets without perfect correlation. The remaining risk is the systematic risk of the market and is non-diversifiable. The model was in the 50s not very practical, without great computing power, it could be time-consuming calculating thousands of covariance matrixes and returns.

2.4.2 The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is a result of work from several economists, Sharpe (1964), Lintner (1965a, b), Mossin (1996) and Black (1972). The central proposal of the model is that the market is in equilibrium when the expected return reflect the risk and that investors

[7] Assuming non-perfect coloration between the assets.

will not take on additional risk without higher expected return. CAPM is a linear regression model formulated mathematically like this:

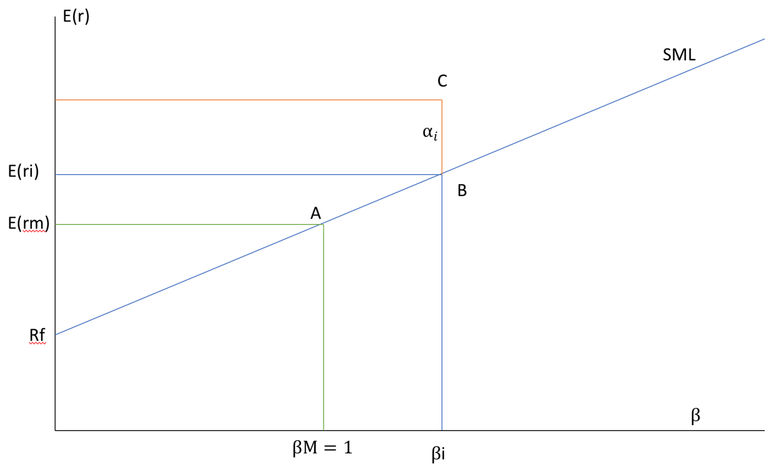
$$E[R_i] = R_f + \beta_i[E(R_M) - R_f] \tag{3}$$

Where $E[R_i]$ is the expected return of the asset or portfolio. R_f is the risk-free rate, $E(R_m)$ is the expected return of the market and β_i is the sensitivity to the market index/portfolio. Beta is calculated like this:

$$\beta_i = \frac{COV(r_i, r_M)}{VAR(r_M)} \tag{4}$$

Where the covariance between the asset and the market return is divided by the variance of the market. Beta is a representation of the market risk, the systematic risk. The beta coefficient used in CAPM models tells us how much the market's movement contributes to the asset or portfolio return. The linear relationship between the expected return and the systematic risk is illustrated with a security market line.

Figure 2.5.1 – Capital Asset Pricing Model and the Security market line



The figure above shows the risk (beta) on the horizontal line axes and the expected return on the vertical axis. According to the CAPM theory, an asset should lay on the security market line (SML), if its expected return is commensurate with the risk (beta). If the asset lay above the SML-line, it is priced lower than an asset with the same beta laying on or under the SML-line. In this case, the asset called C is above the SML-line, the asset B with the same risk are priced higher. Asset C is priced too low because the risk of asset B is equal (beta). This would suggest that there would be arbitrage opportunities.

2.4.2.1 Jensen's alpha

Jensen (1967) presented evidence for markets not being perfectly efficient by showing the existence of both positive and negative alpha when applying the CAPM to market data. Both results should not occur in efficient markets. Jensen's alpha is mathematically described by rearranging the CAPM as follows:

$$R_i - R_f = \alpha_i + \beta_i[E(R_M) - R_f] + \varepsilon_f \quad (5)$$

The CAPM assumptions:

- Asset returns are normally distributed random variables
- Investors attempt to maximize market returns, and all have the same view on expected return (homogeneous expectations).
- Investors are rational, have the same holding period and are risk-averse
- All investors have access to the same sources of information for investment decisions.
- Taxes and commissions are not considered, and there is unlimited access to borrow (and lend) money at the risk-free rate.
- Investors are all mean-variance optimizers and are limited to public traded investments.
- Investors are not large enough players in the market to influence the price.

The assumptions above is of course only true in a simplified world, for example, we all know there are taxes to pay. And that not all investors have the same view of the future and therefore not the same view of the expected return and risk. Furthermore, a substantial amount of research like the behavioural finance research explored in section 2.3.4.1 point to humans not always acting rationally. Fama and French (2004) criticised CAPM for failing to stand up to empirical tests, since alphas have been demonstrated in various data samples. The CAPM is, however, widely used in lack of better models but does give an indication of the fair market price of an asset.

2.4.3 The arbitrage pricing model

The Arbitrage pricing model (APT) was introduced by Ross (1976) and is another linear model based on the principle that expected returns of an asset is related to at least one factor. The model is expressed as:

$$r_j = \alpha_j + b_{j1}F_1 + b_{j2}F_2 + b_{ji}F_i + \varepsilon_i \quad (6)$$

$r_j$is the return of the asset, α_j is a constant, $F_i$is the factors, $b_{ji}$is the sensitivity (beta) of the asset to the factor and $\varepsilon_i$is the assets idiosyncratic risk. The expected return according to APT is as follows:

$$E(r_j) - r_f = b_{j1}RF_1 + b_{j2}RF_2 + b_{ji}RF_i + \varepsilon_i \quad (7)$$

RF is the risk-premium of the factor F. The assumptions of the APT needs only one investor to act “rationally” and buy or sell the asset in question until the price arbitrage opportunity is gone. Forcing the price back into equilibrium.

2.4.4 Fama-French three-factor model

The Fama-French three-factor model was created in 1993 by Fama and French (1993) to try to expand on the CAPM by adding factors that could help to account for some of the anomalies described in section 2.2.4.4. Academics had made observations about small stocks (small market capitalization), and value stocks (high book-to-market ratio) tended to outperform the market. The introduction of the new risk factors should make the model more robust and is expressed like this:

$$E[r_i] - R_f = \alpha_i + \beta_i[E(R_{rm}) - R_f] + \beta_{iSMB} * SMB_t + \beta_{iHML} * HML_t + \varepsilon_i \quad (8)$$

The new factors introduced was HML (high minus low) which is a factor that comes from ranking all the stocks by book-to-market ratio, then subtract the return of the lowest 30 % from the highest 30 %. The next factor is the SMB (small minus big), where the stocks are ranked by market capitalization (size) and subtracted the return from the 30 % highest ranked stocks (largest) from the return of the 30 % lowest ranked stocks (smallest). With the addition of these factors, Fama and French tries to explain the anomalies that the CAPM model struggles with like the small stocks tend to outperform large ones and that the high book-to-market ratio stocks tend to outperform stocks with low book-to-market ratios.

Fama and French (1996) show that the long-term reversal effect can be accounted for in their three-factor model and the factors introduced did indeed capture the value and small stocks effect. The model gave higher explanatory power but failed to explain the price momentum effect. This has led Fama to revisit the efficient market hypothesis. In the last revision Fama (1998) points out that the expected return from the anomalies would be zero. However, randomness generates both positive and negative abnormalities. The randomness will secure that it is not possible to develop a systematic investment strategy that captures the positive abnormalities.

2.4.5 Carhart Four-factor model

Because the Fama-French three-factor model could not account for certain returns, like momentum, Carhart (1997) added the momentum factor to the Fama-French model using the methodology of Jagadeesh and Titman (1993). The Carhart factor is long the previous 12-months return winners and short the previous 12-month losers. Carhart believes that adding the momentum factor and adding the transaction costs, as discussed in section 2.3.4.2, would eliminate the momentum effect.

The Carhart four-factor model did better explaining the momentum but was not satisfactory (Fama and French, 2011). As shown partly in section 2.3.4.2 there has been a "factor sickness" and researchers have bordered close to the datamining trying to find factors to explain the price momentum with little luck. Perhaps because some of the factors are related to human behaviour discussed in section 2.3.4.1 and hard to quantify.

2.5 Performance measures

It is essential to have a range of tools ready to evaluate performances as no single measure alone is sufficient in analysing the range of concerns about portfolio results. Below we will explain the different measurements used. Together they will provide a useful framework for evaluating the strategy and its results.

2.5.1 Portfolio Return

The obvious measurement of success, the return. The return will be measured in various ways;

- Cumulative return over the period
- Annual average return
- Monthly average return

In addition, we provide a portfolio starting with NOK 100 and holding to the end of the period. To add to the realism, since "no one" buys once and hold for decades. We will also calculate a portfolio starting with NOK 100 and invest another NOK 100 every month throughout the sample period. This will provide us with a more realistic example of a person saving long-term for pension or retirement by adding monthly to the investment from his/her salary.

2.5.2 Variance and standard deviation

The standard measurements of the volatility of the returns will be provided for each index and portfolio. The variance is calculated from the average of the squared differences from the mean, and the standard deviation is the square root of the variance. The standard deviation provides a well-known measurement of price-fluctuations risk for the portfolios and assets compared. Standard deviations are a measurement of total risk.

2.5.3 Systematic risk (beta) and unsystematic risk

The beta is the market risk, the systematic risk. A beta of one indicates that the asset has the same risk as the market. Beta is, therefore, a measure of the risk related to the exposure to the market. Systematic risk is the risk inherent to the entire market and is undiversifiable. Unsystematic risk is unique to a specific company or industry and is diversifiable. The systematic risk is believed to incorporate interest rate changes, inflation, political events, recessions, cultural events, wars and other macroeconomic events that all assets are affected by.

2.5.4 The Sharpe ratio and the Treynor ratio

The sharpe ratio is widely used to measure risk-adjusted performance. The sharpe ratio was conceived to rank mutual fund performance, by looking at not only the return but also the risk involved in getting the returns. It is calculated by dividing the average excess return over the sample period by the standard deviation of the return in the sample period. Providing a measure of reward to total volatility trade-off. The sharpe ratio is calculated like this and the higher, the better:

$$S_H = \frac{\overline{R_T}}{\sigma_{RT}} \tag{9}$$

Where $\overline{R_T}$ is the average return less the risk-free rate of the period and σ_{RT} is the standard deviation of the return in the period.

The Treynor measure is similar to the Sharpe ratio but uses the systematic risk instead of total risk (standard deviation), meaning the beta instead of the sigma. The Treynor ratio will in this context have limited use because the portfolios tested is not a sub-portfolio of a fully diversified portfolio. The portfolios tested hold the whole market in several countries and is therefore in some sense more diversified than the beta used from only one of these markets. The Treynor ratio will be provided nonetheless but is not the best proxy.

2.5.5 Maximum drawdown and Downside deviation

Maximum drawdown is interesting because investors psychology is affected directly by the losses and according to loss aversion, hit harder by losses than gains. Furthermore, the willingness to overtime stick to a strategy with substantial losses can be hard. Less drawdown will help investors stick to their strategy. Maximum drawdown is a good indicator of the risk and protection in the worst-case scenarios. Downside deviations is a measure of downside risk that focuses on returns that fall below the mean return. It is used in the calculation of the Sortino ratio and can evaluate funds with similar returns but different downside risk.

2.5.6 Modigliani and the Sortinio ratio

The Modigliani risk-adjusted performance (M^2) is a measure that sought to improve on the way to interpret the Sharpe ratio. It can easier be understood then the Sharpe ratio, because it gives us a percentage number. The M^2 is calculated like this:

$$M^{\wedge 2} = \frac{\overline{R_T}}{\sigma_{RT}} * \sigma_m + R_f \tag{10}$$

The Sortinio ratio is yet another attempt to improve on the Sharpe ratio by using the downside risk (downside deviation) to adjust the performance instead of the standard deviation. The downside deviation is the standard deviation of all the returns that are less than the mean.

2.5.7 Jensen's alpha, Fama-French and Carhart models

The CAPM alpha measures the portfolio risk-adjusted return in relation to the expected market return. The alpha is the average return on the portfolio that exceeds the predicted return by CAPM, given the portfolio beta and market average return. It is widely used by to measure the performance of active strategies to passive. Jensen's alpha is expressed mathematically like this:

$$\alpha_i = R_i - [R_f + \beta_i(R_M - R_{f)}] \tag{11}$$

The alpha will be calculated using simple- and multiple regression analysis. The CAPM Jensen's alphas of the portfolios will be calculated and the alphas are tested for significance and the t-statistic and the p-value are provided for each portfolio. In addition, the Fama-French three-factor and Carhart four-factor models will be used to check if the additional factors can explain the price momentum any better than the CAPM.

2.5.8 Information ratio

The information ratio divides the alpha of the portfolio by the non-systematic risk of the portfolio. The results show abnormal returns per unit of risk that could be diversified away by holding the market index. A positive information ratio shows that the portfolio has outperformed its benchmark. Often contributed to the portfolio manager's ability to pick stocks.

2.5.9 VAR and RAROC

VAR is a measurement of potential loss given a probability. It gives us the ability to say with 95 % confidence that the monthly expected maximum loss will not exceed a percentage. This gives us information about what is to be the expected losses for an investment given a confidence level. Using the VAR, we can calculate the Risk-Adjusted Return On Capital (RAROC), which measures how much risk is involved in producing the return.

2.5.10 Statistics measurements

It is essential to consider the third and fourth moments of risk in the relation with customarily used metrics like means and variance of the returns. Skewness and excess kurtosis of the returns are provided to shed light on the distribution of the returns. One of the problems with the mean-variance is precisely the assumption of normal distribution. Returns have been observed not to be normally distributed and to exhibit fat tails. In particular, rational investors would not like negative skewness and would expect higher returns for taking on fat tail risk.

2.5.11 Months with profits and turnover

Months with profit will indicate the robustness of the strategy in comparing to the overall market. This is another factor that may affect the investor psychology and willingness to stick to the strategy, as it is no fun doing worse than the market, month by month.

Numbers of trades (turnover) per year will give an indication of the costs of implementing the strategy. A high number of trades increase the costs and the practicality of implementing the strategy. As discussed in section 2.3.4.3 higher transaction costs seriously reduce the momentum profits.

2.5.12 Benchmarks

The last thing we will discuss in the performance section is benchmarks. Comparing results to a benchmark is the probably one of the most popular methods of evaluating any strategy. As the neighbour always compare his grass to the grass on the other side, which always happens to be greener. Investors are also prone to this comparing of returns and risk. This comparison is a serious problem for the psyche of the investors, as they will always find something that does better than their strategy in any period. We have all heard “did you beat the market?” What is a good benchmark? Usually, the answer is the market index, typically the home country index or any index that could be a real alternative. In this thesis, we will use the OBX index, as it is the natural alternative and low-cost option to the active strategy, seen from the Norwegian perspective.

3 Methods

3.1 Look-back period

The formation period or look-back period is vital to both relative and absolute momentum as the historical price changes form the foundation for the price momentum effect. As mentioned in section 2.3 many different look-back periods have been tested, and the momentum effect has been observed in the short term as well as more extended periods of time. Antonacci (2014) uses the most common look-back period, which is 12 months. According to Antonacci (2014), the majority of the academic literature uses 12 months and concludes that it gives the best performance. The longer look-back periods also tend to lower portfolio turnover, and thereby the costs of the strategy. There are a few reasons to stick with 12-month look-back period; the first is that this is what Antonacci (2014) uses and since this is a replication there is no reason not to use the same method. The second is to avoid the accusation of fitting the model to the data since it is a rather simple task to optimise the look-back period to give the best results from historical data. The third is that the literature suggest it is the optimal period to use for long-term strategies. The look back period is calculated as:

$$R_{i,t=k} = \frac{P_{i,t=0} - P_{i,t-k}}{P_{i,t-k}} \tag{12}$$

Where the return of asset i in the time period t, with look-back period k, $R_{i,t=k}$ is calculated by subtracting the current price of asset i, $P_{i,t=0}$, by the price of the asset at t-k, $P_{i,t-k}$, where k is the months back in time, in this case 12 and divide on $P_{i,t-k}$.

3.2 Absolute momentum

Time-series momentum or absolute momentum as Antonacci names it is calculated like this:

$$AM_i = R_{i,t=k} - Rf_{r,t=k} \tag{13}$$

AM_i is the absolute momentum for the asset. It is calculated using the assets own return in the formation period $R_{i,t=0}$ less the return of the risk-free asset over the formation period ($Rf_{r,t=k}$).[8] This is done each month to check if the assets have positive or negative absolute momentum over the past months. The check is as follows:

$$\text{Positive absolute momentum if } AM_i > 0 \tag{14}$$

$$\text{Negative absolute momentum if } AM_i < 0 \tag{15}$$

[8] Antonacci (2013) use the 90-day U.S Treasury bills.

3.3 Relative momentum

Cross-sectional or relative momentum as Antonacci calls it is calculated using the following formula:

$$R_{i,t=k} = \frac{P_{i,t=0} - P_{i,t-k}}{P_{i,t-k}} \tag{16}$$

Every month the return of asset i for a given look-back period is calculated ($R_{i,t=k}$). Using the current price P of the asset i ($P_{i,t=0}$), less the price of the asset i at time t-k, divided by the price of the asset at time t-k. K=12 since we use 12 months look-back period. In simpler terms, we use the current price and the price 12 months ago to calculate the assets percentage performance over the period.

3.4 The Dual Momentum method

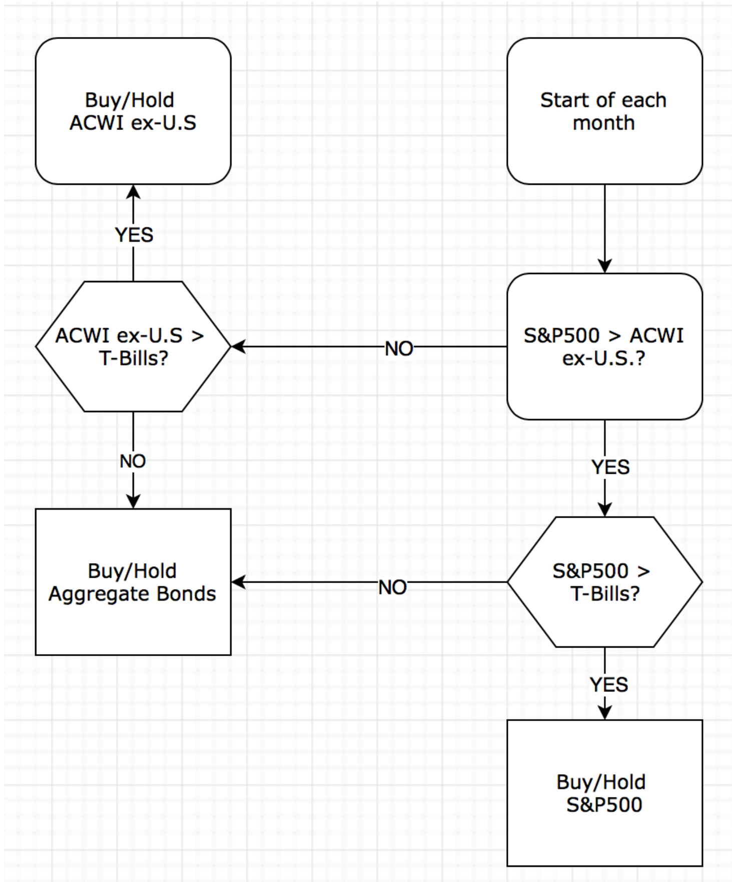
Dual Momentum comes about by using a combination of the two momentum methods described above and in section 2.3.1.3. Antonacci (2014) uses absolute momentum to find out whether or not the S&P500 has had positive or negative absolute momentum for the past 12-months. If the S&P500 has had positive absolute momentum for the past 12-months he stays invested in the index. If the absolute momentum is negative, he exits the position in S&P500 and put on the safe haven asset of aggregate bonds. High-quality bonds, typically government bonds, have historically performed well during bear markets and have served as a safe haven, unless the whole country's finances are in jeopardy. It is a simple and easy flight to safety if the stock trend is down. Antonacci (2014) claims that the strategy holds bonds about 30 % of the sample period.

$$\text{Positive absolute momentum if } AM_{s\&p500} > 0 = \text{invested in S\&P500} \tag{17}$$

$$\text{Negative absolute momentum if } AM_{s\&p500} < 0 = \text{invested in Aggregate bonds} \tag{18}$$

Next, he adds the relative momentum to the method by including another asset. Antonacci (2014) uses the ACWI ex U.S. index as the second index. This will give him a rotation between the U.S. markets with S&P500, the ACWI ex-U.S. that consists of developed and emerging countries outside the U.S. and the protection from bear markets with bonds.[9][10] Antonacci (2014) also points out how simple it is to implement the strategy with the use of exchange-traded funds (ETFs) and using free web services for getting the data to calculate the monthly signals, making the strategy of Dual Momentum practical. The Dual Momentum method for each month can be visualized in the flowchart below:

Figure 3.1 - Dual Momentum Strategy flowchart



3.5 Applying Dual Momentum from the Norwegian perspective

To apply the Dual Momentum strategy from a Norwegian perspective, we will need to find Norwegian alternatives to replace the core components in the strategy. The OBX Total return index as stated in section 1 will serve as the replacement for the local market (S&P500). The replacement for the aggregated bonds will be the "statsobligasjonsind. 5.00" (ST5X) and the

[9] The MSCI ACWI ex USA Index captures large and mid-cap representation across 22 of 23 Developed Markets (DM) countries (excluding the U.S.) and 24 Emerging Markets (EM) countries. The index covers approximately 85% of the global equity opportunity set outside the U.S.
[10] For aggregate bonds, Antonacci (2014) uses the Barclays U.S. Aggregate Bond index with a high holding of investment grade bonds (78 % AAA-rated) and an average maturity of just under five years.

replacement for 90-day T-bills will be the NIBOR 3 month (N3M). There is a terrible selection of ETFs traded in NOK in general and the bond ETF selection is equal to zero. In Norway a couple of banks, insurance and pension providers such as DNB, KLP and Storebrand are among several bond funds managers using the ST5X as the benchmark for some of their bond funds.[11] So, there is a decent selection of alternative ways to implement the strategy in real life, but no ETFs. The more sophisticated investor might check out the option to buy government bonds directly. The last asset is the replacement for the AWCI ex-U.S. In this thesis we will replace this asset with a whole list of foreign assets from country indexes, regional indexes to broad market indexes. By creating several portfolios with the Norwegian cornerstone components of OBX and ST5X and a foreign asset, we will expect the strategy to stay in the home market of Norway (OBX) unless the momentum effect points to better opportunities in foreign markets or go to ST5X when the markets are in stress. By testing a range of international indexes, we will ensure that the strategy does not only randomly produce momentum profits in the sample period and avoid accusations of selecting the third asset because of good performance. It is also worth noting that there is no real good replacement for AWCI ex-U.S. as there is no World ex-Norway indexes to use. Therefore, it is hard to say what a great replacement would look like, hence the test of many alternatives.

[11] Some of the Norwegian bond funds using ST5X as their benchmark; DNB Lang Obligasjon 20, KLP Obligasjon 5 år and Storebrand Stat.

4 Data

4.1 Sample period

Historical end of month close price data in both local currencies and NOK from 41 (including OBX and ST5X) indexes including country indexes, regional indexes and broad market indexes have been collected. A complete list of indexes compiled can be found in appendix 9.1, the same list show in what portfolio the data is used. All the data collected stretches from 31.01.1996 to 31.01.2018. The period was picked because of the availability of the index data for all the indexes in this period. The data will be used to create 39 portfolios that all stretches over both the dotcom bubble of 2000 and the financial crisis of 2008, which in principal will provide a great challenge to both the psyche of the investor holding the portfolio in this period and the portfolio itself.

4.2 Sources of the data

The one-month and one-year risk-free rate data, and the Norwegian (OSE) Fama-French three-factor and the Carhart Four-factor model pricing factors has been collected from Ødegaard (2018). The monthly pricing factor data was not updated to cover all the sample period of the dataset when it was collected from Bernt Arne Ødegaard´s webpage[12]. Therefore, the factors have only been tested between 31.01.1997 and 30.06.2017. Furthermore, because much of the data used is international the Fama/French Global 3 Factors and the Global Momentum Factors was downloaded from Kenneth R. French's data library[13] (French, 2018).[14] The rest of the data, meaning the index data, used in this thesis is collected from a Bloomberg Terminal and with the help of the Excel add-in imported to Microsoft Excel.

4.3 Analysis of the data

The data was loaded into Microsoft Excel from Bloomberg and from files downloaded from Bernt Arne Ødegaard's website. In Microsoft Excel, the Dual Momentum strategy, described in section 3, was written and the data tested. The Excel model was built to provide the performance measurements in section 2.6. Simple (CAPM) and multiple regression (Fama-French and Carhart factor models) was used to calculate alpha, beta and provide the t-statistics and p-values to test if the alphas are significant or not.

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[12] http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html
[13] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[14] The data is not presented in the thesis because the Ødegaard's factors have higher explanatory power. The data is mentioned because of a discussion in section 6.5.

5 Results

5.1 Presentation of the results

The first year has been used to create the first look-back-period, and the portfolios have been simulated for 252 months (21 years) starting directly after the first formation year. It is once again important to point out that only 245 months have been used when the Fama-French and Carhart factors have been applied to calculate and test the significance of the alphas of each portfolio. The reason is that the risk factor data for the whole sample period was not available at Ødegaard´s website at the time the test was conducted. The portfolios have been given the names, Dual Momentum Portfolio 1-39 or DMPX for short, where x is the number of the portfolio. An overview of the DMPs and the foreign asset used in the portfolios can be found in the appendix 9.1, table 9.1. In appendix 9.3, Table 9.3 – 9.22 all the performance statistics for each DMP and the foreign asset used in the sample period is listed. The returns are calculated in NOK. Below the OBX and one of the DMP performance in the sample period will be presented. Followed by a section on general DMP results and the robustness testing. The section ends with a summary of the results.

5.2 OBX - The benchmark performance

First, we look at the OBX and the ST5X (table 5.1) to get an impression of the returns and risk for the default investment for the Norwegian investor in the sample period.

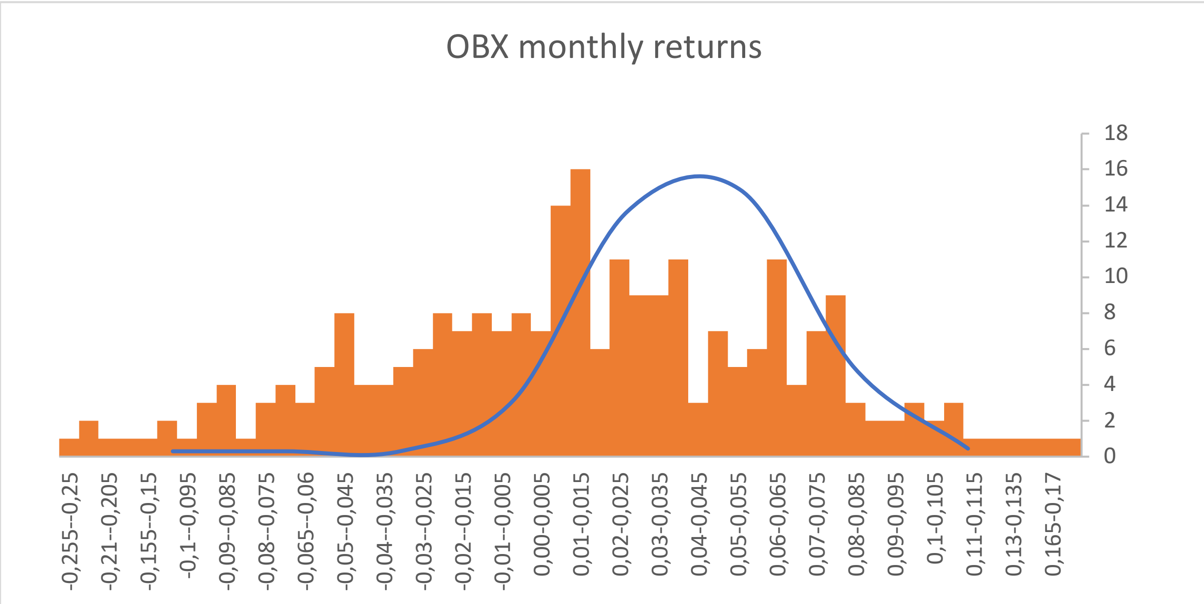
Table 5.1 - OBX & ST5X

Metrics, measurements and ratios	OBX	ST5X
Cumulative return	559,04 %	179,87 %
Average monthly return	0,95 %	0,41 %
Average yearly return	11,35 %	4,96 %
Months with profit (%)	61 %	61 %
Standard deviation	21,41 %	3,74 %
Variance	0,0459	0,0014
Sharpe ratio	0,3835	0,4866
Treynor ratio	0,0821	-0,4613
M^2	0	2,21 %
CAPM Beta	1	-0,0395
Maximum drawdown	-56,27 %	-4,31 %
Annualised Downside Deviation	11,41 %	2,38 %
VAR (5 percent)	-8,89 %	-1,22 %
Sortino ratio	0,7197	0,7662
RAROC	0,4058	0,2946

NOK 100 Invested	659	280
NOK 100 every month	84 119	41 968
Skewness	-0,9533	0,2481
Excess kurtosis	2,9410	0,7377

The OBX average yearly returns in the sample period is good, but the risk that comes with it seems high. ST5X is stable, safe, low risk, looks like a great alternative to bank deposits.

Figure 5.1 - OBX - Monthly returns frequency



The histogram above shows the frequency of the monthly returns of OBX in the sample period and a distribution curve.[15] First, the monthly returns are not normally distributed. The distribution has leptokurtosis, and we can observe fat tails, and a substantial one below zero. Secondly, the skew is negative, which is detrimental to a potential investor. Thirdly, the range of the monthly returns goes from negative 25,35 % to positive 17,23 %. A massive spread of monthly returns, hence a large standard deviation and in general vast downside risk has to be expected if invested in OBX.

5.3 DMP1 - Statistics and graphs

The portfolios were alphabetically sorted by country name and named. DMP1 was the first portfolio on the list and hence not a result of being cherry-picked, to show a good performing portfolio. In fact, it performed below the average of all the DMPs. DMP1 is created from OBX,

[15] The bell curve calculated from the mean and standard deviation frequency of the monthly returns of OBX.

ST5X and the Australian All Ordinaries Index, full statistics can be found in table 9.3 in the appendix and below in table 5.2. The DMP1 has an average yearly return of 14,99 % compared to 11,35 % of OBX, 7,13 % from AS30 and 4,96 % for ST5X.[16] The sharpe ratio for DMP1 is higher, lower maximum drawdown and overall higher risk-adjusted returns. The table below shows monthly data where alpha is calculated with regression and the alpha tested with Student's t-test. Adding more factors does not explain the much more of the alphas, introducing Fama-French factors increases the p-value of the CAPM alpha from 0,006 to 0,013 and using the Carhart model the p-value rises somewhat to 0,0289 far from the model's intentions of explaining the abnormal price momentum returns. For an illustration of the momentum effect and the Dual Momentum strategy, a few graphs of DMP1 have been included to show some of the effects of the Dual Momentum portfolios.

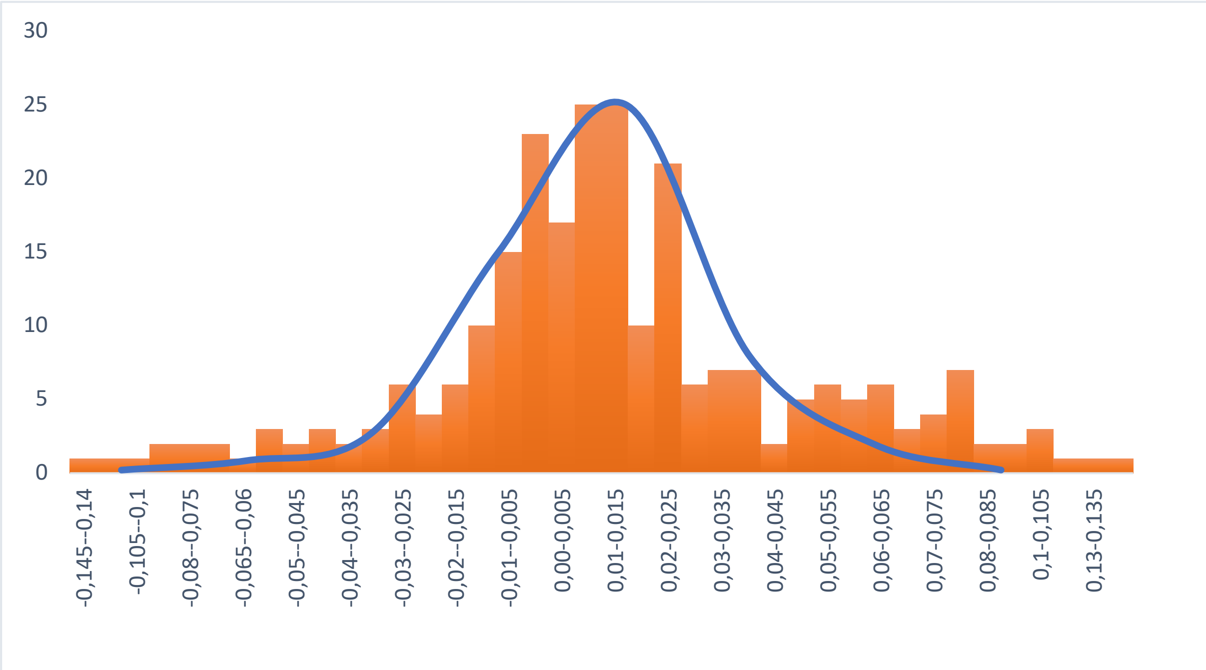
Table 5.2 - DMP1 and AS30 Statistics

Metrics, measurements and ratios	DMP1	AS30
Cumulative return	1805,70 %	218,12 %
Average monthly return	1,25 %	0,59 %
Average yearly return	14,99 %	7,13 %
Months with profit (%)	65 %	58 %
Standard deviation	13,72 %	17,95 %
Variance	0,1038	0,0322
Sharpe ratio	0,8638	0,2224
Treynor ratio	0,4016	0,0755
M^2	10,28 %	-3,45 %
Beta	0,2951	0,5287
Information Ratio	0,7835	-0,0107
Annualised CAPM Alpha	9,16 %	
Maximum drawdown	-27,99 %	-55,85 %
Annualised Downside Deviation	10,38 %	9,54 %
VAR (5 percent)	-4,98 %	-8,63 %
Sortino ratio	1,1412	0,4183
RAROC	0,5933	0,2532
Trades per year	2	0
NOK 100 Invested	1 906	318
NOK 100 every month	153 944	47 485
Skewness	0,0387	-0,5161
Excess kurtosis	2,3294	0,4351
CAPM alpha (monthly)	0,79 %	
T-statistic (monthly CAPM)	3,4832	
P-value (monthly CAPM)	0,0006	

[16] Returns are in NOK. Foreign indexes are converted from local currency to NOK. Meaning that the currency market could improve or degrade the performance of foreign indexes.

3 factor alpha	0,76 %
3 factor t-statistic	3,2610
3 factor p-value	0,0013
4 factor alpha	0,75 %
4 factor t-statistic	2,1976
4 factor p-value	0,0289

Figure 5.2 - DMP1 - Monthly returns frequency



The histogram above shows the frequency of the monthly returns of DMP1 in the sample period and a distribution curve. First, the monthly returns are closer to normally distributed than the OBX returns shown in figure 5.1. Second, the skew is positive, and this portfolio also has fat tails (excess kurtosis), but less than OBX, especially on the downside. Third, the range of the monthly returns goes from negative 14,26 % to positive 17,23 %, a smaller spread and the downside is substantiality smaller. The maximum monthly drawdown also confirms this, and so does various risk measurements, like the sortino ratio, VAR and downside deviation. One of the major takeaways is the downside that is substantially smaller compared with OBX, but also the upside is smaller. Volatility in general is reduced compared with OBX.

Figure 5.3 - DMP1 - Buy and Hold Returns in NOK

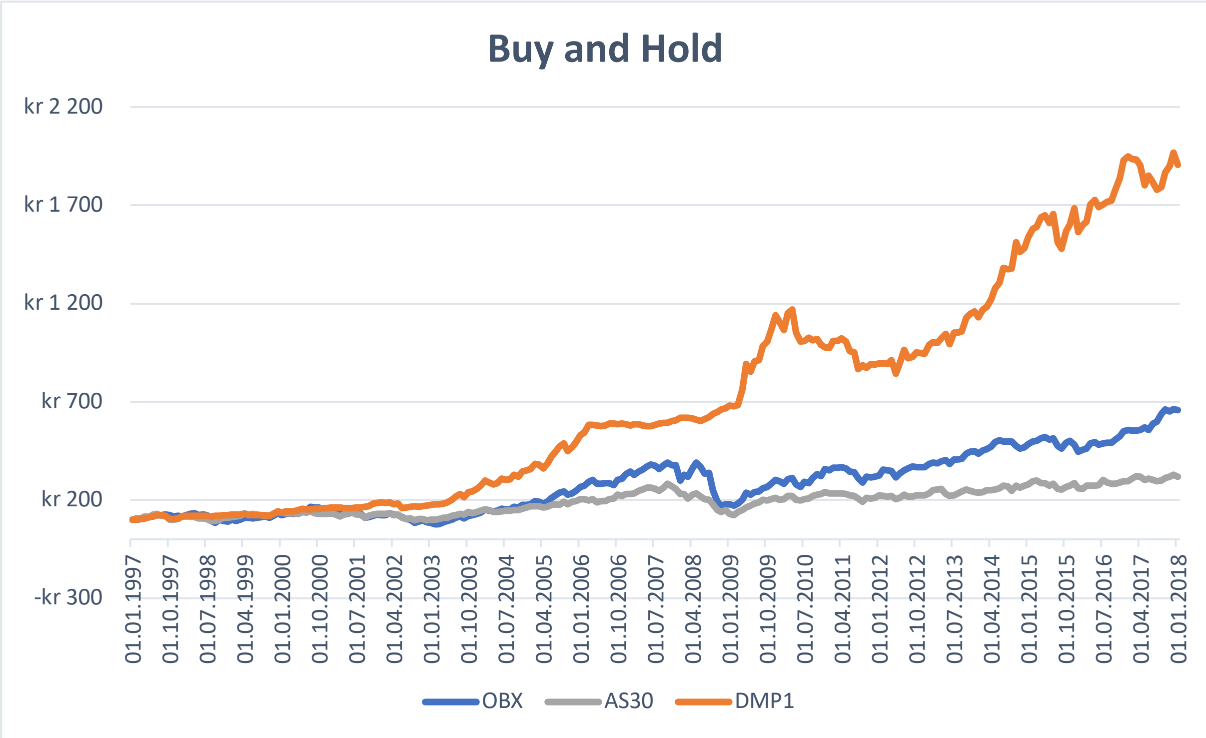
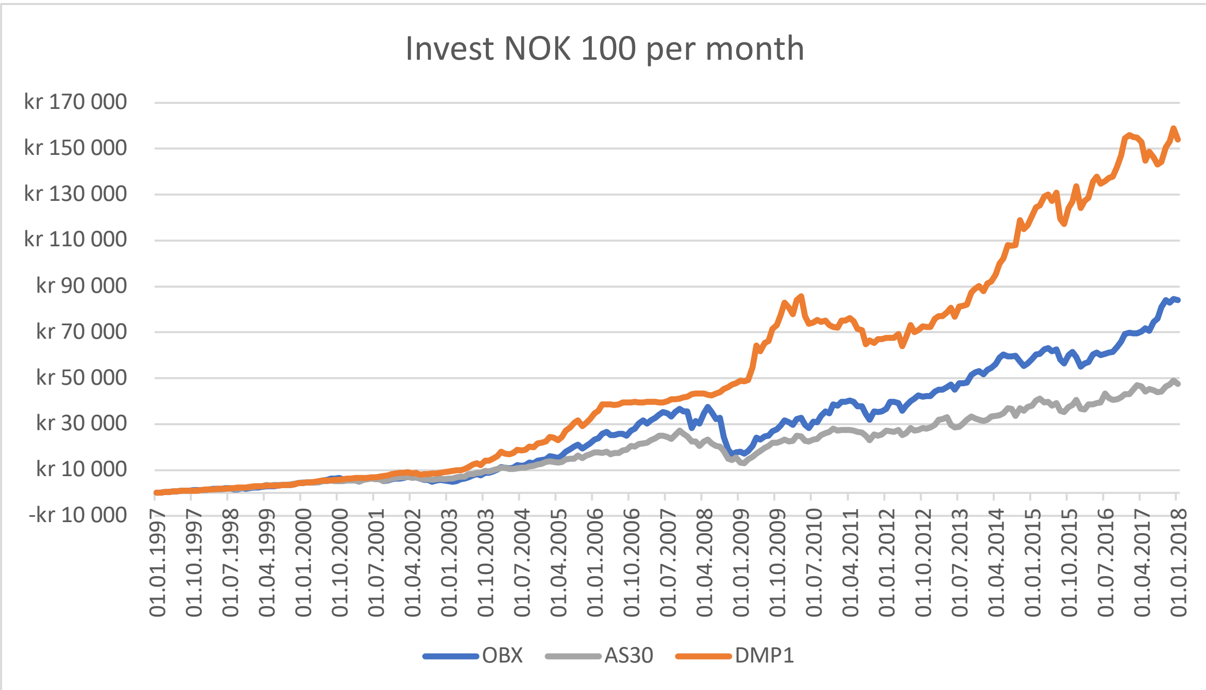
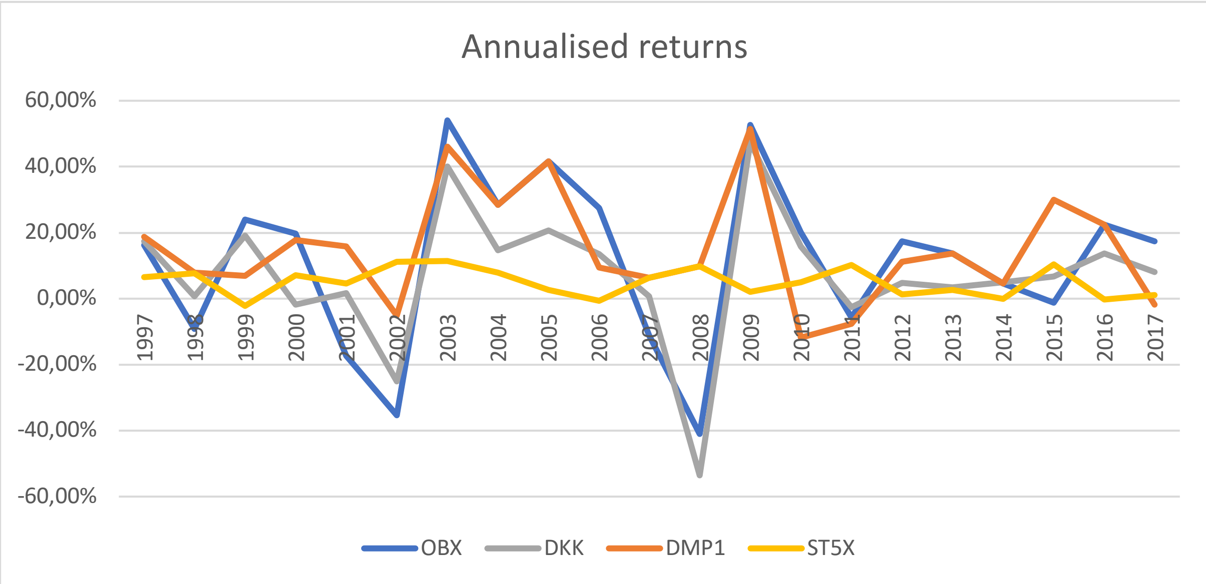


Figure 5.4 - DMP1 - Monthly Investment of NOK 100



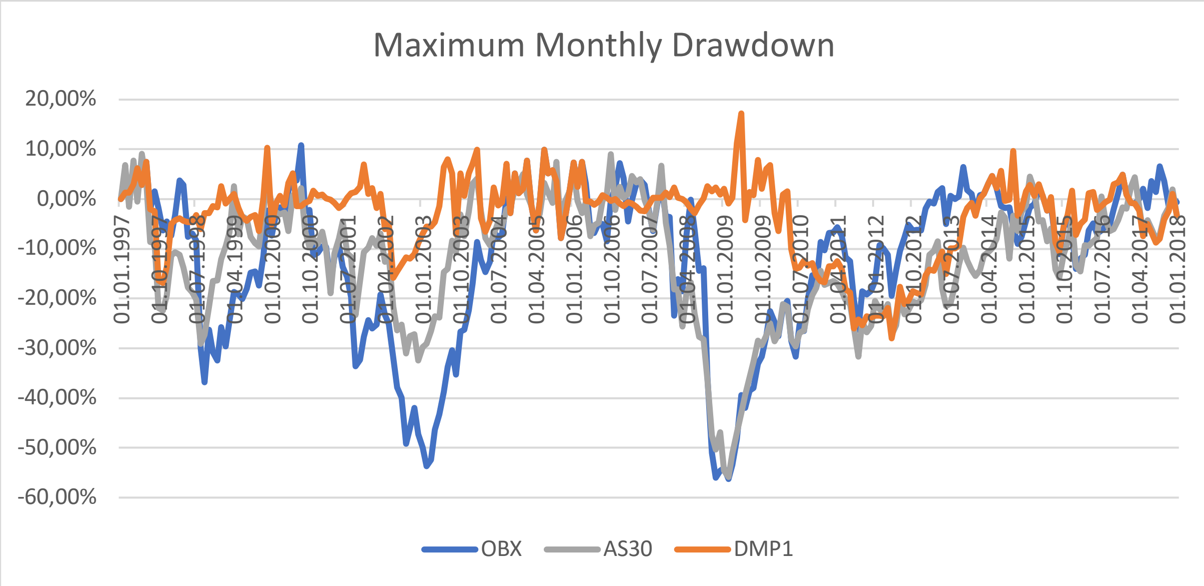
The graphs displaying the growth of NOK 100 and monthly added investment shows the strength of being out of stocks and in bonds when the stock market is under stress which can be observed around the financial crisis in these charts. Staying in bonds earns money when the stock market crashes, and the strategy returns to the stock market after the market momentum turns around. Losing less and growing in the best stock market with the highest momentum after a crash makes a considerable impact on the growth of the money invested.

Figure 5.5 - DMP1 - Annualised returns



The DMP1 annualised return is smoother than that of OBX and AS30, the standard deviation of the returns is lower. It can be observed that the entering into bonds in 2001 and 2007 saves the portfolio from sharp drawdowns and massive losses. We can also observe one of the weaknesses of the Dual Momentum strategy around 2010 in this chart, no clear signal results in many trades between the assets and short stays in the assets dragging down the returns, below that of the stock indexes. From 2014 to 2016 we observe the bull trend and switches between assets with high momentum making the strategy perform better than any asset, because of the switching between the assets with the highest momentum. In bear markets this switching adds to the drawdown, if the strategy does not go out of the market into the safety of ST5X. This might happen in “directionless markets” or when the momentum is weak or not present.

Figure 5.6 - DMP1 - Maximum Monthly Drawdown



The maximum monthly drawdown shows the strength of the Dual Momentum strategy. Not only does the strategy give lower volatility, but also lower downside volatility, by avoiding the huge losses inflicted on portfolios from fat tail events like the dotcom and financial crisis. By flying to safety with all the money during the crisis, the strategy has a better starting point with more cash when the market turns around, making the growth rate of the money higher. The maximum monthly drawdown is only 27,99 % compared to 55,85 % for AS30 and 56,27 % for OBX. In the chart, we once again observe a weakness of the strategy around 2010-2013 when the signal fails to put the strategy into bonds during a downtrend and many trades in the period are conducted on "false signals" or the momentum is weak or not present.

5.4 General DMP results

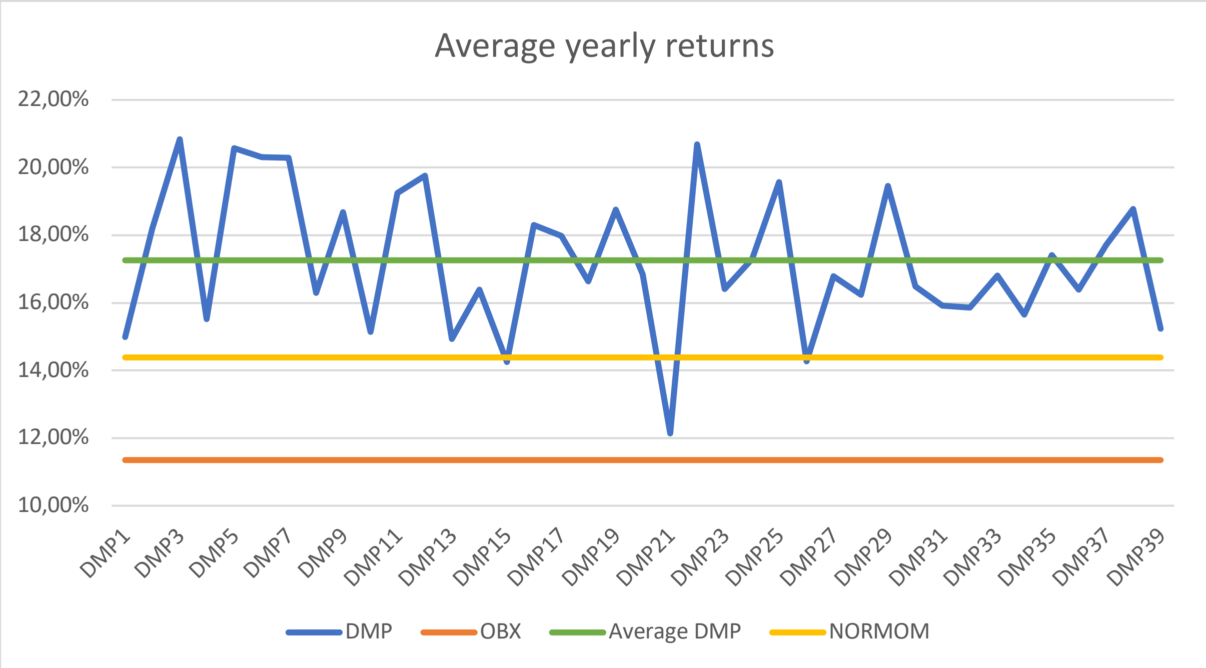
Below is a table presenting the average of the DMPs and a portfolio called NORMOM, which consists of only OBX and ST5X. NORMOM is only using Norwegian stock and bond indexes but is based on the same price momentum rules as the DMPs. This can be an alternative for investors who only want to have exposure in NOK but want to use the Dual Momentum strategy. NORMOM beats OBX and three out of thirty-nine DMPs. Comparing NORMOM to the DMPs helps to show the benefit of the Dual Momentum strategy and having a third and foreign asset in the portfolio. The difference between the average of all DMPs and NORMOM clearly show the strength of adding a third non-Norwegian index to your portfolio.

Table 5.3 - Average DMP and NORMOM

Metrics, measurements and ratios	Average DMP	NORMOM
Cumulative return	3130,01 %	1597,35 %
Average monthly return	1,44 %	1,20 %
Average yearly return	17,26 %	14,38 %
Months with profit (%)	65 %	64 %
Standard deviation	14,57 %	13,39 %
Variance	0,0215	0,0179
Sharpe ratio	0,9743	0,8399
Treynor rato	0,4703	0,3205
M^2	12,65 %	9,77 %
Beta	0,3085	0,3509
Information ratio	0,9082	0,7669
Annualised CAPM Alpha	11,33 %	8,12 %
Maximum drawdown	-28,33 %	-31,52 %
Annualised Downside Deviation	11,38 %	10,23 %
VAR (5 percent)	-5,04 %	-4,98 %
Sortino ratio	1,2540	1,0988
RAROC	63,07 %	58,06 %
Trades per year	2	1
NOK 100 Invested	3 230	1 697
NOK 100 every month	199 599	133 267
Skewness	0,3207	0,2869
Excess kurtosis	2,3092	1,6806
CAPM alpha (monthly)	0,96 %	0,65 %
T-statistic (monthly CAPM)	4,0140	3,1505
P-value (monthly CAPM)	0,0023	0,0018
3 factor alpha	0,91 %	0,62 %
3 factor t-statistic	3,6880	2,8898
3 factor p-value	0,0054	0,0042
4 factor alpha	0,86 %	0,55 %
4 factor t-statistic	2,5029	1,6196
4 factor p-value	0,0289	0,1066

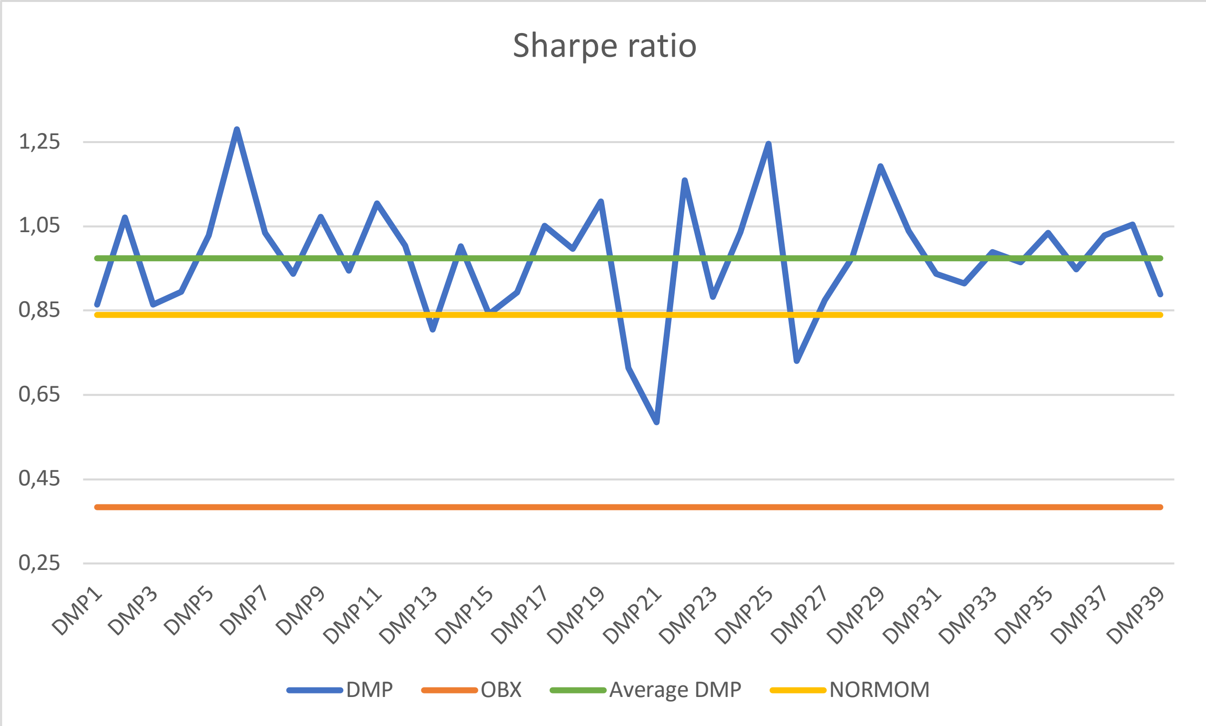
The average DMP measured by almost any metric, measurement or ratio provided is performing very strong compared to OBX. The relationship between risk and return is better than the alternative of OBX. NORMOM also have good performance, but as expected a little weaker than the average DMP.

Figure 5.7 - Average Yearly Returns of the DMPs, average DMP, OBX and NORMOM



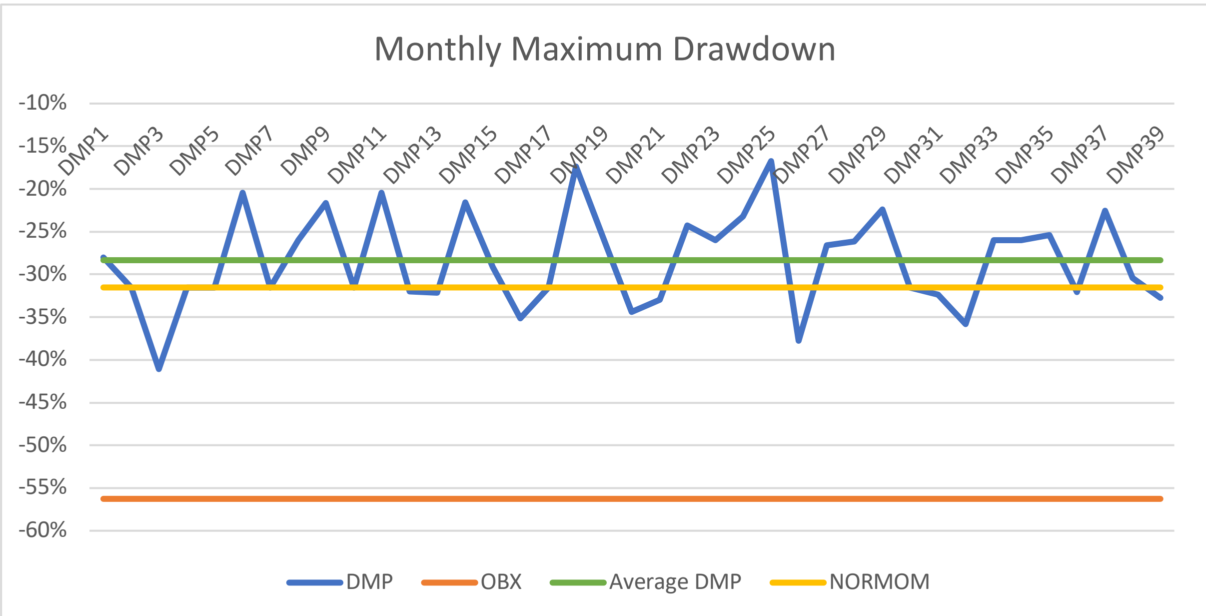
The graph above illustrates the average yearly returns of DMP1-39 (blue line) compared with the OBX (red line) the average return of all DMPs (green line) and the return of NORMOM (yellow line). The graph above sums up the average yearly return results. The most considerable difference is the DMP3 with 9,49 % average excess return over OBX per year. The average outperformance was 5,91 % per year, and the weakest yearly average excess return is found in DMP21 with 0,79 %. All the DMPs have higher average yearly returns than OBX. The average DMP has an impressive return of 17,26 %. The NORMOM portfolio follows just behind with 14,38 %. The graph shows the consistency of the higher returns among the DMPs. The DMP21 alpha is, however, as one might expect by the look of the graph not significantly different from OBX above a ninety percent confidence level.

Figure 5.8 - Sharpe ratio - DMPs, average DMP, OBX and NORMOM



The graph above shows the sharpe ratio for each DMPs, OBX, the average DMP and NORMOM. This risk-adjusted performance metric shows that the Dual Momentum Portfolios vastly outperforms the OBX in the sample period.

Figure 5.9 - Monthly Maximum Drawdown



All the DMPs has a significantly better drawdown profile over the sample period than the alternative of holding OBX. Providing strong protection in the worst market conditions. This is one of the strengths of the Dual Momentum strategy and how much of the high risk-adjusted returns are made. By avoiding the worst conditions and maybe even earning money in bonds during crashes, for an example see section 5.6.4 and the financial crisis of 2008.

Figure 5.10 - Returns on monthly investments of NOK 100

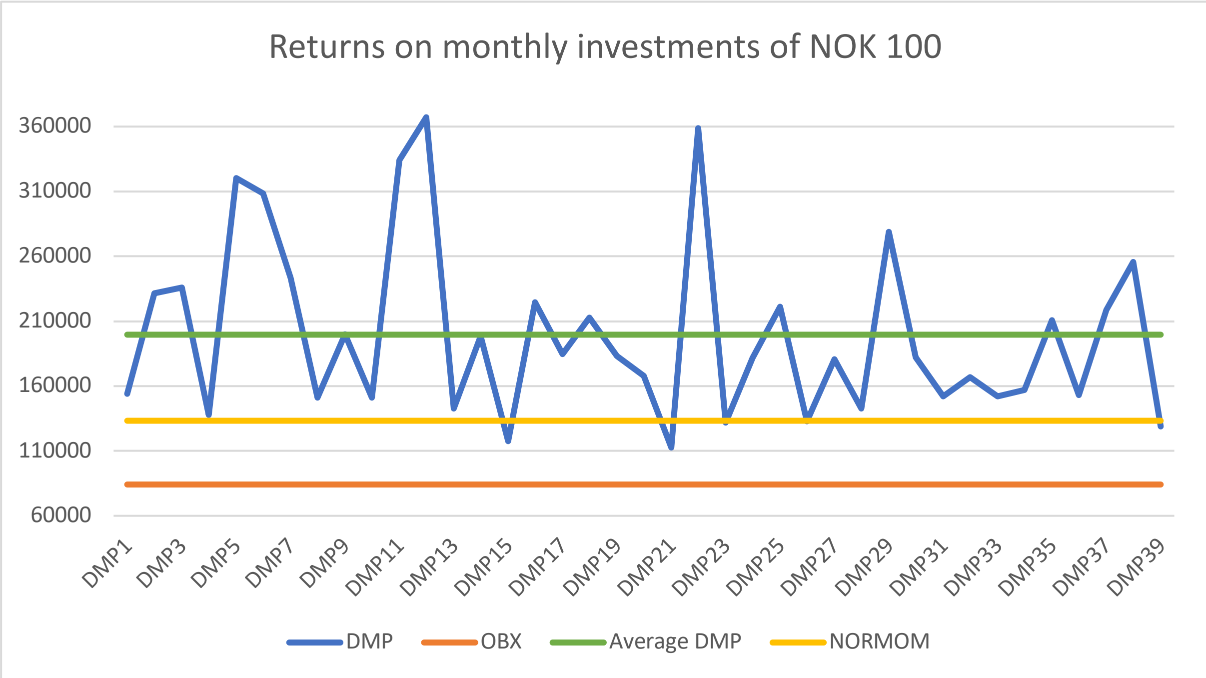
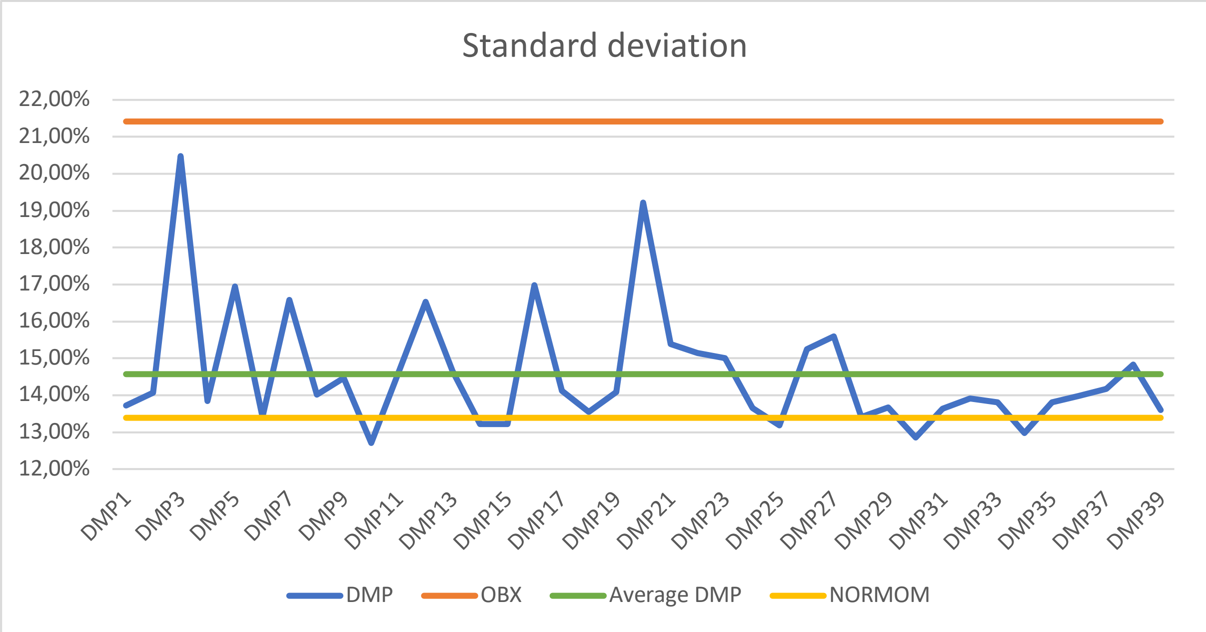


Figure 5.10 show the DMPs return of monthly investment for each portfolio in NOK. The tangible returns in cash are on average more than double that of OBX investment in the same period. OBX ends up with NOK 84 119 while the average DMP ends up with NOK 199 598. For investors this is a very strong argument for the Dual Momentum strategy. If tracked the cash return of the alternative compared to the DMP is a very strong psychological confirmation for any investor that the right thing is to hold the DMP.

Figure 5.11 - Standard deviation of returns



The risk measured by the standard deviation of returns is lower for the DMPs than of OBX. Several of the DMPs that have high returns like the DMP3 also have a large standard deviation. Since standard deviation include both upside and downside this might not indicate that the DMP3 have higher risk. Furthermore, NORMOM have even lower standard deviation than the average of the DMPs but lower returns.

5.5 CAPM, Fama-French three factor and Carhart four factor tests

In addition to providing annualised CAPM alpha for each portfolio. The alphas are calculated from the monthly data using the CAPM model, Fama-French three-factors and Carhart four-factors. The results show the CAPM and both factor models limited use when explaining momentum alpha as discussed in section 2. All the DMPs show low p-values below 0,10, except one portfolio, the DMP21. The majority of the DMP alphas calculated with CAPM and Fama-French three-factor model is statistically significant with p-values well below 0,01. For the Carhart four-factor model, 44 % of the DMP alphas are significant at the same confidence level. All the DMP alphas calculated with the CAPM model have p-values below 0,10. For Fama-French three-factor and Carhart four-factor tests, 97 % of the DMPs have P-values below 0,10, meaning only one portfolio, DMP21 have p-value above 0,10.

Below is a table that present the t-statistics and p-values for the alphas based on the monthly data for each portfolio.[17] Both the CAPM, Fama-French and Carhart factor model's statistics are provided. For easy visuals of the results, the green colour is assigned to cells with p-values below 0,05 and associated t-statistics. Yellow for p-values between 0,05-0,10 and t-statistics in the associated range. Red for p-value below 0,10 and the associated t-statistics.

Table 5.4 - DMPs CAPM, Fama-French and Carhart alpha t-statistics and p-values

	CAPM		Fama-French		Carhart	
Portfolio	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value
DMP1	3,4832	0,0006	3,2610	0,0013	2,1976	0,0289
DMP2	4,3579	0,0000	3,9481	0,0001	2,6288	0,0091
DMP3	3,2727	0,0012	3,0922	0,0022	3,1345	0,0019
DMP4	3,7027	0,0003	3,4801	0,0006	2,1265	0,0345
DMP5	4,2396	0,0000	3,8153	0,0002	3,4921	0,0006
DMP6	5,5630	0,0000	5,1777	0,0000	3,3535	0,0009
DMP7	4,4080	0,0000	4,1310	0,0000	3,1043	0,0021
DMP8	3,8239	0,0002	3,5891	0,0004	2,3082	0,0218
DMP9	4,5162	0,0000	4,2778	0,0000	2,9567	0,0034
DMP10	3,6428	0,0003	3,4119	0,0008	2,0134	0,0452
DMP11	4,8281	0,0000	4,1941	0,0000	2,9559	0,0034
DMP12	4,1505	0,0000	3,9670	0,0001	3,0653	0,0024
DMP13	3,2391	0,0014	2,9843	0,0031	2,0254	0,0439
DMP14	4,1429	0,0000	3,8087	0,0002	2,3027	0,0222
DMP15	3,2975	0,0011	2,9080	0,0040	1,7183	0,0870
DMP16	3,8505	0,0002	3,5252	0,0005	2,9138	0,0039
DMP17	4,3429	0,0000	4,0210	0,0001	2,6026	0,0098
DMP18	4,2138	0,0000	3,7994	0,0002	2,4445	0,0152
DMP19	4,6261	0,0000	4,3399	0,0000	3,0195	0,0028
DMP20	2,5455	0,0115	2,1588	0,0319	1,7921	0,0744
DMP21	1,8546	0,0649	1,4917	0,1371	0,9924	0,3220
DMP22	5,0486	0,0000	4,7113	0,0000	3,4028	0,0008
DMP23	3,6472	0,0003	3,4919	0,0006	2,5294	0,0121
DMP24	4,4482	0,0000	4,0467	0,0001	2,6410	0,0088
DMP25	5,5358	0,0000	5,1553	0,0000	3,2658	0,0013
DMP26	2,8366	0,0049	2,4652	0,0144	1,7655	0,0787
DMP27	3,3834	0,0008	2,6940	0,0076	2,1571	0,0320
DMP28	4,1224	0,0001	3,9034	0,0001	2,3465	0,0198
DMP29	5,0841	0,0000	4,6502	0,0000	2,9493	0,0035
DMP30	4,3121	0,0000	4,0916	0,0001	2,3817	0,0180
DMP31	3,8295	0,0002	3,6017	0,0004	2,2030	0,0285
DMP32	3,6251	0,0004	3,1710	0,0017	1,9515	0,0522
DMP33	4,1203	0,0001	3,8457	0,0002	2,4618	0,0145

[17] The lowest P-value shown is 0,0000. P-values lower than this is highly significant and will not be displayed.

DMP34	3,9886	0,0001	3,7504	0,0002	2,2445	0,0257
DMP35	4,2026	0,0000	3,9757	0,0001	2,5009	0,0131
DMP36	3,9780	0,0001	3,6805	0,0003	2,3476	0,0197
DMP37	4,3958	0,0000	3,9660	0,0001	2,6426	0,0088
DMP38	4,3189	0,0000	3,9177	0,0001	2,6550	0,0085
DMP39	3,5655	0,0004	3,3299	0,0010	2,0170	0,0448

As we can observe in the table above, the majority of the DMPs have very low p-values when the alphas are tested in regression analysis with the CAPM, Fama-French and Carhart factors. This data would suggest that the alphas generated in this sample period with all the portfolios based on the same Dual Momentum strategy are not simply due to chance and that the Dual Momentum strategy can exploit the momentum effect and harvest abnormal momentum profits in the tested sample period. The findings are unexpectedly strong.

Table 5.5 - Alpha tests between OBX, NORMOM and the average DMP

	NORMOM VS OBX	Average DMP VS OBX	Average DMP VS NORMOM
CAPM alpha	0,66 %	1,12 %	1,06 %
T-Statistic	3,1781	4,9495	4,6903
P-value	0,0017	0,0000	0,0000
Fama-French alpha	0,62 %	1,01 %	0,99 %
T-Statistic	2,9155	4,3695	4,2113
P-value	0,0039	0,0000	0,0000
Carchart alpha	0,56 %	0,98 %	0,98 %
T-Statistic	2,5946	4,1714	4,1096
P-value	0,0100	0,0000	0,0001

The table above using NORMOM as the control for isolating the momentum on the upside and downside. By testing NORMOM against OBX, the alpha tests above would suggest that the downside protection contribute significantly to the Dual Momentum strategy returns. Furthermore, the average DMP has a third asset; this third asset seems on average to produce significant alphas, when NORMOM excess returns are used in regression together with the CAPM, Fama-French and Carhart factors instead of the OBX excess returns. These findings would suggest that the price momentum and the alpha on the upside, attributed to the addition of the third asset is significant on average. There is a significant contribution from both the downside protection and upside price momentum from switching between two stock indexes.

5.6 Robustness

Any strategy should be dissected and tested for robustness. A common way of conducting a robustness test of a data sample is by creating sub-periods of the entire sample period and study them. The main sample has been split into 3 periods of 120 months (10 year), 4 periods of 60 months (5 year), and 6 periods of 36 (3 years).[18] From these new periods 507 portfolios were simulated. However, to not overwhelm the reader, only the DMP1 and averages will be presented. The presented data should be sufficient to show the results of the robustness test. [19]

5.6.1 10-year sub-periods

Table 5.6 - DMP1 Robustness - 10-year periods

DMP1	1997-2007	2002-2012	2007-2017
CAPM alpha	0,87 %	0,86 %	0,77 %
T-statistic	2,6250	2,4410	2,4157
P-value	0,0098	0,0161	0,0172
Fama-French alpha	0,89 %	0,76 %	0,81 %
T-statistic	2,5616	2,1182	2,4932
P-value	0,0117	0,0362	0,0140
Carhart alpha	0,84 %	0,68 %	0,91 %
T-statistic	2,4007	1,9650	2,7234
P-value	0,0179	0,0517	0,0074

Table 5.7 - Average DMP alpha tests - 10-year periods

Average DMP	1997-2007	2002-2012	2007-2017
CAPM alpha	1,13 %	1,05 %	0,78 %
T-statistic	4,1322	3,3055	2,9190
P-value	0,0001	0,0013	0,0042
Fama-French alpha	1,12 %	0,94 %	0,79 %
T-statistic	3,9071	2,9082	2,9086
P-value	0,0002	0,0043	0,0043
Carhart alpha	1,02 %	0,83 %	0,90 %
T-statistic	3,6527	2,6846	3,2316
P-value	0,0004	0,0083	0,0016

When splitting the sample period into 10-year sub-periods we can observe that the t-statistic in general is getting lower than for the whole period. The results would suggest that significant alpha momentum is present in the sub-periods.

[18] The middle 10-year period overlaps parts of the first and last period.
[19] The data from the robustness simulation of each portfolio is not included in the attachment because of the hundreds of extra pages it would take up.

Table 5.8 - OBX performance - 10-year periods

OBX	1997-2007	2002-2012	2007-2017
Cumulative return	231,42 %	159,05 %	66,34 %
Average monthly return	1,21 %	1,06 %	0,63 %
Annualised return	14,55 %	12,68 %	7,55 %
Annualised standard deviation	22,19 %	25,13 %	21,64 %
Maximum drawdown	-53,63 %	-56,27 %	-56,27 %
Annualised Sharpe-ratio	0,4408	0,3852	0,2668

Table 5.9 - DMP1 performance - 10-year periods

DMP1	1997-2007	2002-2012	2007-2017
Cumulative return	484,51 %	385,41 %	230,14 %
Average monthly return	1,57 %	1,42 %	1,07 %
Annualised return	18,82 %	17,04 %	12,86 %
Annualised standard deviation	14,46 %	15,28 %	13,28 %
Maximum drawdown	-16,91 %	-25,96 %	-27,99 %
Annualised Sharpe-ratio	0,9718	0,9189	0,8346

Table 5.10 - Average DMP performance - 10-year periods

Average DMP	1997-2007	2002-2012	2007-2017
Cumulative return	739,34 %	502,55 %	238,93 %
Average monthly return	1,86 %	1,59 %	1,07 %
Annualised return	22,30 %	19,03 %	12,89 %
Annualised standard deviation	13,12 %	13,92 %	11,34 %
Maximum drawdown	-9,01 %	-21,11 %	-23,92 %
Annualised Sharpe-ratio	1,3361	1,1520	0,9803

The DMPs performance is stronger than OBX in the 10-year sub periods and risk-adjusted returns are present. The results from the 10-year sub-period performance is similar to the general findings.

5.6.2 5-year sub-periods

Table 5.11 - DMP1 alpha tests - 5-year periods

DMP1	1997-2001	2002-2006	2007-2012	2013-2017
CAPM alpha	0,61 %	0,86 %	0,51 %	0,68 %
T-statistic	1,3593	1,8652	1,0321	1,9038
P-value	0,1792	0,0671	0,3062	0,0618
Fama-French alpha	0,60 %	0,88 %	0,62 %	0,72 %
T-statistic	1,3006	5,7626E+12	1,2498	1,8738
P-value	0,1984	0,0000	0,2163	0,0659
Carhart alpha	0,61 %	0,68 %	0,74 %	0,60 %

T-statistic	1,3164	2,0130E+12	1,5187	1,4295
P-value	0,1931	0,0000	0,1342	0,1581

Table 5.12 - Average DMP alpha tests - 5-year periods

Average DMP	1997-2001	2002-2006	2007-2012	2013-2017
CAPM alpha	0,99 %	1,08 %	0,68 %	0,50 %
T-statistic	2,7329	2,7139	1,4925	2,7016
P-value	0,0083	0,0087	0,1409	0,0090
Fama-French alpha	0,96 %	1,08 %	0,77 %	0,49 %
T-statistic	2,5414	9,9436E+12	1,6928	2,4623
P-value	0,0137	0,0000	0,0958	0,0167
Carhart alpha	0,96 %	0,83 %	0,89 %	0,37 %
T-statistic	2,5159	2,4878E+12	2,0066	1,7476
P-value	0,0146	0,0000	0,0494	0,0857

When splitting the sample further down into periods of 60 months (5 years) we can observe that the alphas are still positive, but the alphas do not pass the significance test at an acceptable level[20]. Many of the DMPs like DMP1, shown above, display signs of weakness when broken down into short sub-periods. While the average of the DMPs still show some significance in this period.

Table 5.13 - OBX performance - 5-year periods

OBX	1997-2001	2002-2006	2007-2012	2013-2017
Cumulative return	22,17 %	182,77 %	-5,47 %	70,39 %
Average monthly return	0,55 %	1,94 %	0,25 %	0,95 %
Annualised return	6,58 %	23,25 %	3,02 %	11,43 %
Annualised standard deviation	23 %	21 %	28 %	12 %
Maximum drawdown	-36,84 %	-42,67 %	-56,27 %	-14,00 %
Annualised Sharpe-ratio	0,0194	0,9323	0,0398	0,8822

Table 5.14 - DMP1 performance - 5-year periods

DMP1	1997-2001	2002-2006	2007-2012	2013-2017
Cumulative return	87,44 %	209,98 %	54,18 %	117,43 %
Average monthly return	1,10 %	2,01 %	0,80 %	1,37 %
Annualised return	13,18 %	24,12 %	9,65 %	16,39 %
Annualised standard deviation	12 %	16 %	14 %	12 %
Maximum drawdown	-16,91 %	-15,83 %	-25,96 %	-10,54 %
Annualised Sharpe-ratio	0,5688	1,2916	0,5473	1,2651

[20] Above 95 % confidence level.

Table 5.15 - Average DMP performance - 5-year period

Average DMP	1997-2001	2002-2006	2007-2012	2013-2017
Cumulative return	138,45 %	249,96 %	71,50 %	100,17 %
Average monthly return	1,49 %	2,20 %	0,97 %	1,20 %
Annualised return	17,82 %	26,36 %	11,62 %	14,42 %
Annualised standard deviation	11 %	15 %	13 %	10 %
Maximum drawdown	-8,20 %	-9,01 %	-21,11 %	-9,83 %
Annualised Sharpe-ratio	1,0393	1,5713	0,7574	1,4130

Even if the alphas are not significant anymore, other performance measurements from section 2.5 indicate that the Dual Momentum strategy performs very well compared to OBX over the same sub-period. The split in results is one of the reasons one should not rely on only a couple of performance measurements but use many in combination.

5.6.3 3-year sub-periods

Table 5.16 - DMP1 alpha test - 3-year period

DMP1	1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
CAPM alpha	0,53 %	0,20 %	0,68 %	0,45 %	-0,27 %	0,81 %
T-statistic	0,7684	0,3790	1,4236	1,3750	-0,4378	1,5193
P-value	0,4474	0,7070	0,1634	0,1779	0,6642	0,1377
Fama-French alpha	0,33 %	0,62 %	0,38 %	0,45 %	-0,35 %	0,95 %
T-statistic	0,4594	1,1369	0,7213	1,3026	-0,5449	1,6489
P-value	0,6490	0,2638	0,4758	0,2017	0,5895	0,1087
Carhart alpha	0,36 %	0,59 %	0,47 %	0,39 %	-0,24 %	0,64 %
T-statistic	0,5047	1,0656	0,9068	1,0633	-0,3656	1,0151
P-value	0,6173	0,2946	0,3713	0,2956	0,7170	0,3177

Table 5.17 - Average DMP alpha tests - 3-year periods

Average DMP	1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
CAPM alpha	1,20 %	0,41 %	1,02 %	0,42 %	0,11 %	0,58 %
T-statistic	2,2233	1,0340	2,2798	1,2385	0,1968	2,1788
P-value	0,0328	0,3082	0,0288	0,2238	0,8451	0,0362
Fama-French alpha	1,04 %	0,59 %	0,73 %	0,44 %	0,03 %	0,55 %
T-statistic	1,8761	1,4090	1,5061	1,2785	0,0458	1,8893
P-value	0,0695	0,1682	0,1415	0,2100	0,9638	0,0677
Carhart alpha	1,03 %	0,66 %	0,80 %	0,31 %	0,15 %	0,30 %
T-statistic	1,8248	1,6183	1,6493	0,8703	0,2553	0,9725
P-value	0,0774	0,1154	0,1089	0,3906	0,8001	0,3381

The Dual Momentum strategy shows weaknesses in the short sub-periods. The strategy is not able to consistently produce statistical significant momentum profits in the short subperiods.

Table 5.18 - OBX performance - 3-year periods

OBX	1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Cumulative return	31,29 %	-33,59 %	184,46 %	-28,35 %	79,58 %	46,44 %
Average monthly return	1,00 %	-0,91 %	3,10 %	-0,51 %	1,83 %	1,13 %
Annualised return	12,04 %	-10,95 %	37,22 %	-6,11 %	21,95 %	13,51 %
Annualised standard deviation	24,00 %	22,78 %	19,71 %	30,44 %	21,92 %	12,21 %
Maximum drawdown	-36,84 %	-49,13 %	-5,16 %	-55,99 %	-21,88 %	-11,12 %
Annualised Sharpe-ratio	0,2610	-0,7617	1,7714	-0,3253	0,9130	1,0043

Table 5.19 - DMP1 performance - 3-year periods

DMP1	1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Cumulative return	42,36 %	21,16 %	186,26 %	35,33 %	33,22 %	66,66 %
Average monthly return	1,07 %	0,59 %	3,08 %	0,86 %	0,93 %	1,49 %
Annualised return	12,88 %	7,04 %	37,00 %	10,34 %	11,15 %	17,89 %
Annualised standard deviation	14,61 %	11,12 %	17,27 %	6,67 %	18,12 %	12,46 %
Maximum drawdown	-16,91 %	-15,83 %	-7,87 %	-2,81 %	-25,96 %	-7,79 %
Annualised Sharpe-ratio	0,4862	0,0571	2,0090	0,9809	0,5084	1,3365

Table 5.20 - Average DMP performance - 3-year periods

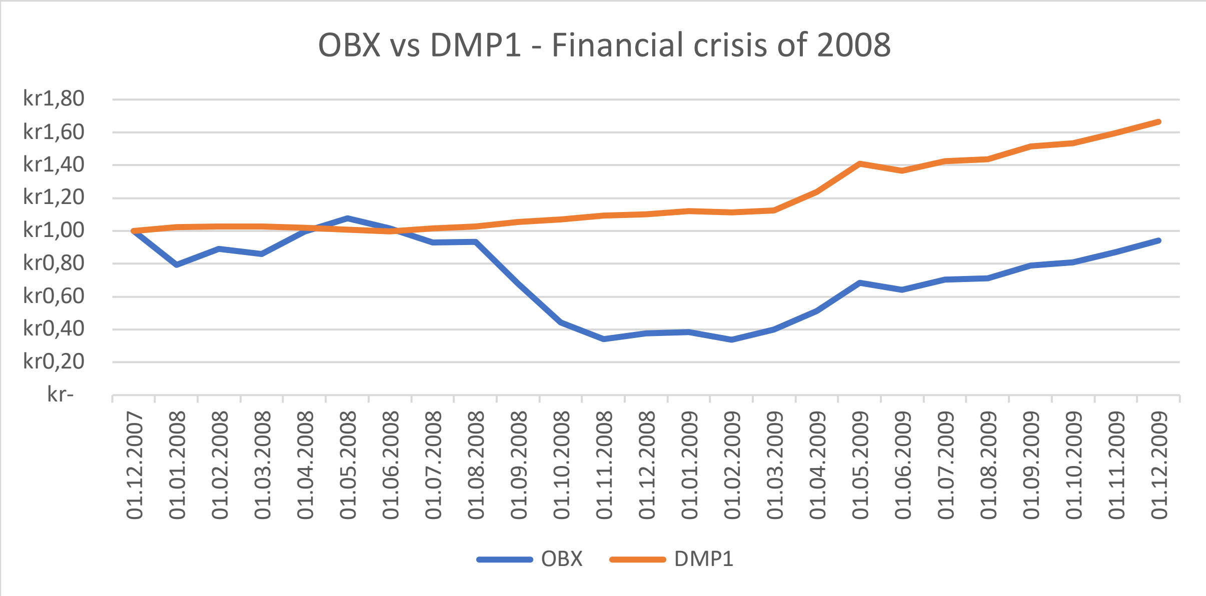
Average DMP	1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2014
Cumulative return	83,00 %	26,44 %	212,93 %	33,24 %	47,43 %	56,45 %
Average monthly return	1,75 %	0,69 %	3,33 %	0,82 %	1,19 %	1,28 %
Annualised return	21,04 %	8,24 %	39,92 %	9,83 %	14,26 %	15,38 %
Annualised standard deviation	12,33 %	9,05 %	16,42 %	6,90 %	16,34 %	8,66 %
Maximum drawdown	-8,20 %	-9,01 %	-6,37 %	-5,31 %	-21,11 %	-7,24 %
Annualised Sharpe-ratio	1,2377	0,2028	2,2901	0,8753	0,7540	1,6318

When alpha tests in the sub-periods of the data set are calculated, no significant price momentum premiums are captured by the Dual Momentum strategy in these shorter timeframes. But by looking at the annualised return, standard deviation, drawdown and sharpe ratio compared to the benchmark; OBX, in the same subperiods, the strategy looks pretty attractive even if the alphas are not significant in the same sub-sample periods.

5.6.4 Financial crisis of 2008

To take a look at a smaller sample period, the financial crisis of 2008, the period has no significant alphas. The DMP1 CAPM alpha is -0,09 % for the year 2008 and t-statistic of – 0,5881. However, using the performance measures from section 2.6 shows the strength of the strategy's ability to exit the market and hide in bonds during market stress.

Figure 5.12 - OBX vs DMP1 - Financial crisis of 2008



From the chart in figure 5.12 we can see that by avoiding the downturns and actually making money during the bear market of 2009. The portfolio also grows after the crash but from a higher level. While the OBX investors uses the 2009 year to gain back the losses the DMP investor continues to grow. This contributes significantly to the cash end results and the cumulative returns over the whole period.

Table 5.21 - OBX, DMP1 and Average DMP performance in the financial crisis of 2008

2008	OBX	DMP1	Average of all DMP
Cumulative return	-52,82 %	10,53 %	10,03 %
Average monthly return	-5,21 %	0,85 %	0,81 %
Annualised return	-62,55 %	10,15 %	9,70 %
Annualised standard deviation	43,42 %	4,45 %	4,58 %
Maximum drawdown	-55,95 %	-2,81 %	-3,24 %
Annualised Sharpe-ratio	-1,4914	1,7849	1,6348

The table 5.22 show the effect of the bear market protection of exciting the stock market and flying into the safety of bonds. The DMP investors make money during the year when most OBX investors lose half of their money.

5.7 Summary of the results

In the robustness section, a vast number of portfolios have been calculated in different sub-periods. The main findings are that the momentum profit is not statistically significant in the smaller sub-periods of the sample. The alphas are in general statistically significant in the longer sub-periods of 5-10 years, but not in periods lower than five years like the three-year periods and the financial crisis year of 2008. Suggesting that the momentum effect is not present at all times of the sample period. The same has also been observed by other researchers (Lillelien, 2003; Kloster-Jensen, 2006). Another explanations might be that the momentum price effect is too small to show statistical significance in short term. This is a part of what makes the momentum effect hard to explain and exploit.

By checking out the minimum and maximum values from the all the DMPs, it is clear that the DMPs outperformed OBX by providing higher risk-adjusted returns in the sample period. The only performance measurements that the OBX beats a few of the DMPs on are annualised downside deviation, variance and excess kurtosis. However, the investor with the worst performing DMP ends up with 33,8 % more money, when comparing the portfolio to monthly investing in OBX.[21]

Furthermore, by analysing the graphs above and the tables of performance in the appendix 9.3, we can observe the DMPs is outperforming the OBX on almost any measurement of the performance metric in the whole sample period. The pattern is clear the Dual Momentum strategy provides risk-adjusted returns above that of OBX. Both the returns, the sharpe-ratio and other metrics of the DMPs is showing the consistency one would want if one were to invest in a contrarian investment strategy like the Dual Momentum strategy. The consistency is very visibly in the graphs displaying all the portfolios consistently outperforming OBX on different mesurements. The Dual Momentum strategy applying both cross-sectional and time-series momentum substantially improves the return and decreases the overall risk of the portfolios constructed in the sample period. The strategy systematically outperforms the OBX on a risk-adjusted bases in the sample period.

[21] Before transaction costs. The transaction cost issue will be discussed in the next section.

6 Discussion

6.1 Risk and return

The replication of the Dual Momentum strategy form the Norwegian perspective supports the findings of Antonacci's (2014). The Dual Momentum strategy does have a high potential of providing higher risk-adjusted returns compared to a passive buy-hold strategy. After applying the CAPM, Fama-French and Carhart risk factors, the alphas of the vast majority of the DMPs are statistically significant above the 95 % confidence level. The findings are mainly in line with the momentum literature and confirm that the modern portfolio theories struggle with accounting for the price momentum. This thesis finds evidence of predictive power in the historical prices in the tested sample period. These findings contradict the weak form efficient market hypothesis. The results add to the pressure on the efficient market hypothesis.

The returns are a product of being exposed to the stock market with the highest price momentum and staying in the safety of bonds when the market is under severe stress. The strategy is in line with the findings of Cooper, Gutierrez and Hameed (2004) that momentum only works during bull markets and when the market crashes the strategy, rightfully, goes into the safety of bonds and cut the losses significantly compared to the passive strategy. When the price momentum turns the DMPs re-enter the stock markets from a higher point than the passive approach and has fewer losses to recover from, resulting in higher compounding rate over time. The lower drawdown in the strategy may help investors overcome the loss aversion effect and help them stay with their plan during market stress. The risk of the DMPs is tied to timing element of the market price momentum, the risk of many switches that results in transaction costs that can come from for example whipsaw events[22]. One of the other risks include the currency risks involved in taking on a foreign asset; this has not been explored too much in this thesis, but the international indexes used cover a range of foreign currencies during the period. This can also be seen as a positive diversification effect as the DMPs can avoid a whole countries stock market and the country risk. The strategy does provide higher risk-adjusted returns than the OBX in the same period. This is arguably what it is all about. In the sample period, monthly investment in OBX returns NOK 84 119, and the average DMP ends up with NOK 199 599. More than the double of the index in the same period. For a long-term investor, the Dual Momentum strategy pays off in the sample period.

[22] Sharp market movements one direction then the other in a very short time.

6.2 Robustness

In the robustness tests, the general findings show that the alphas are not statistically significant in the smaller sub-periods of the sample. Several of the smaller sub-periods that show positive alphas that are not statistically significant on acceptable level. A reason can be that the momentum effect is not present or very strong in the data sample at all times. The Dual Momentum strategy seems to generate alpha over longer periods by avoiding the worst downturns. This observation supports the findings of the momentum alphas being statistically present in longer samples that typically include a crisis or two. The performance measurements from section 2.6 show that the DMPs hold up very well in the different sub-periods compared to OBX. Risk-adjusted returns measured by the sharpe-ratio is higher in the average of the DMPs for all the sub-periods of the sample, except the 2009-2011, where the DMP lag the market coming out of bonds and into the rally out of the financial crisis. Overall the findings suggest robustness over longer time frames than five years. The tested sample period point to the Dual Momentum strategy to be able to capture statistical significant momentum profits over the longer timeframes.

6.3 Transaction costs

As identified in section 2.4.5.2 transaction costs can pose a serious problem for momentum strategies. The Dual Momentum strategy does not suffer from liquidity or large bid-ask spreads because all the indexes used are very liquid and trade at high volume. The concerns are the number of trades and the taxes. Taxes can be delayed until the money are withdrawn, by investing through a company or special tax-sheltered accounts. Anyhow, all the alternatives in this thesis will be prone to taxes. In the case of Dual Momentum, the question is whether or not the added transactions from the strategy will make the overall approach unprofitable or unpractical. The trades per year metric has been set up to count every time there is a switch between the indexes and are rounded up to get a yearly average.[23] This means that the correct numbers of trades for the DMPs with buy and hold strategy will be the double of the count. The trade count is correct for the DMPs with monthly investments, because the trades come in addition to the monthly buys, meaning if there is signal to switch one have to sell first and then buy (the monthly strategy buys 12 times a year, only when there are switches one have to sell first and then buy). One of the main concerns is the number of transactions the Dual Momentum

[23] Because the number of trades is rounded up to a yearly average, summing the number of yearly average trades gives a higher number than it actually was traded over the whole period.

strategy needs to function. There are also costs of buying and selling the foreign currency. The spreads and liquidity, trading the indexes should not be a huge issue, because of the liquidity in the large indexes. However, the costs that might worry the investor is related to the commission for the transactions. This analysis did not include transaction costs as they can vary a lot from broker to broker or be different for each ETF or fund representing the index that is used in the Dual Momentum strategy. However, if we consider the buy every month strategy with an average of two transactions in addition to the monthly investments are added. The portfolios would still be profitable after removing a whole percentage point per transaction; only the DMP21 would have lower yearly average returns than the OBX in this scenario. This would suggest that the alphas are high enough to sustain the added transaction costs. Furthermore, since the data used in this thesis is based on market indexes that cannot be directly invested in, the investor pursuing this strategy must find investable alternatives that typically have a tracking error in relation to the index they emulate. This will lower the real returns somewhat compared to the index data used in the thesis. Transaction costs can be highly individual in many cases and would have to be investigated rigorously before considering using momentum strategies like the Dual Momentum strategy. There is, however, reasons to believe the transactions are few and that they do not add high enough costs to make the strategy unprofitable.

6.4 Benchmark, factors and performance measurement

What index should you use when applying this strategy? Many different countries indexes have been tested, but it is not obvious why one would pick a particular country over another as the foreign asset in the Dual Momentum portfolio. For instance, it is hard to find a defendable reason to pick the South Korea index over the French index. However, the Dual Momentum strategy seems to work with almost whatever index chosen, only the portfolio (DMP21) which included the South-African index did not perform very well. A suggestion would be to use one of the major indexes and not a single country index, unless you can come up with a solid reason for doing so. The major indexes are a more realistic buy and hold option for many investors than a random country index. The major indexes used in DMP29-39 had an average yearly return of 16,88 %, not far from the average of all the DMPs.

In this thesis, OBX has been used as the benchmark as it is the primary alternative for any investor in Norway. OBX is the right alternative for a Norwegian investor, but technically maybe not the right benchmark for the DMPs since they consist of international and Norwegian exposure. Using OBX provides some weaknesses in the way the calculations that have been conducted, for example, the beta has been regressed from the DMPs returns and OBX returns. For example, the results are a beta calculated between OBX and S&P500, when the DMP29 is 100 % invested in S&P500. In fact, you end up with a smaller index like OBX being the market and the broader index, S&P500, is the portfolio. The beta is later used in various calculations of performance measurements. Furthermore, the risk-free rate is the Norwegian rate and Norwegian Fama-French and Carhart risk-factors calculated from OSE; this might have created a spurious relationship between the factors and the portfolios in the regression analysis especially when a foreign asset is held, kind of the same way as explained above with the beta.[24] The NORMOM portfolio which is only created from OBX and ST5X is not showing statistical significant alpha when applying regression with the Carhart risk four factors, ending up with a p-value of 0,1066. Furthermore, in the early stages of the regression analysis, the Fama/French Global 3 Factors and the Global Momentum Factor was downloaded from Kenneth R. French data library webpage[25]. The factors gave higher alphas, higher t-statistics and lower p-values than the factors downloaded from Bernt Arne Ødegaards webpage. In this thesis, the factors downloaded from Ødegaard (2018) were used as they on average had higher explanatory power, measured by r-squared and gave lower alphas, lower t-statistics and higher p-values.[26]

However, the returns, the standard deviation of the returns, drawdowns, Sharpe ratio, Sortino ratio, VAR and RAROC, skewness, excess kurtosis and months with profits provide proper measurements for risk-adjusted returns and comparison of the portfolios and alternatives. These mentioned measurements are not in question by the underlying factors. By examining the all, the performance measurements they are all in line and together provide a just picture of the actual performance of the portfolios and alternatives in the sample period.

6.5 Limits to the analysis and future research recommendations

The analysis does not provide any further insight into what price momentum is or how it can be explained. It was not the thesis intention to do so, and no observations have been made that could be used to explain the price momentum effect. There can be no guarantee that the strategy

[24] The factors used are collected from an external source and calculated from OSE, this might not fit very well to analyse portfolios consisting of international indexes, as the DMPs does from time to time.
[25] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[26] Both factors were tested. Only the factors that on average explained most of the momentum are presented.

will work in other periods or the future. However, if the momentum effect is tied to behaviours, there are few reasons to believe that the momentum effects will disappear anytime soon. More replications and further validation of the methods with indexes should be conducted. The realism with transaction costs are not included, as the transaction costs, in general, is highly individual. To apply transaction costs, one would have to find assets like EFTs and funds representing the indexes used and run a simulation applying transaction costs for each transaction. This demanding task has not been conducted in this thesis. Furthermore, the portfolios have been calculated over the same sample period, and in general, the indexes are very highly correlated.[27] The data has split into sub-periods for robustness testing, but other formation periods have not been tested. If this were to be tested, it must be done carefully to avoid data mining and optimisation with historical data, that might not show general trends that will be valid in the future. It would be interesting to see an application of Jagadeesh and Titman's (1993) to international indexes. Holding the top performing indexes, short the worst and rotation of indexes, instead of stocks or a combination of several asset classes. In effect creating a portfolio of indexes with price momentum style strategies. Alternatively, holding more than one index at the same time, triple momentum or quadruple momentum strategies. Furthermore, as discussed there is room to apply transaction costs and continue to investigate the reason(s) for the momentum effect. As discussed in section 2.4.5.1 if the price momentum effect is tied to human market interactions, a research topic of the future might be to investigate if the introduction of algorithms has reduced the momentum effect?

[27] Correlation data provided in appendix 9.2

7 Conclusion

7.1 Research question 1

The momentum literature has been reviewed, and the results in this thesis have been compared to the current literature. The findings in the thesis are in line with the majority of the current momentum literature. The price momentum effect is present in the sample period and can be exploited by applying the Dual Momentum strategy, which provides statistically significant momentum returns in the sample period. The modern portfolio theory models do not provide factors that can explain the momentum effect at a satisfactory level in the sample period. The tested sample adds to the growing criticism of the efficient market hypothesis as the findings in the sample period suggest that past prices can be used to predict future prices.

7.2 Research question 2

Antonacci's (2014) Dual Momentum strategy holds up in a replication from the Norwegian perspective. The results are impressive; all the tested portfolios have better results than the OBX in the sample period, measured by the same criteria as Antonacci's (2014) GEM shown in table 1.1 in section 1. Thus, this thesis adds validation to the method of Dual Momentum created by Antonacci (2014) to exploit the price momentum effect by combining both cross-sectional, time-series momentum and using bonds as safety.

Research question 2 has been positively answered by the results of applying the Dual Momentum strategy which shows significantly higher risk-adjusted return than holding OBX in the sample period. The Dual Momentum portfolios have all higher return, lower standard deviation, lower maximum drawdown, higher or the same number of months with profit and higher sharpe ratio than OBX in the sample period.[28] The vast majority of the Dual Momentum portfolios show significant positive alphas when tested with both the CAPM, Fama-French and Carhart factors in the sample period. All of the Dual Momentum portfolios provide risk-adjusted returns in excess of OBX in the sample period.

[28] OBX has 61,51 % months with profit and the worst performing DMP have 61,90 %. Rounded to the same number of whole months in the sample period.

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9 Appendix

9.1 Appendix - Portfolio and asset overview

Table 9.1 - Portfolio and asset overview

Portfolio	Country / Description	Asset name
All	Norway (Stock index)	OBX
All	Norway (Bond index)	ST5X
DMP1	Australia	AS30
DMP2	Austria	ATX
DMP3	Brasil	IBOV
DMP4	Canada	S&P/TSX Composite Index
DMP5	China	Shanghai Composite Index
DMP6	Danmark	OMXC20
DMP7	Finland	OMXH25
DMP8	France	CAC40
DMP9	Germany	DAX
DMP10	Hong Kong	Hang Seng
DMP11	Iceland	ICEEXI
DMP12	India	SENSEX
DMP13	Isreal	TA35
DMP14	Japan	Nikkei 225
DMP15	Malaysia	KLCI
DMP16	Mexico	S&P/BMV IPC
DMP17	Netherland	AEX
DMP18	New Zealand	NZX 50 Index
DMP19	Portugal	PSI-20
DMP20	Russia	MXRU
DMP21	South Afrika	Johannesburg All-Share Index
DMP22	South Korea	KOSPI
DMP23	Spain	IBEX
DMP24	Sweden	OMXS30
DMP25	Switzerland	SMI
DMP26	Taiwan	TAIEX
DMP27	Thailand	SET Index
DMP28	United Kingdom	FTSE100
DMP29	USA	S&P500
DMP30	Asia	MSCI ASIA
DMP31	Developed world	MSCI World index
DMP32	Emerging markets	MSCI MXEF
DMP33	Euro zone	EURO STOXX
DMP34	Europe, Australasia, and Far East	MSCI EAFE Index
DMP35	Large Cap / USA	Dow Jones Industrial Average
DMP36	Nordic countries	FTSE Nordic
DMP37	Small Cap / USA	RUSSEL 2000
DMP38	USA / World	NASDAQ

DMP39	World Index	ACWI Index
NORMOM	Norwegian only momentum	OBX & ST5X

9.2 Appendix - Correlations

Table 9.2 - Correlations - OBX and ST5X vs Foreign Assets

Correlations				
	NOK		Local currency	
Asset name	OBX	ST5X	OBX	ST5X
OBX	1	0,9221	1	0,9221
ST5X	0,9221	1	0,9221	1
OMXC20	0,9169	0,8415	0,9438	0,8718
OMXS30	0,8783	0,7662	0,8544	0,7333
S&P500	0,7008	0,5753	0,8899	0,7637
OMXH25	0,4155	0,2513	0,3331	0,1730
ICEEXI	-0,0521	-0,2126	0,0456	-0,1169
DAX	0,9057	0,7822	0,9233	0,7984
FTSE100	0,3804	0,1547	0,7550	0,5629
CAC40	0,4904	0,2805	0,3892	0,1759
MSCI EAFE	0,6379	0,4120	0,7604	0,5472
MSCI WORLD	0,7039	0,5441	0,9121	0,7465
ACWI	0,7399	0,5801	0,9290	0,7697
NIKKEI 225	0,3135	0,0909	0,2718	-0,0259
FTSE NORDIC	0,9008	0,7888	0,9114	0,8079
EURO STOXX	0,2674	0,0485	0,1497	-0,0670
MSCI MXEF	0,9628	0,8738	0,8519	0,7925
HANG SENG	0,8768	0,7515	0,9149	0,8151
AS30	0,9777	0,9089	0,9066	0,8177
ATX	0,6988	0,5559	0,6340	0,4986
S&P/TSX	0,9584	0,8945	0,9476	0,8790
SMI	0,8836	0,7857	0,7246	0,5322
Shanghai	0,8088	0,7376	0,7249	0,6350
IBOV	0,7202	0,7093	0,8660	0,8684
SENSEX	0,9588	0,8979	0,9786	0,9428
IBEX	0,5423	0,3753	0,4510	0,2869
J.ASI	0,9783	0,9367	0,9801	0,9580
TA35	0,9542	0,9162	0,9590	0,9518
AEX	0,2450	-0,0108	0,1282	-0,1310
MSCI ASIA	0,7490	0,5489	0,8242	0,6447
KLCI	0,7610	0,7167	0,8887	0,8659
S&P/BMV IPC	0,9600	0,9517	0,9591	0,9691
DJIA	0,7587	0,6499	0,9329	0,8330
Russel2000	0,8712	0,7801	0,9731	0,8942
NASDAQ	0,7190	0,6048	0,8510	0,7421
SET	0,7842	0,7246	0,8472	0,8119
TAIEX	0,5579	0,3689	0,7241	0,5397
KOSPI	0,9515	0,8659	0,9372	0,9200
PSI20	-0,2618	-0,4521	-0,3092	-0,4915
NZX50	0,8341	0,7168	0,8078	0,6504

MXRU	0,6378	0,5638	0,5263	0,4656

9.3 Appendix - DMPs and asset statistics

Table 9.3 - DMP1, AS30, DMP2 & ATX

Metrics, measurements and ratios	DMP1	AS30	DMP2	ATX
Cumulative return	1805,70 %	218,12 %	3582,75 %	278,34 %
Average monthly return	1,25 %	0,59 %	1,52 %	0,71 %
Average yearly return	14,99 %	7,13 %	18,19 %	8,48 %
Months with profit (%)	65 %	58 %	70 %	60 %
Standard deviation	13,72 %	17,95 %	14,06 %	20,53 %
Variance	0,1038	0,0322	0,1067	0,0421
Sharpe ratio	0,8638	0,2224	1,0705	0,2602
Treynor ratio	0,4016	0,0755	0,4575	0,0851
M^2	10,28 %	-3,45 %	14,71 %	-2,64 %
Beta	0,2951	0,5287	0,3290	0,6278
Information ratio	0,7835	-0,0107	1,0253	0,0274
Annualized CAPM Alpha	9,16 %		12,10 %	
Maximum drawdown	-27,99 %	-55,85 %	-31,52 %	-66,67 %
Annualized Downside Deviation	10,38 %	9,54 %	10,67 %	11,26 %
VAR (5 percent)	-4,98 %	-8,63 %	-5,13 %	-9,79 %
Sortino ratio	1,1412	0,4183	1,4106	0,4745
RAROC	0,5933	0,2532	0,6455	0,2924
Trades per year	2	0	2	0
NOK 100 Invested	1 906	318	3 683	378
NOK 100 every month	153 944	47 485	231 447	56 641
Skewness	0,0387	-0,5161	0,2878	-0,6574
Excess kurtosis	2,3294	0,4351	1,7246	1,7430
CAPM alpha (monthly)	0,79 %		1,00 %	
T-statistic (monthly CAPM)	3,4832		4,3579	
P-value (monthly CAPM)	0,0006		0,0000	
3 factor alpha	0,76 %		0,93 %	
3 factor t-statistic	3,2610		3,9481	
3 factor p-value	0,0013		0,0001	
4 factor alpha	0,75 %		0,90 %	
4 factor t-statistic	2,1976		2,6288	
4 factor p-value	0,0289		0,0091	

Table 9.4 - DMP3, IBOV, DMP4 & S&P/TSX Compisite index

Metrics, measurements and ratios	DMP3	IBOV	DMP4	S&P/TSX Composite Index
Cumulative return	5028,26 %	316,08 %	2023,42 %	270,94 %
Average monthly return	1,74 %	1,16 %	1,29 %	0,66 %
Average yearly return	20,84 %	13,95 %	15,52 %	7,96 %
Months with profit (%)	63 %	55 %	65 %	58 %
Standard deviation	20,48 %	37,49 %	13,84 %	18,53 %
Variance	0,1767	0,1405	0,1075	0,0343
Sharpe ratio	0,8642	0,2885	0,8943	0,2602
Treynor ratio	0,4206	0,1070	0,3777	0,0844
M^2	10,29 %	-2,04 %	10,94 %	-2,64 %
Beta	0,4208	1,0109	0,3277	0,5714
Information ratio	0,7832	0,0947	0,8225	0,0250
Annualized CAPM Alpha	14,05 %	0,00 %	9,44 %	0,00 %
Maximum drawdown	-41,08 %	-81,58 %	-31,52 %	-61,98 %
Annualized Downside Deviation	17,67 %	24,22 %	10,75 %	10,99 %
VAR (5 percent)	-8,45 %	-15,73 %	-5,11 %	-8,13 %
Sortino ratio	1,0016	0,4465	1,1509	0,4387
RAROC	0,6042	0,3643	0,5999	0,2996
Trades per year	3	0	2	0
NOK 100 Invested	5 128	416	2 123	371
NOK 100 every month	236 132	65 560	137 770	47 823
Skewness	0,6931	-0,1504	0,3667	-0,3412
Excess kurtosis	2,8217	1,6787	1,3890	1,2177
CAPM alpha (monthly)	1,13 %		0,82 %	
T-statistic (monthly CAPM)	3,2727		3,7027	
P-value (monthly CAPM)	0,0012		0,0003	
3 factor alpha	1,09 %		0,79 %	
3 factor t-statistic	3,0922		3,4801	
3 factor p-value	0,0022		0,0006	
4 factor alpha	1,07 %		0,73 %	
4 factor t-statistic	3,1345		2,1265	
4 factor p-value	0,0019		0,0345	

Table 9.5 - DMP5, Shanghai composite index, DMP6 & OMXC20

Metrics, measurements and ratios	DMP5	Shanghai Composite Index	DMP6	OMXC20
Cumulative return	5469,28 %	465,83 %	5721,12 %	753,16 %
Average monthly return	1,71 %	0,99 %	1,69 %	0,99 %
Average yearly return	20,57 %	11,91 %	20,31 %	11,85 %
Months with profit (%)	65 %	52 %	67 %	59 %
Standard deviation	16,95 %	27,27 %	13,41 %	18,08 %
Variance	0,1709	0,0744	0,0985	0,0327
Sharpe ratio	1,0281	0,3214	1,2804	0,4820
Treynor ratio	0,7371	0,4572	0,6465	0,1657
M^2	13,80 %	-1,33 %	19,21 %	2,11 %
Beta	0,2364	0,1917	0,2655	0,5256
Information ratio	0,9629	0,2695	1,2427	0,3249
Annualized CAPM Alpha	15,22 %	0,00 %	14,72 %	0,00 %
Maximum drawdown	-31,52 %	-67,09 %	-20,44 %	-51,64 %
Annualized Downside Deviation	17,09 %	19,67 %	9,85 %	9,99 %
VAR (5 percent)	-4,62 %	-10,65 %	-4,19 %	-8,18 %
Sortino ratio	1,0198	0,4457	1,7425	0,8720
RAROC	0,6919	0,3886	0,7008	0,4348
Trades per year	2	0	2	0
NOK 100 Invested	5 569	566	5 821	853
NOK 100 every month	320 456	61 720	308 509	88 851
Skewness	1,6204	0,3126	0,3808	-0,4011
Excess kurtosis	7,6996	2,0916	1,2297	0,6778
CAPM alpha (monthly)	1,29 %		1,27 %	
T-statistic (monthly CAPM)	4,2396		5,5630	
P-value (monthly CAPM)	0,0000		0,0000	
3 factor alpha	1,19 %		1,21 %	
3 factor t-statistic	3,8153		5,1777	
3 factor p-value	0,0002		0,0000	
4 factor alpha	1,20 %		1,15 %	
4 factor t-statistic	3,4921		3,3535	
4 factor p-value	0,0006		0,0009	

Table 9.6 - DMP7, OMXH25, DMP8 & CAC40

Metrics, measurements and ratios	DMP7	OMXH25	DMP8	CAC40
Cumulative return	5163,96 %	324,05 %	2379,27 %	171,15 %
Average monthly return	1,69 %	0,84 %	1,36 %	0,53 %
Average yearly return	20,29 %	10,09 %	16,29 %	6,42 %
Months with profit (%)	67 %	56 %	65 %	57 %
Standard deviation	16,58 %	25,42 %	14,02 %	18,22 %
Variance	0,1304	0,0646	0,1057	0,0332
Sharpe ratio	1,0344	0,2733	0,9378	0,1800
Treynor ratio	0,4843	0,1135	0,4123	0,0589
M^2	13,94 %	-2,36 %	11,87 %	-4,36 %
Beta	0,3541	0,6118	0,3188	0,5564
Information ratio	0,9752	0,0990	0,8699	-0,0782
Annualized CAPM Alpha	14,02 %	0,00 %	10,27 %	0,00 %
Maximum drawdown	-31,52 %	-73,88 %	-25,96 %	-62,12 %
Annualized Downside Deviation	13,04 %	17,37 %	10,57 %	9,63 %
VAR (5 percent)	-5,03 %	-11,35 %	-5,05 %	-8,63 %
Sortino ratio	1,3156	0,4000	1,2443	0,3404
RAROC	0,6772	0,3241	0,6160	0,2180
Trades per year	2	0	2	0
NOK 100 Invested	5 264	424	2 479	271
NOK 100 every month	243 184	42 666	151 266	40 026
Skewness	0,2642	0,1035	0,2767	-0,4773
Excess kurtosis	3,3005	2,3068	1,4313	0,5242
CAPM alpha (monthly)	1,22 %		0,87 %	
T-statistic (monthly CAPM	4,4080		3,8239	
P-value (monthly CAPM)	0,0000		0,0002	
3 factor alpha	1,17 %		0,84 %	
3 factor t-statistic	4,1310		3,5891	
3 factor p-value	0,0000		0,0004	
4 factor alpha	1,06 %		0,79 %	
4 factor t-statistic	3,1043		2,3082	
4 factor p-value	0,0021		0,0218	

Table 9.7 - DMP9, DAX, DMP10 & Hang Seng

Metrics, measurements and ratios	DMP9	DAX	DMP10	Hang Seng
Cumulative return	3922,45 %	437,69 %	1927,78 %	190,77 %
Average monthly return	1,56 %	0,87 %	1,26 %	0,65 %
Average yearly return	18,67 %	10,43 %	15,15 %	7,84 %
Months with profit (%)	66 %	58 %	65 %	60 %
Standard deviation	14,47 %	21,82 %	12,71 %	23,54 %
Variance	0,1099	0,0476	0,1051	0,0554
Sharpe ratio	1,0732	0,3343	0,9450	0,1996
Treynor ratio	0,5172	0,1140	0,4172	0,0819
M^2	14,77 %	-1,06 %	12,02 %	-3,94 %
Beta	0,3003	0,6398	0,2878	0,5738
Information ratio	1,0166	0,1345	0,8778	0,0102
Annualized CAPM Alpha	12,81 %	0,00 %	9,37 %	0,00 %
Maximum drawdown	-21,62 %	-68,87 %	-31,52 %	-60,71 %
Annualized Downside Deviation	10,99 %	12,34 %	10,51 %	15,86 %
VAR (5 percent)	-4,98 %	-9,96 %	-4,26 %	-11,11 %
Sortino ratio	1,4128	0,5913	1,1423	0,2964
RAROC	0,6566	0,3577	0,6188	0,2479
Trades per year	2	0	2	0
NOK 100 Invested	4 022	538	2 028	291
NOK 100 every month	199 695	68 048	151 086	57 269
Skewness	0,3591	-0,5731	0,4734	0,0875
Excess kurtosis	1,4569	1,9121	2,3473	2,9958
CAPM alpha (monthly)	1,09 %		0,76 %	
T-statistic (monthly CAPM)	4,5162		3,6428	
P-value (monthly CAPM)	0,0000		0,0003	
3 factor alpha	1,06 %		0,73 %	
3 factor t-statistic	4,2778		3,4119	
3 factor p-value	0,0000		0,0008	
4 factor alpha	1,01 %		0,69 %	
4 factor t-statistic	2,9567		2,0134	
4 factor p-value	0,0034		0,0452	

Table 9.8 - DMP11, ICEEXI, DMP12 & SENSEX

Metrics, measurements and ratios	DMP11	ICEEXI	DMP12	SENSEX
Cumulative return	4425,57 %	20,83 %	4650,43 %	612,61 %
Average monthly return	1,60 %	0,55 %	1,65 %	1,08 %
Average yearly return	19,26 %	6,60 %	19,76 %	12,91 %
Months with profit (%)	66 %	59 %	65 %	54 %
Standard deviation	14,60 %	29,21 %	16,54 %	26,86 %
Variance	0,1147	0,0853	0,1444	0,0721
Sharpe ratio	1,1042	0,1184	1,0049	0,3636
Treynor ratio	0,9736	0,0842	0,5025	0,1798
M^2	15,43 %	-5,68 %	13,31 %	-0,43 %
Beta	0,1655	0,4108	0,3307	0,5433
Information ratio	1,0468	0,0087	0,9388	0,2277
Annualized CAPM Alpha	14,44 %	0,00 %	13,66 %	0,00 %
Maximum drawdown	-20,47 %	-97,30 %	-31,97 %	-57,97 %
Annualized Downside Deviation	11,47 %	14,26 %	14,44 %	17,23 %
VAR (5 percent)	-4,95 %	-13,07 %	-5,35 %	-11,47 %
Sortino ratio	1,4051	0,2426	1,1508	0,5667
RAROC	0,6659	0,1758	0,6619	0,4007
Trades per year	2	0	3	0
NOK 100 Invested	4 526	121	4 750	713
NOK 100 every month	334 087	38 503	367 189	95 742
Skewness	0,4114	-2,7992	1,0799	0,1708
Excess kurtosis	2,2315	21,4796	6,2141	0,8217
CAPM alpha (monthly)	1,27 %		1,16 %	
T-statistic (monthly CAPM)	4,8281		4,1505	
P-value (monthly CAPM)	0,0000		0,0000	
3 factor alpha	1,12 %		1,14 %	
3 factor t-statistic	4,1941		3,9670	
3 factor p-value	0,0000		0,0001	
4 factor alpha	1,01 %		1,05 %	
4 factor t-statistic	2,9559		3,0653	
4 factor p-value	0,0034		0,0024	

Table 9.9 - DMP13, TA35, DMP14 & Nikkei 225

Metrics, measurements and ratios	DMP13	TA35	DMP14	Nikkei 225
Cumulative return	1733,14 %	609,68 %	2496,76 %	66,28 %
Average monthly return	1,24 %	0,98 %	1,37 %	0,36 %
Average yearly return	14,93 %	11,72 %	16,40 %	4,37 %
Months with profit (%)	65 %	58 %	64 %	50 %
Standard deviation	14,66 %	21,84 %	13,22 %	19,86 %
Variance	0,1098	0,0477	0,1046	0,0395
Sharpe ratio	0,8043	0,3929	1,0026	0,0619
Treynor ratio	0,4230	0,1847	0,4959	0,0372
M^2	9,01 %	0,20 %	13,26 %	-6,89 %
Beta	0,2788	0,4646	0,2674	0,3307
Information ratio	0,7177	0,2542	0,9367	-0,0733
Annualized CAPM Alpha	9,23 %	0,00 %	10,79 %	0,00 %
Maximum drawdown	-32,15 %	-65,51 %	-21,55 %	-72,50 %
Annualized Downside Deviation	10,98 %	12,21 %	10,46 %	12,48 %
VAR (5 percent)	-6,97 %	-10,04 %	-4,30 %	-8,81 %
Sortino ratio	1,0739	0,7029	1,2677	0,0985
RAROC	0,5384	0,3943	0,6406	0,0932
Trades per year	2	0	2	0
NOK 100 Invested	1 833	710	2 597	166
NOK 100 every month	142 910	78 058	198 258	49 911
Skewness	0,1146	-0,2593	0,4987	0,1568
Excess kurtosis	1,7003	-0,0548	1,5082	0,1013
CAPM alpha (monthly)	0,80 %		0,90 %	
T-statistic (monthly CAPM)	3,2391		4,1429	
P-value (monthly CAPM)	0,0014		0,0000	
3 factor alpha	0,76 %		0,86 %	
3 factor t-statistic	2,9843		3,8087	
3 factor p-value	0,0031		0,0002	
4 factor alpha	0,69 %		0,79 %	
4 factor t-statistic	2,0254		2,3027	
4 factor p-value	0,0439		0,0222	

Table 9.10 - DMP15, KLCI, DMP16 & S&P/BMV ICO

Metrics, measurements and ratios	DMP15	KLCI	DMP16	S&P/BMV IPC
Cumulative return	1558,45 %	16,35 %	3330,57 %	590,44 %
Average monthly return	1,19 %	0,37 %	1,53 %	1,05 %
Average yearly return	14,26 %	4,49 %	18,31 %	12,57 %
Months with profit (%)	65 %	55 %	64 %	53 %
Standard deviation	13,22 %	28,33 %	16,97 %	25,66 %
Variance	0,1004	0,0803	0,1256	0,0658
Sharpe ratio	0,8411	0,0478	0,8936	0,3674
Treynor ratio	0,3775	0,0464	0,4556	0,1489
M^2	9,80 %	-7,19 %	10,92 %	-0,35 %
Beta	0,2945	0,2919	0,3329	0,6332
Information ratio	0,7586	-0,0337	0,8155	0,2051
Annualized CAPM Alpha	8,43 %	0,00 %	12,19 %	0,00 %
Maximum drawdown	-29,15 %	-83,40 %	-35,11 %	-53,26 %
Annualized Downside Deviation	10,04 %	24,78 %	12,56 %	14,97 %
VAR (5 percent)	-4,72 %	-11,88 %	-5,18 %	-11,08 %
Sortino ratio	1,1076	0,0546	1,2076	0,6296
RAROC	0,5858	0,0827	0,6456	0,3987
Trades per year	2	0	3	0
NOK 100 Invested	1 658	116	3 431	690
NOK 100 every month	117 651	48 283	224 569	64 002
Skewness	0,0992	1,7720	-0,0094	-0,4791
Excess kurtosis	2,5664	15,4787	2,0691	1,9947
CAPM alpha (monthly)	0,71 %		1,10 %	
T-statistic (monthly CAPM)	3,2975		3,8505	
P-value (monthly CAPM)	0,0011		0,0002	
3 factor alpha	0,64 %		1,04 %	
3 factor t-statistic	2,9080		3,5252	
3 factor p-value	0,0040		0,0005	
4 factor alpha	0,59 %		1,00 %	
4 factor t-statistic	1,7183		2,9138	
4 factor p-value	0,0870		0,0039	

Table 9.11 - DMP17, AEX, DMP18 & NZX 50 Index

Metrics, measurements and ratios	DMP17	AEX	DMP18	NZX 50 Index
Cumulative return	3411,87 %	125,28 %	2605,19 %	129,36 %
Average monthly return	1,50 %	0,48 %	1,39 %	0,46 %
Average yearly return	17,97 %	5,75 %	16,64 %	5,57 %
Months with profit (%)	67 %	56 %	65 %	55 %
Standard deviation	14,12 %	19,28 %	13,55 %	18,01 %
Variance	0,1074	0,0372	0,1036	0,0324
Sharpe ratio	1,0507	0,1355	0,9964	0,1351
Treynor ratio	0,4642	0,0421	0,4687	0,0635
M^2	14,29 %	-5,31 %	13,12 %	-5,32 %
Beta	0,3195	0,6210	0,2880	0,3831
Information ratio	0,9986	-0,1611	0,9321	-0,0353
Annualized CAPM Alpha	11,96 %	0,00 %	10,87 %	0,00 %
Maximum drawdown	-31,52 %	-65,08 %	-17,34 %	-57,43 %
Annualized Downside Deviation	10,74 %	10,58 %	10,36 %	10,17 %
VAR (5 percent)	-4,98 %	-9,11 %	-4,98 %	-8,20 %
Sortino ratio	1,3814	0,2469	1,3035	0,2393
RAROC	0,6462	0,1759	0,6244	0,1767
Trades per year	2	0	2	0
NOK 100 Invested	3 512	225	2 705	229
NOK 100 every month	184 795	41 397	212 851	57 490
Skewness	0,2739	-0,5947	0,3690	-0,2566
Excess kurtosis	1,6299	1,3187	1,3680	0,5104
CAPM alpha (monthly)	1,01 %		0,95 %	
T-statistic (monthly CAPM)	4,3429		4,2138	
P-value (monthly CAPM)	0,0000		0,0000	
3 factor alpha	0,96 %		0,88 %	
3 factor t-statistic	4,0210		3,7994	
3 factor p-value	0,0001		0,0002	
4 factor alpha	0,89 %		0,84 %	
4 factor t-statistic	2,6026		2,4445	
4 factor p-value	0,0098		0,0152	

Table 9.12 - DMP19, PSI-20, DMP20 & MXRU

Metrics, measurements and ratios	DMP19	PSI-20	DMP20	MXRU
Cumulative return	4050,42 %	18,20 %	2216,47 %	223,85 %
Average monthly return	1,56 %	0,25 %	1,40 %	1,34 %
Average yearly return	18,76 %	2,97 %	16,85 %	16,10 %
Months with profit (%)	66 %	50 %	62 %	55 %
Standard deviation	14,08 %	20,85 %	19,22 %	45,20 %
Variance	0,1162	0,0435	0,1499	0,2043
Sharpe ratio	1,1093	-0,0080	0,7135	0,2868
Treynor ratio	0,5363	-0,0033	0,3589	0,1149
M^2	15,54 %	-8,38 %	7,07 %	-2,07 %
Beta	0,2913	0,4981	0,3820	1,1281
Information ratio	1,0567	-0,2271	0,6165	0,1081
Annualized CAPM Alpha	12,98 %	0,00 %	10,35 %	0,00 %
Maximum drawdown	-25,96 %	-71,17 %	-34,40 %	-91,90 %
Annualized Downside Deviation	11,62 %	12,12 %	14,99 %	34,24 %
VAR (5 percent)	-4,33 %	-9,23 %	-6,53 %	-16,73 %
Sortino ratio	1,3442	-0,0137	0,9145	0,3786
RAROC	0,6764	-0,0136	0,5864	0,3948
Trades per year	2	0	2	0
NOK 100 Invested	4 150	118	2 316	324
NOK 100 every month	183 211	23 310	167 852	50 246
Skewness	0,6575	-0,1108	-0,2244	0,2456
Excess kurtosis	1,5693	0,5057	5,1997	4,7252
CAPM alpha (monthly)	1,09 %		0,83 %	
T-statistic (monthly CAPM)	4,6261		2,5455	
P-value (monthly CAPM)	0,0000		0,0115	
3 factor alpha	1,05 %		0,71 %	
3 factor t-statistic	4,3399		2,1588	
3 factor p-value	0,0000		0,0319	
4 factor alpha	1,03 %		0,61 %	
4 factor t-statistic	3,0195		1,7921	
4 factor p-value	0,0028		0,0744	

Table 9.13 - DMP21, Johannesburg all-share index, DMP22 & KOSPI

Metrics, measurements and ratios	DMP21	Johannesburg All-Share Index	DMP22	KOSPI
Cumulative return	897,64 %	351,29 %	5905,74 %	259,85 %
Average monthly return	1,01 %	0,82 %	1,72 %	0,98 %
Average yearly return	12,14 %	9,83 %	20,69 %	11,76 %
Months with profit (%)	62 %	57 %	68 %	54 %
Standard deviation	15,38 %	22,76 %	15,15 %	34,29 %
Variance	0,1137	0,0518	0,1265	0,1176
Sharpe ratio	0,5851	0,2941	1,1587	0,2514
Treynor ratio	0,2640	0,0957	0,5349	0,1211
M^2	4,32 %	-1,92 %	1,66 %	-2,83 %
Beta	0,3409	0,6993	0,3281	0,7121
Information ratio	0,4676	0,0710	1,1165	0,0992
Annualized CAPM Alpha	5,93 %	0,00 %	14,62 %	0,00 %
Maximum drawdown	-32,93 %	-51,49 %	-24,24 %	-73,78 %
Annualized Downside Deviation	11,37 %	12,89 %	12,65 %	28,00 %
VAR (5 percent)	-5,55 %	-11,05 %	-4,84 %	-13,35 %
Sortino ratio	0,7917	0,5193	1,3877	0,3079
RAROC	0,5086	0,3206	0,6874	0,3434
Trades per year	3	0	2	0
NOK 100 Invested	998	451	6 006	360
NOK 100 every month	112 606	67 907	359 014	73 708
Skewness	-0,1862	-0,6821	0,6897	0,7742
Excess kurtosis	2,6760	2,3344	2,7884	4,4302
CAPM alpha (monthly)	0,47 %		1,25 %	
T-statistic (monthly CAPM)	1,8546		5,0486	
P-value (monthly CAPM))	0,0649		0,0000	
3 factor alpha	0,38 %		1,20 %	
3 factor t-statistic	1,4917		4,7113	
3 factor p-value	0,1371		0,0000	
4 factor alpha	0,34 %		1,17 %	
4 factor t-statistic	0,9924		3,4028	
4 factor p-value	0,3220		0,0008	

Table 9.14 - DMP23, IBEX, DMP24 & OMXS30

Metrics, measurements and ratios	DMP23	IBEX	DMP24	OMXS30
Cumulative return	2363,14 %	141,27 %	2990,06 %	216,99 %
Average monthly return	1,37 %	0,54 %	1,44 %	0,62 %
Average yearly return	16,40 %	6,53 %	17,29 %	7,46 %
Months with profit (%)	65 %	54 %	65 %	58 %
Standard deviation	15,01 %	21,61 %	13,65 %	19,86 %
Variance	0,1198	0,0467	0,1056	0,0394
Sharpe ratio	0,8834	0,1567	1,0368	0,2178
Treynor ratio	0,4071	0,0615	0,4988	0,0695
M^2	10,70 %	-4,86 %	13,99 %	-3,55 %
Beta	0,3258	0,5507	0,2837	0,6221
Information atio	0,8058	-0,0511	0,9761	-0,0371
Annualized CAPM Alpha	10,34 %	0,00 %	11,56 %	0,00 %
Maximum drawdown	-25,96 %	-64,06 %	-23,23 %	-68,90 %
Annualized Downside Deviation	11,98 %	13,41 %	10,56 %	12,36 %
VAR (5 percent)	-4,41 %	-9,97 %	-4,72 %	-10,64 %
Sortino ratio	1,1065	0,2525	1,3404	0,3499
RAROC	0,6371	0,2053	0,6431	0,2388
Trades per year	2	0	2	0
NOK 100 Invested	2 463	241	3 090	317
NOK 100 every month	131 908	33 649	181 426	44 392
Skewness	0,1724	-0,1622	0,3469	-0,2353
Excess kurtosis	2,5271	0,4620	1,6593	1,1238
CAPM alpha (monthly)	0,91 %		1,01 %	
T-statistic (monthly CAPM)	3,6472		4,4482	
P-value (monthly CAPM)	0,0003		0,0000	
3 factor alpha	0,89 %		0,95 %	
3 factor t-statistic	3,4919		4,0467	
3 factor p-value	0,0006		0,0001	
4 factor alpha	0,87 %		0,90 %	
4 factor t-statistic	2,5294		2,6410	
4 factor p-value	0,0121		0,0088	

Table 9.15 - DMP25, SMI, DMP26 & TAIEX

Metrics, measurements and ratios	DMP25	SMI	DMP26	TAIEX
Cumulative return	4931,61 %	296,15 %	1460,76 %	70,42 %
Average monthly return	1,63 %	0,65 %	1,19 %	0,49 %
Average yearly return	19,58 %	7,74 %	14,28 %	5,86 %
Months with profit (%)	69 %	61 %	65 %	55 %
Standard deviation	13,19 %	15,39 %	15,25 %	25,96 %
Variance	0,1019	0,0237	0,1035	0,0674
Sharpe ratio	1,2462	0,2990	0,7303	0,1050
Treynor ratio	0,6084	0,1430	0,2959	0,0526
M^2	18,47 %	-18,1 %	7,43 %	-5,97 %
Beta	0,2702	0,3217	0,3764	0,5183
Information ratio	1,2083	0,1513	0,6327	-0,0569
Annualized CAPM Alpha	13,96 %	0,00 %	7,81 %	0,00 %
Maximum drawdown	-16,74 %	-50,73 %	-37,80 %	-69,61 %
Annualized Downside Deviation	10,19 %	8,53 %	10,35 %	17,81 %
VAR (5 percent)	-3,92 %	-6,78 %	-5,65 %	-11,48 %
Sortino ratio	1,6131	0,5396	1,0758	0,1530
RAROC	0,6995	0,3168	0,5589	0,1571
Trades per year	2	0	2	0
NOK 100 Invested	5 032	396	1 561	170
NOK 100 every month	221 000	50 637	132 625	48 848
Skewness	0,3813	-0,5069	-0,6305	0,2326
Excess kurtosis	1,8140	1,3076	4,4156	1,1618
CAPM alpha (monthly)	1,22 %		0,68 %	
T-statistic (monthly CAPM))	5,5358		2,8366	
P-value (monthly CAPM)	0,0000		0,0049	
3 factor alpha	1,16 %		0,61 %	
3 factor t-statistic	5,1553		2,4652	
3 factor p-value	0,0000		0,0144	
4 factor alpha	1,12 %		0,60 %	
4 factor t-statistic	3,2658		1,7655	
4 factor p-value	0,0013		0,0787	

Table 9.16 - DMP27, SET index, DMP28 & FTSE100

Metrics, measurements and ratios	DMP27	SET Index	DMP28	FTSE100
Cumulative return	2523,35 %	127,72 %	2392,86 %	85,77 %
Average monthly return	1,40 %	0,73 %	1,35 %	0,33 %
Average yearly return	16,79 %	8,78 %	16,23 %	3,93 %
Months with profit (%)	67 %	57 %	65 %	56 %
Standard deviation	15,59 %	31,26 %	13,41 %	14,05 %
Variance	0,1206	0,0977	0,1033	0,0197
Sharpe ratio	0,8752	0,1805	0,9763	0,0561
Treynor ratio	0,4045	0,1049	0,4164	0,0190
M^2	10,53 %	-4,35 %	12,69 %	-7,01 %
Beta	0,3374	0,5377	0,3143	0,4154
Information ratio	0,7965	0,0492	0,9167	-0,2268
Annualized CAPM Alpha	10,63 %	0,00 %	10,26 %	0,00 %
Maximum drawdown	-26,55 %	-79,73 %	-26,11 %	-57,80 %
Annualized Downside Deviation	12,06 %	22,77 %	10,33 %	7,68 %
VAR (5 percent)	-5,37 %	-13,38 %	-4,81 %	-6,76 %
Sortino ratio	1,1321	0,2477	1,2671	0,1025
RAROC	0,6159	0,2546	0,6220	0,0737
Trades per year	2	0	2	0
NOK 100 Invested	2 623	228	2 493	186
NOK 100 every month	180 704	96 624	142 463	33 935
Skewness	0,2665	0,2225	0,3907	-0,2023
Excess kurtosis	3,2418	3,0618	1,4606	-0,1332
CAPM alpha (monthly)	0,87 %		0,89 %	
T-statistic (monthly CAPM)	3,3834		4,1224	
P-value (monthly CAPM)	0,0008		0,0001	
3 factor alpha	0,71 %		0,86 %	
3 factor t-statistic	2,6940		3,9034	
3 factor p-value	0,0076		0,0001	
4 factor alpha	0,74 %		0,80 %	
4 factor t-statistic	2,1571		2,3465	
4 factor p-value	0,0320		0,0198	

Table 9.17 - DMP29, S&P500, DMP30 & MSCI ASIA

Metrics, measurements and ratios	DMP29	S&P500	DMP30	MSCI ASIA
Cumulative return	4734,01 %	327,07 %	2572,32 %	111,50 %
Average monthly return	1,62 %	0,68 %	1,37 %	0,41 %
Average yearly return	19,45 %	8,14 %	16,49 %	4,97 %
Months with profit (%)	66 %	58 %	67 %	54 %
Standard deviation	13,67 %	15,71 %	12,85 %	16,83 %
Variance	0,1043	0,0247	0,1051	0,0283
Sharpe ratio	1,1929	0,3185	1,0391	0,1086
Treynor ratio	0,5924	0,1401	0,4431	0,0429
M^2	17,33 %	-1,39 %	14,04 %	-5,89 %
Beta	0,2753	0,3571	0,3013	0,4265
Information ratio	1,1475	0,1608	0,9894	-0,1070
Annualized CAPM alpha	13,78 %	0,00 %	10,62 %	0,00 %
Maximum drawdown	-22,39 %	-62,61 %	-31,52 %	-60,77 %
Annualized Downside Deviation	10,43 %	8,68 %	10,51 %	10,48 %
VAR (5 percent)	-4,62 %	-7,46 %	-4,26 %	-8,20 %
Sortino ratio	1,5637	0,5760	1,2705	0,1744
RAROC	0,6775	0,3206	0,6435	0,1389
Trades per year	2	0	2	0
NOK 100 Invested	4 834	427	2 672	212
NOK 100 every month	279 051	63 122	182 017	48 425
Skewness	0,3858	-0,3498	0,5058	-0,0213
Excess kurtosis	1,5795	0,4166	2,0203	0,4519
CAPM alpha (monthly)	1,17 %		0,89 %	
T-statistic (monthly CAPM)	5,0841		4,3121	
P-value (monthly CAPM)	0,0000		0,0000	
3 factor alpha	1,10 %		0,87 %	
3 factor t-statistic	4,6502		4,0916	
3 factor p-value	0,0000		0,0001	
4 factor alpha	1,01 %		0,82 %	
4 factor t-statistic	2,9493		2,3817	
4 factor p-value	0,0035		0,0180	

Table 9.18 - DMP31, MSCI World index, DMP32 & MSCI MXEF

Metrics, measurements and ratios	DMP31	MSCI World index	DMP32	MSCI MXEF
Cumulative return	2222,06 %	217,40 %	2166,17 %	193,40 %
Average monthly return	1,33 %	0,55 %	1,32 %	0,62 %
Average yearly return	15,92 %	6,56 %	15,85 %	7,38 %
Months with profit (%)	65 %	58 %	67 %	57 %
Standard deviation	13,63 %	14,57 %	13,91 %	21,03 %
Variance	0,1034	0,0212	0,0980	0,0442
Sharpe ratio	0,9376	0,2346	0,9140	0,2017
Treynor ratio	0,4163	0,0833	0,3475	0,0632
M^2	11,86 %	-3,19 %	11,36 %	-3,90 %
Beta	0,3070	0,4107	0,3657	0,6708
Information ratio	0,8690	0,0175	0,8570	-0,0659
Annualized CAPM Alpha	10,00 %	0,00 %	9,47 %	0,00 %
Maximum drawdown	-32,33 %	-58,00 %	-35,82 %	-56,34 %
Annualized Downside Deviation	10,34 %	7,64 %	9,80 %	11,59 %
VAR (5 percent)	-4,96 %	-7,92 %	-5,07 %	-9,59 %
Sortino ratio	1,2353	0,4477	1,2964	0,3658
RAROC	0,6122	0,2361	0,6075	0,2498
Trades per year	2	0	2	0
NOK 100 Invested	2 322	317	2 266	293
NOK 100 every month	152 146	51 750	166 806	59 071
Skewness	0,3042	-0,4762	-0,1246	-0,6465
Excess kurtosis	1,4766	0,3211	1,6826	1,7125
CAPM alpha (monthly)	0,85 %		0,78 %	
T-statistic (monthly CAPM))	3,8295		3,6251	
P-value (monthly CAPM)	0,0002		0,0004	
3 factor alpha	0,82 %		0,70 %	
3 factor t-statistic	3,6017		3,1710	
3 factor p-value	0,0004		0,0017	
4 factor alpha	0,75 %		0,67 %	
4 factor t-statistic	2,2030		1,9515	
4 factor p-value	0,0285		0,0522	

Table 9.19 - DMP33, EURO STOXX, DMP34 & MSCI EAFE index

Metrics, measurements and ratios	DMP33	EURO STOXX	DMP34	MSCI EAFE Index
Cumulative return	2675,17 %	125,11 %	2139,38 %	124,05 %
Average monthly return	1,40 %	0,47 %	1,30 %	0,41 %
Average yearly return	16,80 %	5,69 %	15,66 %	4,90 %
Months with profit (%)	67 %	57 %	66 %	56 %
Standard deviation	13,81 %	19,05 %	12,97 %	14,57 %
Variance	0,1045	0,0363	0,1030	0,0212
Sharpe ratio	0,9893	0,1340	0,9652	0,1210
Treynor ratio	0,4467	0,0451	0,4232	0,0386
M^2	12,97 %	-5,34 %	12,46 %	-5,62 %
Beta	0,3058	0,5661	0,2958	0,4564
Information ratio	0,9268	-0,1280	0,9015	-0,1676
Annualized CAPM Alpha	10,89 %	0,00 %	9,83 %	0,00 %
Maximum drawdown	-25,96 %	-63,06 %	-25,96 %	-57,37 %
Annualized Downside Deviation	10,45 %	10,28 %	10,30 %	7,56 %
VAR (5 percent)	-4,98 %	-9,82 %	-4,33 %	-8,52 %
Sortino ratio	1,3075	0,2484	1,2155	0,2333
RAROC	0,6271	0,1646	0,6262	0,1314
Trades per year	2	0	2	0
NOK 100 Invested	2 775	225	2 239	224
NOK 100 every month	152 009	34 817	157 140	40 803
Skewness	0,2587	-0,4727	0,3940	-0,4947
Excess kurtosis	1,4717	0,6341	1,9348	0,3211
CAPM alpha (monthly)	0,93 %		0,84 %	
T-statistic (monthly CAPM)	4,1203		3,9886	
P-value (monthly CAPM)	0,0001		0,0001	
3 factor alpha	0,90 %		0,81 %	
3 factor t-statistic	3,8457		3,7504	
3 factor p-value	0,0002		0,0002	
4 factor alpha	0,84 %		0,77 %	
4 factor t-statistic	2,4618		2,2445	
4 factor p-value	0,0145		0,0257	

Table 9.20 - DMP35, Dow Jones Industrial Average, DMP36 & FTSE Nordic

Metrics, measurements and ratios	DMP35	Dow Jones Industrial Average	DMP36	FTSE Nordic
Cumulative return	3057,96 %	356,35 %	2436,55 %	358,33 %
Average monthly return	1,45 %	0,71 %	1,37 %	0,76 %
Average yearly return	17,42 %	8,50 %	16,39 %	9,16 %
Months with profit (%)	68 %	57 %	65 %	57 %
Standard deviation	13,81 %	15,99 %	13,98 %	19,49 %
Variance	0,1069	0,0256	0,1053	0,0380
Sharpe ratio	1,0339	0,3353	0,9482	0,3088
Treynor ratio	0,5018	0,1652	0,4114	0,0925
M^2	13,93 %	-1,03 %	12,09 %	-1,60 %
Beta	0,2846	0,3247	0,3222	0,6510
Information ratio	0,9724	0,1958	0,8828	0,0677
Annualized CAPM Alpha	11,67 %	0,00 %	10,36 %	0,00 %
Maximum drawdown	-25,40 %	-51,51 %	-32,09 %	-65,64 %
Annualized Downside Deviation	10,69 %	9,22 %	10,53 %	10,94 %
VAR (5 percent)	-5,07 %	-7,10 %	-4,84 %	-10,84 %
Sortino ratio	1,3360	0,5814	1,2592	0,5500
RAROC	0,6348	0,3437	0,6242	0,3010
Trades per year	2	0	2	0
NOK 100 Invested	3 158	456	2 537	458
NOK 100 every month	210 661	65 957	152 961	50 462
Skewness	0,3284	-0,3042	0,1472	-0,4259
Excess kurtosis	1,6317	0,6338	1,8178	0,6456
CAPM alpha (monthly)	0,97 %		0,91 %	
T-statistic (monthly CAPM)	4,2026		3,9780	
P-value (monthly CAPM)	0,0000		0,0001	
3 factor alpha	0,94 %		0,86 %	
3 factor t-statistic	3,9757		3,6805	
3 factor p-value	0,0001		0,0003	
4 factor alpha	0,86 %		0,80 %	
4 factor t-statistic	2,5009		2,3476	
4 factor p-value	0,0131		0,0197	

Table 9.21 - DMP37, Russel 2000, DMP38 & Nasdaq

Metrics, measurements and ratios	DMP37	RUSSEL 2000	DMP38	NASDAQ
Cumulative return	3229,01 %	404,67 %	3958,15 %	538,63 %
Average monthly return	1,48 %	0,80 %	1,56 %	0,96 %
Average yearly return	17,72 %	9,58 %	18,77 %	11,55 %
Months with profit (%)	66 %	57 %	65 %	58 %
Standard deviation	14,18 %	19,37 %	14,83 %	23,24 %
Variance	0,1057	0,0375	0,1087	0,0540
Sharpe ratio	1,0286	0,3326	1,0539	0,3620
Treynor ratio	0,4904	0,1341	0,5269	0,1557
M^2	13,81 %	-1,09 %	14,35 %	-0,46 %
Beta	0,2973	0,4802	0,2967	0,5402
Information ratio	0,9674	0,1633	0,9930	0,2075
Annualized CAPM Alpha	11,88 %	0,00 %	12,93 %	0,00 %
Maximum drawdown	-22,52 %	-47,22 %	-30,43 %	-77,87 %
Annualized Downside Deviation	10,57 %	10,67 %	10,87 %	13,85 %
VAR (5 percent)	-4,98 %	-8,87 %	-5,07 %	-11,26 %
Sortino ratio	1,3803	0,6034	1,4384	0,6075
RAROC	0,6423	0,3490	0,6557	0,3687
Trades per year	2	0	2	0
NOK 100 Invested	3 329	505	4 058	639
NOK 100 every month	218 500	70 593	255 669	88 153
Skewness	0,3030	-0,2555	0,2168	-0,3380
Excess Kurtosis	1,2004	0,0377	1,3138	1,1890
CAPM alpha (monthly)	1,03 %		1,08 %	
T-statistic (monthly CAPM)	4,3958		4,3189	
P-value (monthly CAPM)	0,0000		0,0000	
3 factor alpha	0,95 %		1,01 %	
3 factor t-statistic	3,9660		3,9177	
3 factor p-value	0,0001		0,0001	
4 factor alpha	0,91 %		0,91 %	
4 factor t-statistic	2,6426		2,6550	
4 factor p-value	0,0088		0,0085	

Table 9.22 - DMP39 & ACWI Index

Metrics, measurements and ratios	DMP39	ACWI Index
Cumulative return	1911,75 %	214,38 %
Average monthly return	1,27 %	0,54 %
Average yearly return	15,23 %	6,53 %
Months with profit (%)	63 %	58 %
Standard deviation	13,59 %	14,67 %
Variance	0,1050	0,0215
Sharpe ratio	0,8890	0,2310
Treynor ratio	0,3833	0,0786
M^2	10,82 %	-3,27 %
Beta	0,3153	0,4312
Information ratio	0,8151	0,0011
Annualized CAPM alpha	9,24 %	0,00 %
Maximum drawdown	-32,71 %	-57,02 %
Annualized Downside Deviation	10,50 %	7,63 %
VAR (5 percent)	-4,98 %	-8,02 %
Sortino ratio	1,1506	0,4441
RAROC	0,5981	0,2330
Trades per year	2	0
NOK 100 Invested	2 012	314
NOK 100 every month	128 785	51 443
Skewness	0,3240	-0,5012
Excess kurtosis	1,5594	0,3853
CAPM alpha (monthly)	0,78 %	
T-statistic (monthly CAPM)	3,5655	
P-value (monthly CAPM)	0,0004	
3 factor alpha	0,75 %	
3 factor t-statistic	3,3299	
3 factor p-value	0,0010	
4 factor alpha	0,69 %	
4 factor t-statistic	2,0170	
4 factor p-value	0,0448	