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Active and passive momentum strategies on Nordic financial market*

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Abstract

The aim of this thesis was to backtest some of the approaches to capturing and investing in momentum in Nordic financial market. Data for more than one hundred Nordic stocks from Jan 2012 to Jul 2019 was used. Due to increase popularity of algorithmic trading, all the backtesting strategies were developed in Matlab. The first strategy was investing in 10 "winners" on an equal-weighted basis based on historical returns. Alternative strategy used mean-variance optimization problem with optimal weights to be used for holding period. Historical and holding periods of 3, 6, 9 and 12 months were applied for both strategies. Equal-weighted strategy ended to be more profitable and efficient. 9 by 3 strategy was the most profitable (mean annual return of 52.3%), while 6 by 12 was the most efficient (Shape of 1.19).

Active strategies were based on MACD and Chaikin indicators. Both of them were less efficient than passive management strategies. MACD strategy based on half-month and one-month holding periods was superior to Chaikin in terms of return and efficiency.

Keywords: Momentum, oscillator, MACD, Chaikin, exponential moving average

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1 Introduction

Momentum is one of the most discussed issues in finance. Some theories like efficient market hypothesis state, that all the available to market information is in asset prices and making continues abnormal returns should not be possible. At the same time, multiple academic evidence proved the existence of momentum and profitability of strategies, based on it. Simplicity is among the core attractive features of momentum strategy to explain the popularity it has. The essence idea of momentum is to stay in motion for the one that moves. Regarding the world of financial markets, if a stock was doing well in the past, it might perform well over the next period as well. That is the reasoning, used by momentum investors. They define “winner” stocks and invest in them. Momentum strategies developed in this thesis would contribute to empirical knowledge concerning momentum, for the Nordic market in particular.

One of the intentions of this thesis was to develop a passive management momentum strategy. Due to the fact, that momentum is typically a temporary condition on the markets choosing appropriate length of historical and holding periods is a matter of high importance. Thus, momentum might be exploited, however if tracked properly. Historical period should provide the insight concerning of which stocks might experience momentum going on. After choosing “winners”, subsequently, the next step would be to decide how long the holding period to choose. The intention here was to capture momentum of stocks, defined during the historical period and not to over keep stocks, when momentum ends and might even reverse. Thus, 3, 6, 9 and 12 months historical and holding periods same as in Jegadeesh and Titman (1993) were used. The intention was to apply equal-weighted weights in one passive strategy and mean-variance optimized to alternative one.

Another approach was to capture momentum rather in the short term. Technical analysis indicators are conventionally helpful there. Combinations of moving averages of prices are used in order to define appropriate indicators of short-term momentum. MACD and Chaikin are two well-known oscillators among professionals based on exponential moving averages. For the sake of their popularity and simplicity, it was decided to develop and test investment strategies based on those two oscillators within this thesis.

Many modern investment strategies especially those, based on technical analysis, are implemented by machines. Even though humans provide oversight, algorithm trading becomes more common. Thus, it was decided to back test passive and active momentum strategies by developing the script in Matlab. By providing updated input data, it could be rerun in couple of seconds in order to track possible momentum occurring on the market.

The results of that thesis might be valuable for passive investors. It would help to answer the question, whether there is benefit in using mean-variance optimization for portfolio building. This thesis would also point into the most profitable and efficient active and passive strategies on Nordic financial market, based on historical data.

2 Literature review

2.1 Efficient market hypothesis

The question of whether financial markets are efficient or not has been highly debated among economists. According to Fama (1970), all the available information is in asset prices. In other words, assets are priced at their fundamentals given the information on the market. By absorbing new information, prices adjust appropriately. Therefore as new information coming to the market is unpredictable, so are asset prices. Jensen (1967) concluded that mutual funds, used in his research, failed to predict asset prices good enough to beat the market. All that might bring to a conclusion, that constant generating of positive alpha would be impossible. Technical analysis and fundamental research would be of little use if all the assets were fairly priced. Thus, if market efficiency hypothesis holds there should not be a room for active management as it should not be able to generate constant abnormal returns. Then, the best investor can do would be to make passive investments and reap the market return, without spending on portfolio managers fees. However, the fact of existence of active manager's compensations along with examples of continuous generating alpha returns put some doubts about validity of efficient market hypothesis theory.

An alternative theory of market inefficiency, proposed by Shiller, states that markets are not efficient. Humans are not rational creations and prompt to making mistakes. In addition, there are behavioral biases, heuristics, simplified decision rules, which direct people not necessarily to the optimal decisions. Thus, mental biases, irrationality and simplifications are among the main reasons, why asset prices might be pushed away from fundamentals at least in short-term. Thus, deepening of inefficiency in financial markets creates possibilities for more educated and/or rational investors.

Following that logic, it should be comparatively easy for many investors to beat the market. Nonetheless, beating of market is not that easy task.

Pedersen (2015) states, that the true form of market efficiency lies somewhere in between efficient and inefficient forms. According to Pedersen (2015), markets are efficiently inefficient. Due to behavioral biases, irrationality, institutional frictions assets prices might diverge from fundamentals. Thus, there are always investors hunger for trading against those kinds of inefficiencies. By competing with each other, they are making markets inefficient to efficient extent. Thus, it is possible to profit on efficiently inefficient markets, but it is a rather complex task. Pedersen (2015) compares efficiently inefficient markets with a traffic line. By driving a highway, each line moves equally fast due to line-switchers making sure there is more or less the same amount of cars in each line. Active switching between the lines of intensive traffics hardly helps. That procedure is also risky, as switching between the lines increases risk of traffic accident, heart attack etc. However, it still make sense to switch for those, who have comparable advantage.

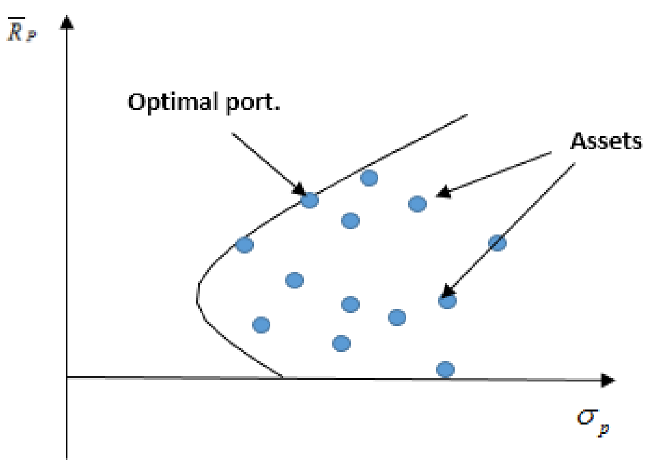
2.2 Portfolio risk and return

Return and risk are among the key metrics of interest for investors. Markowitz (1952) brought a breakthrough in financial world by educating investors of diversification possibilities while building portfolios. Should today one build a portfolio, idea of Markowitz (1952) from his “Portfolio Selection” most likely will come into play.

Building investment portfolios was traditional procedure for many investors. “Do not put all the eggs in one basket” – is probably the most famous recommendation in the world of investments. However, any “basket” has a risk, due to the fact, that financial instruments are risky. Thus, portfolio an investor builds and risks he takes are the matters of high importance.

Efficient frontier (Figure 1) was analytically derived by Merton (1972). Investors got the tool to build their portfolios in optimal way – the one, which provides the highest return for a given level of risk or the lowest risk for a given rate of return. Thus, risk-averse individuals could reap the benefits of diversification by choosing the assets, which correlated negatively. Combining different assets in various proportions creates plenty of possibilities of portfolio construction. However, according to mean-variance analysis approach, there is only one efficient portfolio for a given level of risk. Efficient frontier (Figure 1) would be result of drawing the line through all the efficient (optimal) portfolios. Portfolios with return above efficient frontier cannot be attained given the assets available. While the portfolios inside of frontier would be not optimal as there are more rewarding portfolios with the same risk.

Figure 1: Efficient frontier



*Efficient frontier. Two-asset example**

By assumption, financial market consists of two assets (A and B). Expected returns of those assets are $\overline{R}_A$ and $\overline{R}_B$, with variances are σ_A^2 and σ_B^2 respectively. Expected return and standard deviation of asset A is less than those of asset B. If the whole investor's wealth was invested in the both assets, w would be invested in asset A. Then the weight 1-w would be invested in the asset B. Thus, the return of the overall portfolio would be weighted average of returns of assets A and B:

$$\overline{R}_P = w\overline{R}_A + (1-w)\overline{R}_B \tag{1}$$

Assuming the correlation coefficient of returns between assets A and B is φ, the standard deviation of the portfolio would be the following:

$$\sigma_p = \left[w^2\sigma_A^2 + 2w(1-w)\sigma_A\sigma_B\varphi + (1-w)^2\sigma_B^2 \right]^{\frac{1}{2}} \tag{2}$$

The overall risk of the portfolio is a nonlinear function of individual asset weights, standard deviations and co-movements of asset returns. As correlation coefficient is by definition bounded by φ = -1 and φ =1, standard deviation of portfolio given these corner coefficients will be calculated.

For φ =1, which is perfect correlation between the assets, the overall risk of portfolio would be:

$$\sigma_p = \left[w^2\sigma_A^2 + 2w(1-w)\sigma_A\sigma_B + (1-w)^2\sigma_B^2 \right]^{\frac{1}{2}} \tag{3}$$

After defining, explicitly, the square of a sum equation (3) develops into the following:

Two-asset example presented according to Pennacchi (2008). Theory of Asset Pricing.

$$\sigma_p = \left[\left(w\sigma_A + (1-w)\sigma_B \right)^2 \right]^{\frac{1}{2}} = \left| w\sigma_A + (1-w)\sigma_B \right| \tag{4}$$

By rearranging equation (4) with respect to weight, the following equation (5) was obtained:

$$w = \frac{\sigma_B \pm \sigma_P}{\sigma_B - \sigma_A} \tag{5}$$

By plugging in (5) for weight into (1) the following equations were obtained:

$$\overline{R}_P = \frac{\sigma_B \pm \sigma_P}{\sigma_B - \sigma_A} \overline{R}_A + (1 - \frac{\sigma_B \pm \sigma_P}{\sigma_B - \sigma_A}) \overline{R}_B \tag{6}$$

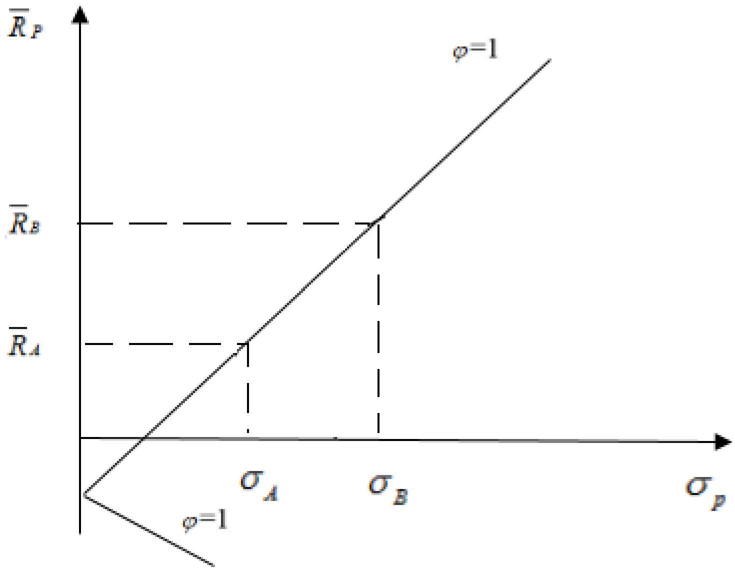
$$\overline{R}_P = \frac{\sigma_B \pm \sigma_P}{\sigma_B - \sigma_A} \overline{R}_A + \overline{R}_B - \overline{R}_B \frac{\sigma_B \pm \sigma_P}{\sigma_B - \sigma_A} \tag{7}$$

$$\overline{R}_P = \overline{R}_B + \frac{\pm\sigma_P - \sigma_B}{\sigma_B - \sigma_A} \left(\overline{R}_B - \overline{R}_A \right) \tag{8}$$

$$\overline{R}_P = \frac{\sigma_B \overline{R}_A - \sigma_A \overline{R}_B}{\sigma_B - \sigma_A} \pm \frac{\overline{R}_B - \overline{R}_A}{\sigma_B - \sigma_A} \sigma_P \tag{9}$$

Given the coefficient of correlation φ =1, equation (9) will be shown in $\overline{R}_P , \sigma_P$ space as in Figure 2. The intercept for both of them would be $\frac{\sigma_B \overline{R}_A - \sigma_A \overline{R}_B}{\sigma_B - \sigma_A}$ (10), while the slope would be either plus or minus $\pm \frac{\overline{R}_B - \overline{R}_A}{\sigma_B - \sigma_A} \sigma_P$ (11).

Figure 2: Efficient frontier given coefficient of correlation is equal to one



By considering the case of perfectly negative correlation the standard deviation of the portfolio would be:

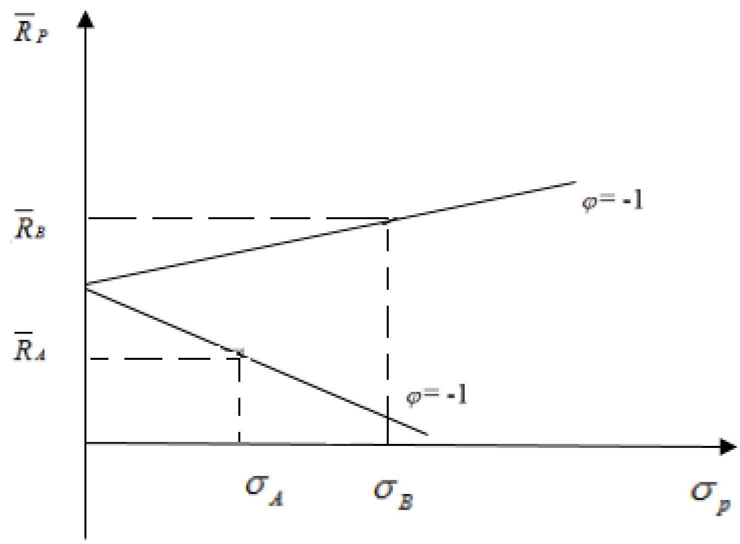
$$\sigma_p = \left[w^2\sigma_A^2 - 2w(1-w)\sigma_A\sigma_B + (1-w)^2\sigma_B^2 \right]^{\frac{1}{2}} = \left| w\sigma_A - (1-w)\sigma_B \right| \qquad (12)$$

By rearranging (12) for weight and plugging in equation (1) the overall return of portfolio would be obtained:

$$\bar{R}_P = \frac{\sigma_A \bar{R}_B + \sigma_B \bar{R}_A}{\sigma_A + \sigma_B} \pm \frac{\bar{R}_B - \bar{R}_A}{\sigma_A + \sigma_B}\sigma_P \qquad (13)$$

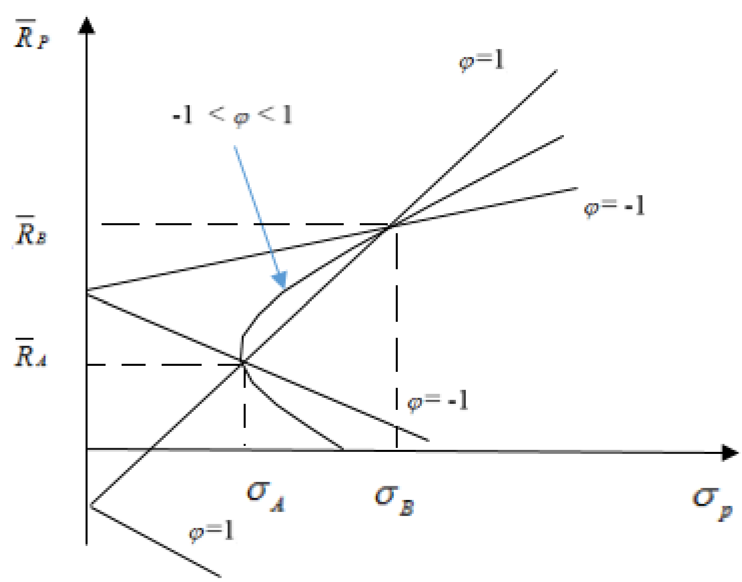
Given the coefficient of correlation φ = -1, the equation (13) will be in $\bar{R}_P, \sigma_p$ space as in Figure 3. The intercept for both of them would be $\frac{\sigma_A \bar{R}_B + \sigma_B \bar{R}_A}{\sigma_A + \sigma_B}$ (14), while the slope would be either plus or minus $\frac{\bar{R}_B - \bar{R}_A}{\sigma_A + \sigma_B}\sigma_P$ (15).

Figure 3: Efficient frontier given coefficient of correlation is equal to minus one



When coefficient of correlation φ lies within boundaries of -1 to 1 the relationship between the variance and expected return of a portfolio is not linear, but rather hyperbolic (Figure 4).

Figure 4: Efficient frontier given coefficient of correlation is from minus to plus one



2.3 Efficient frontier, multiple assets example*

In the previous section, efficient frontier for two-assets example was provided. However, in reality financial markets include thousands of different securities and investors often need choose more than two securities. Therefore, a tool for efficient portfolio construction given desired risk-return properties has been highly needed. As was mentioned before, Merton (1972) provided solution to the problem. Given expected returns, variances and covariance matrix of returns the approach to calculate optimal portfolio weights was highly needed. Those weights, based on historical data, would provide the desired level of return by taking the smallest portfolio risk possible.

By assumption, there are n different financial assets to choose from. Vector of expected asset returns is defined as $\overline{R}=(\overline{R}_1,\overline{R}_2,\overline{R}_3......\overline{R}_n)'$. Vector of weights invested in asset i[th] is the following: $w=(w_1,w_2,w_3.....w_n)'$. Covariance matrix of returns (V) of size $n\times n$ assumed to have full rank. Given that, the expected portfolio return would be $\overline{R}_P = w'\overline{R}$, while the variance would be $\sigma_p^2 = w'Vw$.

The sum of weights is equal to one. Algebraically it can be written as $w'e=1$, where e is $n\times 1$ vector of ones.

The next step would be to set up optimization problem of finding the weights of optimal portfolio given the restrictions on the sum of weights and expected portfolio return. Formally, the Lagrange equation (16) needs to be solved:

$$\min \frac{1}{2} w'Vw + \lambda\left[\overline{R_p} - w'\overline{R}\right] + \gamma\left[1 - w'e\right] \tag{16}$$

By taking the first-order conditions with respect to weights and Lagrange multipliers, the following equations were obtained:

*Multiple asset example presented according to Pennacchi (2008). Theory of Asset Pricing.

$$Vw - \lambda \overline{R} - \gamma e = 0 \tag{17}$$

$$\overline{R_p} - w'\overline{R} = 0 \tag{18}$$

$$1 - w'e = 0 \tag{19}$$

By rearranging (17) with respect to weights, equation (20) was obtained:

$$w^* = \lambda V^{-1}\overline{R} + \gamma V^{-1}e \tag{20}$$

By multiplying (20) by $\overline{R}'$ the following equation (21) was obtained:

$$\overline{R_p} = \overline{R}'w^* = \lambda \overline{R}'V^{-1}\overline{R} + \gamma \overline{R}'V^{-1}e \tag{21}$$

While by multiplying (20) by e, equation (22) was obtained:

$$1 = e'w^* = \lambda e'V^{-1}\overline{R} + \gamma e'V^{-1}e \tag{22}$$

From the last two equations the solutions for unknowns λ and γ are:

$$\lambda = \frac{\delta \overline{R_p} - \tau}{\varsigma\delta - \tau^2} \tag{23}$$

$$\gamma = \frac{\varsigma - \tau \overline{R_p}}{\varsigma\delta - \tau^2} \tag{24}$$

Where, $\tau = \overline{R}'V^{-1}e$, $\varsigma = \overline{R}'V^{-1}\overline{R}$, $\delta = e'V^{-1}e$. By plugging in λ and γ into equation (20) equation (25) will be obtained:

$$w^* = \frac{\delta \overline{R_p} - \tau}{\varsigma\delta - \tau^2} V^{-1}\overline{R} + \frac{\varsigma - \tau \overline{R_p}}{\varsigma\delta - \tau^2} V^{-1}e \tag{25}$$

Equation (25) satisfies the weights of assets in the portfolio, which was expected of receiving $\overline{R_p}$ with the minimum portfolio risk possible. Optimal portfolio weights $w*$ could also be rewritten as:

$$w* = a + b\overline{R_p}\ , \tag{26}$$

Where $a = \dfrac{\varsigma V^{-1}e - \tau V^{-1}\overline{R}}{\varsigma\delta - \tau^2}$ and $b = \dfrac{\delta V^{-1}\overline{R} - \tau V^{-1}e}{\varsigma\delta - \tau^2}$.

After finding the optimal weights of portfolio, the variance could be calculated as:

$$\sigma_p^2 = w*'Vw* = (a + b\overline{R_p})'V(a + b\overline{R_p}) = \frac{\delta\overline{R_p}^2 - 2\tau\overline{R_p} + \varsigma}{\varsigma\delta - \tau^2} = \frac{1}{\delta} + \frac{\delta(\overline{R_p} - \frac{\tau}{\delta})^2}{\varsigma\delta - \tau^2} \tag{27}$$

2.4 Momentum and empirical evidence

Momentum investment strategy is based on expectation of stocks to perform well in the future, given their success in the past. The idea thus would be to buy “winners”, while short the “losers”. Further, some of the most famous papers dealing with momentum will be discussed.

Jegadeesh and Titman (1993) performed one of the first well-known empirical momentum studies. They tested 16 investment momentum strategies based on different historical and holding periods (3, 6, 9 and 12 months). Thus, Jegadeesh and Titman ended with 16 momentum strategies to be tested. They used daily returns on the USA stocks from 1965 to 1989. All the stock returns were sorted in deciles. Top performers fell into “winners” decile, while the poorest performing stocks fell into “losers” decile. The strategy implied buying “winners” and selling “losers”. All the stocks within portfolios were equally-weighted. Jegadeesh and Titman (1993) concluded, that portfolios of “winners” constructed based on performance during formation period of 3, 6, 9 and 12 months, outperformed portfolios of “losers”. The most successful investment strategy was the one with historical period of 12 month and holding period of 3 month. Jegadeesh and Titman (1993) explained the existence of momentum with respect to underreaction and overreaction that happen in financial markets. They stated the idea that market underreacts concerning short-term possibilities of a firm. However, markets might overreact to information regarding long-term perspectives. Jegadeesh and Titman (1993) also found out, that half of the excess returns gained by exploiting momentum strategy disappear within the next two years.

Jegadeesh and Titman (2001) repeated their research for the increased data set. The conclusions were in analogy to Jegadeesh and Titman (1993), which supported the idea, that Jegadeesh and Titman (1993) paper was not the result of snooping bias.

Rouwenhorst (1998) used monthly returns for almost 2200 companies from European countries. The list of countries included in the study was the following: Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the United Kingdom. Capitalization of companies in a country was from 60% to 90% of capitalization of the whole market of that country. The way of portfolio construction along with holding and formation periods corresponded to the Jegadeesh and Titman (1993). Formation and holding periods of 3, 6, 9 and 12 months were used. All the portfolios were equally weighted. Returns were divided into deciles. Portfolios of “winners” and “losers” were defined. Rouwenhorst (1998) concluded that for all the rankings and holding periods, portfolio of winners outperformed portfolio of losers. It was pointed out, that the difference was close to 1% per month. Rouwenhorst (1998) also noticed the tendency of falling returns as holding period increases. On the top of that, the same methodology for every country taken separately was implemented. The result was the following: “winners” outperformed “losers” in any of the given countries. Thus, it was concluded, that momentum was not country specific phenomena. Momentum existed in all the markets taken into consideration in the research. Rouwenhorst (1998) also discovered, that returns continuation was stronger for smaller firms. The tendency with respect of size was noted: portfolio of “winners “on average included larger companies than portfolio of “losers”. In order to distill the size effect, Rouwenhorst (1998) sorted portfolios on size. Thereafter, he divided stocks into deciles within each size. The results showed, that “winners” portfolio outperformed “losers” portfolio in each size category.

Conrad and Kaul (1998) tested the momentum strategy, which was based on continuation of trend in pricing and contrarian strategy, based on price reversals. Conrad and Kaul (1998) used NYSE and AMEX-listed securities data from 1926 to 1989. They analyzed eight strategies with holding period from 1 week to 36 months. There were 120 strategies in total. Conrad and Kaul (1998) found that less than half strategies were profitable. 30 strategies out of 55 profitable strategies were momentum strategies. Conrad and Kaul (1998) also found that momentum strategies would not make profits between 1926 and 1947. However, contrarian strategies would have been profitable exactly during the period between 1926 and 1947. The core finding of the paper with respect to momentum strategies was that they were mainly profitable in medium horizon – form 3 to 12 months.

Jegadeesh and Titman (1993) suggested underreaction as possible explanation of why momentum exist. Chan, Jagadeesh and Lakonishok (1996) studied the possibility of underreaction to be a predictor of future returns. They used beginning of each month data from 1977 to 1993 in order to sort stocks. The criteria for stock sorting was either compound returns for the previous six month either news with respect to earnings. Subsequently, all the stocks were grouped into deciles. Chan, Jagadeesh and Lakonishok (1996) found, that the difference in six months yield between stocks with high and low yield during prior six month. That difference in yield was 8.8%. They also found out, that given the other factors, surprises in past returns might predict shifts in future returns. At the same time, factors like size of a company or relation of book value to market value do not explain shifts in returns. Chan, Jagadeesh and Lakonishok (1996) also stated, that predictions of analysts concerning perspective earnings change slowly if surprises to the earnings hit the market. What is more, analysts change their forecasts even more reluctantly for the stocks, that did not perform that well in the past. Thus, unwillingness of analysts to revise their forecasts when earnings surprises hit the market might influence decision makers. Postponed and or delayed reaction of decision makers might contribute to underreaction in the market.

Dijk & Huibers (2002) pointed on the empirical papers, which discovered momentum in European and US financial markets. The fact of momentum existence was more obvious than the reasons behind of it. Dijk & Huibers (2002) used the methodology of Rouwenhorst (1998) on European stocks from 1987 to 1999. In analogy to Chanm, Jagadeesh and Lakonishok (1996), they stated that underreaction of analysts to new information might be among causes of momentum. Dijk & Huibers (2002) failed to explain momentum trough the size and value effects as in Chan, Jagadeesh and Lakonishok (1996). Strong negative correlation between price momentum and B/M value was discovered while the correlation between capitalization and momentum was close to zero or positive. Dijk & Huibers (2002) confirmed the findings of Rouwenhorst (1998), about profitability of momentum strategies in medium term (based on European market). They concluded, that momentum strategies might be profitable given the existence of underreaction in the market. Thus, Dijk & Huibers (2002) propose to keep the eye open with respect to analyst forecasts and changes of those forecasts, as new information hits the market.

Thus, numerous empirical papers proved the existence of momentum at least in the medium-term. The aim of this thesis is to backtest momentum explicitly in Nordic financial market through developing appropriate algorithm strategies.

2.5 Technical analysis. MACD and Chaikin oscillators

Technical analysis discipline intends to predict future asset movements based on historical prices and volumes data. Proponents of technical analysis believe that past and current trends of prices and volumes tell the story of where the prices might be heading. Unlike fundamental analysis, in which analysts assess intrinsic value of financial instrument, technical analysis deals with market trends. By analyzing trends and charts, analysts find typical patterns and trend behavior in order to exploit them. Some of the most common market patterns are head and shoulders, double bottom, flat base, short stroke etc. Technicians are also using moving averages and oscillator indicators based on them.

Technical analysis has been actively developing from the end of 19th century. Charles Dow formulated the backbone of technical analysis for analyzing market behavior. His reflections on markets has been known as Dow theory. Nowadays, technical analysis experience rapid development due to development of artificial intelligence and neuron networks. Considering momentum, traditional tool of moving averages is still actively used. One of the intentions of this thesis was to develop and backtest active management portfolio strategies based on MACD and Chaikin indicators.

MACD indicator

MACD (moving average convergence/divergence) is an oscillator developed by Gerald Appel. MACD is calculated as the difference of long-term (26-days) and short-term (12-days) exponential moving averages of prices. Signal line, which is 9-day exponential moving average of MACD is used to smooth MACD. Thus, if price of a stock goes up, short-term exponential moving average increases more quickly comparing to long-term exponential moving average. Subsequently, MACD will go up.

$$MACD=EMA\ (Average,\ 12)-EMA\ (Average,\ 26) \tag{28}$$

Exponential moving average (EMA) that is used in MACD is obtained in (29):

$$EMA_t = \alpha P_t + (1-\alpha)EMA_{t-1} \tag{29}$$

where, α is the weight for the most recent observation calculated as in equation (30):

$$\alpha = \frac{2}{N+1} \tag{30}$$

N – is the number of days

By comparing MACD with 9-day lagged value of MACD (signal line), potential momentum and the direction of it could be defined. Thus, if MACD is increasing and above the signal line, that might be the signal of upward momentum going on the market. On the other hand, if MACD indicator goes down and is below the signal line, that is the indication of potential downside momentum. Zero crossover happen, when MACD indicator changes the sign. In that case, there is no difference between long-term and short-term exponential moving average of price.

MACD uses 12, 26 and 9 days as they corresponded to 2 weeks, one month, one and a half week respectively (while the working week was 6 days). The choice of number of days for short-term EMA, long-term EMA and signal line might be optimized.

However, for the sake of alignment, many investors are still using traditional MACD (12, 26, 9).

Chaikin indicator

Chaikin oscillator is another indicator, used in active management algorithm developed within this thesis. It was created by Mark Chaikin. The oscillator measures momentum of accumulation/distribution line indicator.

However, firstly, money flow multiplier (31) based on high, low and close prices needs to be calculated. The higher close price is to high price, the higher money flow multiplier and money flow volumes will be.

$$Money\ Flow\ Multiplier = [(Close - Low) - (High - Close)]/(High - Low) \tag{31}$$

Thereafter, money flow multiplier is multiplied by volume traded in order to find money flow volume indicator (32).

$$Money\ Flow\ Volume = Money\ Flow\ Multiplier * Volume \tag{32}$$

Accumulation/distribution line works like stock indicator, which is adjusted each period by the money flow volume. Chaikin oscillator is calculated in (33) as the difference of short-term (3 days) and long-term (10 days) exponential moving averages of accumulation/distribution line. Thus, if positive momentum is under way and closing price is comparatively high or/and volume traded is on increase than short-term EMA of accumulation/distribution line will grow faster than long-term one. Positive Chaikin scores might signals about positive momentum going on in asset prices and/or comparatively more active trading.

$$CHO = EMA(A/D, 3) - EMA(A/D, 10) \tag{33}$$

2.6 Technical analysis. Empirical evidence

Profitability of strategies based on technical analysis was an issue of high importance in academics. According to the efficient market hypothesis, constant abnormal earnings should not be possible if all the information is already in prices. Thus, profitability of strategies based on technical analysis could provide some clarifications on another highly important issue in academics of market efficiency.

Ratner & Leal (1999) aimed to explore the efficiency of technical analysis trading rules in developing countries. They used ten trading rules, based on moving averages in order to capture momentum in the market. Ratner & Leal (1999) used daily index closing levels from 1882 to 1995. They analyzed short-moving averages of 1, 2 and 5 days. At the same time, 50, 150 and 200 days long-term moving averages were used. If short-term moving average indicator was higher than long-term one, then "buy" signal was generated. That technically meant long position in the index. "Sell" signal meant to go out of the market and to sell shares owned. Short selling was not part of algorithm considered by Ratner & Leal (1999). The conclusion was that strategies with rules based on moving averages were superior to buy and hold strategy. Comparatively steady returns spanning through all the trading rules were generated on developing markets of Mexico, Thailand and Taiwan. Japan profited from one rule, while US did not profit from any rules.

Park & Irwin (2007) provided an overview on the issue of profitability of technical analysis based academic studies. They concluded, that in comparatively "old" studies from 1960 to 1987, technical analysis rules were profitable for foreign exchange and futures markets, but not for the stock market. Concerning "modern" studies, Park & Irwin (2007) concluded, that most of them proved generating profits at least before 1990s.

At the same time, Park & Irwin (2007) pointed attention on numerous limitations in testing procedures, applied in academic papers.

Yu, Nartea, Gan & Yao (2013) conducted similar research to Ratner & Leal (1999). They also used short-term and long-term moving averages as indicators for technical trades. However, Yu, Nartea, Gan & Yao (2013) added a new indicator called “band”. They considered “band” is percentage difference between moving averages, which was required for signal to be generated. The main intention was not to generate signal if the difference between short-term and long-term moving averages was comparatively small. The length of moving averages corresponded to Ratner & Leal (1999). The data came from the index of daily stock prices for the markets in the South of Asia from 1991 to 2008. The results showed that trading rules were successful in predicting asset prices movements in developing markets (both, for variable-length moving average and fixed-length moving averages). Moving averages rules had less predictive power in Singapore. However, according to Yu, Nartea, Gan & Yao (2013), transaction costs vanished profits in most of the South Asian markets.

Tharavanij, Siraprapasiri & Rajchamaha (2015) studied profitability of technical strategies on five Asian markets, based on data from 2000 to 2013. Given transaction costs, Tharavanij, Siraprapasiri & Rajchamaha (2015) concluded, that on all the markets considered except of Thailand, strategies had hard time earning statistically significant returns. They also concluded, that MACD indicator might provide excess return and beat buy and hold strategy. Tharavanij, Siraprapasiri & Rajchamaha (2015) recommend to work over improvements of parameters in the strategies used instead of using conventional parameters. That could of attribute for traditional MACD indicator as discussed above.

3 Data and methodology

3.1 Data

The algorithms developed for backtesting of active and passive portfolio management strategies are using daily stock data. It came from Nasdaq Nordic from Jan 2012 to Jul 2019 for 155 companies. The full list of abbreviations for passive strategies is in Table 18 in Appendix. Algorithms of active management used the sample of 119 companies (Table 19 in Appendix). Algorithms of passive strategies import daily average prices, daily gains and asset abbreviations. All scripts import counts for each trading date in order to define historical and holding datasets respectively. Daily gains were defined as price of a share in the current period divided by the price in previous period. Those gains were used in order to find geometrical average of daily gains. Subsequently, daily stock gains were converted to annual returns. Chaikin active management strategy, on the top of that, inputs close, high and low prices. Those are used in order to calculate money flow multipliers. In addition, Chaikin script imports trade volume data for calculation of money flow volumes. Both money flow volumes and money flow multipliers were used for calculation of Chaikin indicator. Dividends are not included in the data imported.

Portfolio of a holding period can consist of stocks bought from different markets for various currencies (DKK, NOK, SEK). Exchange rate movements were ignored, while assessing portfolio returns in holding periods. All the strategies worked as if at the beginning of any holding period foreign currencies were borrowed in order to buy foreign stocks. At the end of holding period, foreign stocks were redeemed at the exchange rate as from the beginning of the holding period. That was the exchange rate assumption used for all the strategies in this thesis. Transaction costs were ignored.

NASDAQ OMX Nordic 120 Gross Index was used as the proxy for calculation of market returns. Daily gains of the market were imported in order to compare return of strategies against the market in annual terms.

3.2 Methodology

Momentum strategy

The basic idea of momentum investment strategy is to define the top performing stocks in the past and to invest in them during the holding period. If momentum in stock prices continues then the strategy might be profitable. One of the goals of this thesis is to test momentum strategy on different historical and holding periods for Nordic equities. Thus, the optimal momentum strategy that worked best historically will be defined.

According to Conrad and Kaul (1998), momentum strategies are mainly profitable in medium horizon – form 3 to 12 months. In another study, by Titman (1993), medium horizon strategies from 3 to 12 months with the step of 3 months were also considered. Historical periods used by Titman (1993) corresponded to holding periods of 3, 6, 9 and 12 months. Therefore, Titman (1993) ended in 16 momentum strategies by varying historical and holding periods (from 3 to 12 months).

Thus, this thesis considers medium term momentum strategies of 3, 6, 9 and 12 months. Historical periods were set the same ending in total in 16 momentum strategies.

Each of these 16 strategies was tested on Nordic stocks data from 3 Jan 2012 and ending 12 Jul 2019.

The logic of 3 by 12 months momentum strategy is described below.

3 months historical, 12 months holding strategy (3 by 12 strategy)

This strategy inputs daily average prices and capital gains for 155 Nordic stocks from 3 Jan 2012 to 30 Mar 2012. That timeframe corresponds to historical period of 3 months used by that strategy. Then the strategy calculates daily geometric averages of historical capital gains for all the 155 stocks used in the thesis. Dividends in this and other strategies were not taken in consideration. Subsequently, daily geometric averages of historical capital gains for all the stocks are raised to power 250 in order to convert daily gains to annual gains. That step is based on assumption of 250 annual traded days. Following this, the strategy finds returns by subtracting one from all the annual capital gains for all the stocks. Then, returns of all the 155 Nordic stocks are ranked from the highest to the lowest. Top 10 performers (shares) are picked up. Those "winners" form the portfolio on an equal basis to be kept in the holding period starting from 2 Apr 2012 to 28 Mar 2013 (holding period of 12 months). In reality, not all the investors can short stocks. Thus, negative momentum of "losers" and short selling were not considered in the thesis. No changes to portfolio occur during holding period due to the passive character of that momentum strategy. Subsequently, based on daily capital gains of stocks in holding period annual returns are calculated. By calculating equal-weighted portfolio return given the annual returns of the "winners", exchange rate movements are ignored. Momentum strategy works as if at the beginning of holding period foreign currencies were borrowed in order to buy foreign stocks. At the end of holding period, foreign stocks are redeemed at the exchange rate as from the beginning of the holding period. That exchange rate assumption was used in this and other strategies. Nominal return, return over the market, standard deviation of return and Sharpe ratio were calculated. Sharpe ratio was used within the thesis as the measure of excess return per unit of risk. By setting annual interest rate to zero, the excess return of portfolio was defined to be equal to mean return of momentum portfolio. While the standard deviation of those returns was treated as the risk measure to the Sharpe ratio. Higher excess return per unit of the standard deviation of excess return brings higher values of Sharpe ratio (34). That is why the higher Sharpe Ratio is the better.

$$SharpeRatio = \frac{E(R - R^f)}{\sigma(R - R^f)} \tag{34}$$

All the procedures were repeated consequently for all the timeframe of the data available. Thus, the next historical period of 3 months was from 1 Feb 2012 to 30 Apr 2012. The holding strategy was in that case starting from 1 May 2012 and ending 30 Apr 2013. Nominal returns, excess market returns, standard deviations and Sharpe ratio were calculated.

The strategy continued to do the same for the next period by subtracting the first months and adding one more up-to date month into the both historical and holding periods. The algorithm repeated that methodology for the whole data range available.

Mean-variance optimization strategy

An alternative passive portfolio strategy is based on mean-variance optimization approach. In the momentum strategy algorithm calculated top performers of historical period. Thereafter, it invested on an equal-weighted basis in those top performers in holding period.

The idea of mean variance optimization strategy is the same as in momentum strategy, except of the weights used in holding period. While momentum strategy built portfolio for holding period on an equal-weighted basis, mean-variance strategy (MV) used optimal weights from historical period. The idea of MV strategy is to optimize the weights of top 10 performers during the historical period. The output of the optimization problem was the optimized weights for each level of risk, which would provide the highest possible return historically.

The risk of an equal weighted portfolio of top performing stocks in historical period was used as the target risk for the mean variance optimization approach. Optimal weights given that procedure were calculated for holding period portfolio. All the procedures were repeated consequently for all the timeframe of the data available. As such, the first 3 by 12 strategy holding period was starting from 1 May 2012 and ending 30 Apr 2013. While the first 3 by 12 strategy historical period was form 3 Jan 2012 to 30 Mar2012. The strategy was run over the all data scope, by subtracting the first months and adding one more up-to date month into the both historical and holding periods. The same measures of portfolio performance as in momentum strategy were calculated (nominal returns, excess over market returns, annual risk and Sharpe ratio).

The strategy ignored exchange rate movements as in momentum strategy.

MACD strategy

On the top of passive strategies, two active strategies of portfolio management have been developed. The first is MACD strategy. Moving Average Convergence Divergence (MACD) is an oscillator used in technical analysis. The logic of calculation of MACD is to subtract 26-day exponential moving average of security price from 12-day exponential moving average. 9-day exponential moving average of MACD called “signal line” was used for smoothing MACD. Combination of MACD score and signal line is used in decision-making process of active management investors. If MACD crosses signal line upwards that might be a signal of positive momentum in asset’s price and vice versa.

MACD strategy developed in this thesis calculates MACD indicator and signal line for daily data from Jan 2012 up to July 2019 included. Data consists of 119 Nordic stocks. Then for each stock algorithm calculates MACD and signal line. By calculating the difference of MACD and signal line and by dividing that difference by the average price of the stock in same period investment scores were calculated. Those investment scores intend to show the severity of momentum over the price in relative value. All the investment scores for all the stocks are compared and top ten stocks are selected. Those top ten stocks are considered to have the highest momentum opportunity. Thereafter, the return over the holding period is calculated, as if an equal-weighted portfolio of top preforming stocks at the beginning of the period was formed. All the procedures keep going for all the subsequent periods. Exchange rate fluctuations are ignored as in passive portfolio strategies.

It is to be noted, that MACD is short-term momentum oscillator, which intends to show current momentum. That momentum might not exist in long term. However, from our knowledge, in reality portfolio adjustments happen once per couple of weeks. Given the reasoning above, it was decided to use MACD strategy for every half-month and one-month periods. That means that, portfolios of ten stocks with the highest investment scores are build the first trading day of each period. The main goal is to define, which strategy worked best in the past, based on traditional measures of portfolio performance.

Chaikin strategy

Another active portfolio management strategy is based on Chaikin oscillator. This strategy calculates money flow multiplier based on high, low and close prices for all the stocks. The higher closing price is to the daily maximum the higher will be the value of that indicator. Thereafter, money flow multiplier is multiplied by volume in order to find money flow volume indicator. In that case, money flow volume indicator works like momentum indicator, which incorporates the movement in the price and volume traded. That indicator (money flow volume) of the first period is used as the first period value of accumulation/distribution indicator. Second period accumulation/distribution indicator is changing due to the addition of money flow volume indicator of the second period. The procedure keeps going for all the periods (daily) for all 119 Nordic stocks.

By definition, traditional Chaikin oscillator is the difference of 3-day and 10-day exponential moving averages of accumulation/distribution line. Due to the nature of

Chaikin oscillator, which is the difference of exponential moving averages of money flow multiplier times volume, it was decided to use Chaikin oscillator explicitly as the indicator for severity of momentum. The algorithm defines top 10 stocks with the highest scores at the beginning of the holding period. Thereafter, the return over the holding period is calculated. It is done under the assumption of an equal-weighted portfolio. The procedure is repeated every holding period. Traditional measures of portfolio performance are calculated. In analogy to MACD strategy, two holding periods are considered: half of months and one month.

4 Results

4.1 Momentum strategy

In this thesis, 16 passive momentum strategies with different historical and holding periods were backtested. Typical metrics of interest such as Sharpe ratio, annual nominal return and annual return over the market along with annual risk measure were calculated.

Mean returns of portfolios on annual terms were calculated. Minimum, maximum and median returns were extracted. For each strategy, standard deviation of portfolio returns along with 10 and 90 return percentiles were also calculated.

In order to assess the return of a strategy apart from the market conditions, return of the market was subtracted. Based on the highest mean return over the market, 9 by 3 strategy was the most preferable one. However, according to Sharpe ratio, 6 by 12 strategy was the most efficient. Both of them will be considered in detail below.

9 months historical, 3 months holding strategy (9 by 3 strategy)

First historical period considered for the 9 by 3 strategy was from the beginning of Jan 2012 to the end of Sep 2012. The first holding period started at the beginning of Oct 2012 and ended in the end of Dec 2012. The second run of the algorithm switched one month forward for both historical and holding periods. In table 1, the first column "Count" contains the number of times the algorithm of 9 by 3 was run in total. For that strategy there were 79 runs on different historical and holding periods, though most of them overlapped. That means that 79 times equal weighted portfolio based on historical period "winners" was created in order to be kept in holding period. Momentum strategy was subtracting the first months and adding more recent up-to date month constantly for each subsequent period on the whole data set from 3 Jan 2012 to 12 Jul 2019.

Table 1 contains summary statistics for 9 by 3 momentum strategy. Mean value of portfolio returns was 52.3%. The strategy would earn minimum return of -67.9% if it was initiated in the beginning of Sep 2018. However, it would earn maximum return of 270.7% if it was initiated in the beginning of May 2013. Median return was 43.5%, which signals about skew to the right. Standard deviation of portfolio return was 54.4%.
10 percentile return was positive at 1.1%. While 90 percentile return was 124.7%. An example of abbreviations of stocks kept in holding periods are in table 27 in Appendix.

Table 1: Summary returns of 9 by 3 months momentum strategy without market

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
79	-67.9%	270.7%	52.3%	43.5%	54.4%	1.1%	124.7%

Table 2 contains summary statistics for that strategy over the market return. Mean value of portfolio returns over the market was 39.2%. The strategy would earn minimum return of -40.3% if it was initiated in the beginning of Sep 2018. However, it would earn maximum return of 266.6% if it was initiated in the beginning of May 2013. Median return was 27.4%, which signals about skew to the right. Standard deviation of portfolio return was 47.9%. 10 percentile return was negative at -9.3%. While 90 percentile return was positive at 97.6%

Table 2: Summary returns of 9 by 3 months momentum strategy over market

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
79	-40.3%	266.6%	39.2%	27.4%	47.9%	-9.3%	97.6%

In table 3, comparisons of nominal annual returns, standard deviations and Sharpe ratios for 9 by 3 momentum strategy were implemented.

Momentum strategy provides higher returns (52.3% versus 13.1% for market), though at higher risk (54.4% versus 25.5% for market). In the end, Sharpe ratio is higher for the 9 by 3 momentum strategy than for the market (0.96 versus 0.51).

Table 3: Risk versus return of 9 by 3 months holding strategy versus the market

Avg. return, strategy	*Avg. return, market*	*Avg. st. dev., startegy*	*Avg. st. dev., market*	*Sharpe, strategy*	*Sharpe, market*
52.3%	13.1%	54.4%	25.5%	0.96	0.51

To conclude, 9 by 3 momentum strategy earned on average 52.3% in annual nominal return. While return over the market was 39.2%. However, higher nominal return were achieved by taking higher risks. Momentum strategy risk was more than double higher than risk of the market (54.4% versus 25.5%).

In the end, Sharpe ratio was higher for the momentum strategy, which means that from the return-risk perspective 9 by 3 momentum strategy should be considered by investors. Passive investing in the market in that case would be less efficient.

For those investors, caring more about high nominal return and less about the risks that (9 by 3) momentum strategy would be the best. It demonstrated the highest nominal return (52.3% on annual basis) among all the 16 strategies considered in this thesis. The summary data for all the 16 momentum strategies before and after the market are in tables 18 and 19 in Appendix.

However, if risk-adjusted return is the main criteria for investor, then Sharpe ratio would be the first to consider. By screening through the results of all the 16 momentum strategies it is to be noted that 6 by 12 momentum strategy provided the highest Sharpe ratio of 1.19 (table 23 in Appendix). Thus, the results of this strategy would be described in more detail below.

6 months historical, 12 months holding strategy (6 by 12 strategy)

First historical period considered for the 6 by 12 strategy was from the beginning of Jan 2012 to the end of Jun 2012. The first holding period started at the beginning of Jul 2012 and ended in the end of Jun 2013. Momentum strategy was subtracting the first months and adding more recent up-to date month constantly for each subsequent period. That procedure was applied on the whole data set from 3 Jan 2012 to 12 Jul 2019. For that strategy, there were 73 runs on different historical and holding periods.

Table 4 contains summary statistics for 6 by 12 momentum strategy. Mean value of portfolio returns was 26.3%. The strategy would earn minimum return of -12.3% if it was initiated in the beginning of Jun 2018. However, it would earn maximum return of 83.0% if it was initiated in the beginning of May 2013. Median return was 25.3%, which signals about skew to the right. Standard deviation of portfolio return was 22.1%.

10 percentile return was negative at -0.4%. While 90 percentile return was positive at 56.7%

Table 4: Summary returns of 6 by 12 months momentum strategy

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
73	-12.3%	83.0%	26.3%	25.3%	22.1%	-0.4%	56.7%

Table 5 contains summary statistics for that strategy over the market return. Mean value of portfolio returns over the market was 16.1%. The strategy would earn minimum return of -13.1% if it was initiated in the beginning of Feb 2017. However, it would earn maximum return of 65.5% if it was initiated in the beginning of May 2013. Median return was 14.2%, which signals about skew to the right. Standard deviation of portfolio return was 17.2%. 10 percentile return was negative at -6.2%. While 90 percentile return was positive at 38.7%.

Table 5: Summary returns of 6 by 12 months momentum strategy over market

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
73	-13.1%	65.5%	16.1%	14.2%	17.2%	-6.2%	38.7%

In table 6, comparisons of nominal annual returns, standard deviations and Sharpe ratios for 6 by 12 momentum strategy were implemented.

Momentum strategy provides higher returns (26.3% versus 10.2% for market), though at higher risk (22.1% versus 9.5% for market). In the end, Sharpe ratio is higher for the 6 by 12 momentum strategy than for the market (1.19 versus 1.08).

Table 6: Risk versus return of 6 by 12 months holding strategy versus the market

Avg. return, strategy	*Avg. return, market*	*Avg. st. dev., startegy*	*Avg. st. dev., market*	*Sharpe, strategy*	*Sharpe, market*
26.3%	10.2%	22.1%	9.5%	1.19	1.08

To conclude, 6 by 12 momentum strategy earned on average 26.3% in annual nominal return. While return over the market was 16.1%. However, higher nominal return would be achieved by taking higher risks. Momentum strategy risk was more than double higher than risk of the market (22.1% versus 9.5%).

In the end, Sharpe ratio was higher for the momentum strategy, which means that from the return-risk perspective 6 by 12 momentum strategy should be considered by investors. Passive investing in the market in that case would be less efficient.

4.2 Mean-Variance Optimization Strategy

Mean-variance optimization portfolio passive strategy was built in analogy to momentum strategy. The only difference is in weights of assets to be used for holding period portfolio. Those optimal weights come from mean-variance optimization problem, by using the risk of equal-weighted portfolio of "winners" from historical period as target risk.

In analogy to momentum strategy, 16 mean-variance (MV) strategies with different historical and holding periods were back tested. Subsequently, the same metrics of portfolio performance were calculated.

Based on the highest mean return over the market, 6 by 3 strategy was the most preferable one. However, according to Sharpe ratio, 6 by 12 strategy was the most efficient. Both of them will be considered in detail below.

6 months historical, 3 months holding MV strategy (6 by 3 strategy)

First historical period considered for the 6 by 3 strategy was from the beginning of Jan 2012 to the end of Jun 2012. The first holding period started at the beginning of Jul 2012 and ended in the end of Sep 2012. For that strategy, there were 82 runs on different historical and holding periods. In the end 82 times optimally weighted portfolio based on historical period optimal weights of "winners" was created. That portfolio was kept in holding period.

Table 7 contains summary statistics for 6 by 3 MV strategy. Mean value of portfolio returns was 43.1%. The strategy would earn minimum return of -67.9% if it was initiated in the beginning of Sep 2018. However, it would earn maximum return of 293.6% if it was initiated in the beginning of Jul 2017. Median return was 42.0%, which signals about skew to the right. Standard deviation of portfolio return was 50.2%.
10 percentile return was negative at -2.0%. While 90 percentile return was 94.7%

Table 7: Summary returns of 6 by 3 months MV strategy

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
82	-67.9%	293.6%	43.1%	42.0%	50.2%	-2.0%	94.7%

Table 8 contains summary statistics for that strategy over the market return. Mean value of portfolio returns over the market was 29.8%. The strategy would earn minimum return of -44.4% if it was initiated in the beginning of Jan 2015. However, it would earn maximum return of 281.1% if it was initiated in the beginning of Jul 2017. Median return was 28.5%, which signals about skew to the right. Standard deviation of portfolio return was 46.0%. 10 percentile return was negative at -20.8%. While 90 percentile return was positive at 73.8%.

Table 8: Summary returns of 6 by 3 months MV strategy over market

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
82	-44.4%	281.1%	29.8%	28.5%	46.0%	-20.8%	73.8%

In table 9, comparisons of nominal annual returns, standard deviations and Sharpe ratios for 6 by 3 MV strategy were implemented.

MV strategy provides higher returns (43.1% versus 13.3% for market), though at higher risk (50.2% versus 25.3% for market). In the end, Sharpe ratio is higher for the 6 by 3 momentum strategy than for the market (0.86 versus 0.52).

Table 9: Risk versus return of 6 by 3 months holding strategy versus the market

Avg. return, strategy	*Avg. return, market*	*Avg. st. dev., startegy*	*Avg. st. dev., market*	*Sharpe, strategy*	*Sharpe, market*
43.1%	13.3%	50.2%	25.3%	0.86	0.52

To conclude, 6 by 3 MV strategy earned on average 43.1% in annual nominal return. While return over the market was 29.8%. However, higher nominal return would be achieved by taking higher risks. MV strategy risk was almost double higher than risk of the market (50.2% versus 25.3%).

In the end, Sharpe ratio was higher for the MV strategy, which means that from the return-risk perspective 6 by 3 MV strategy should be considered by investors. Passive investing in the market in that case would be less efficient. It is to be noted, that pure momentum 6 by 3 strategy was more profitable and efficient that 6 by 3 MV strategy.

For those investors, caring more about high nominal return and less about the risks that (6 by 3) MV strategy would be the best. It demonstrated the highest nominal return (43.1% on annual basis) among all the 16 MV strategies considered in this thesis. The summary data for all the 16 MV strategies are in tables 21-23 in Appendix A.

If risk-adjusted return is the main criteria for investor, then 6 by 12 MV strategy provided the highest Sharpe ratio of 0.96. Thus, the results of this strategy would be described in more detail below.

6 months historical, 12 months holding MV strategy (6 by 12 strategy)

First historical period considered for the 6 by 12 strategy was from the beginning of Jan 2012 to the end of Jun 2012. The first holding period started at the beginning of Jul 2012 and ended in the end of Jun 2013. For that strategy, there were 73 runs on different historical and holding periods.

Table 10 contains summary statistics for 6 by 12 MV strategy. Mean value of portfolio returns was 23.9%. The strategy would earn minimum return of -21.4% if it was initiated in the beginning of Jun 2018. However, it would earn maximum return of 77.9% if it was initiated in the beginning of Jan 2015. Median return was 19.3%, which signals about skew to the right. Standard deviation of portfolio return was 24.8%. 10 percentile return was negative at -5.5%. While 90 percentile return was 60.0%.

Table 10: Summary returns of 6 by 12 months MV strategy

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
73	-21.4%	77.9%	23.9%	19.3%	24.8%	-5.5%	60.0%

Table 11 contains summary statistics for that strategy over the market return. Mean value of portfolio returns over the market was 13.7%. The strategy would earn minimum return of -24.5% if it was initiated in the beginning of Mar 2017. However, it would earn maximum return of 62.7% if it was initiated in the beginning of Jan 2015. Median return was 10.2%, which signals about skew to the right. Standard deviation of portfolio return was 21.1%. 10 percentile return was negative at -9.7%. While 90 percentile return was positive at 41.4%.

Table 11: Summary returns of 6 by 12 months MV strategy over market

Count	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
73	-24.5%	62.7%	13.7%	10.2%	21.1%	-9.7%	41.4%

In table 12, comparisons of nominal annual returns, standard deviations and Sharpe ratios for 6 by 12 MV strategy were implemented.

MV strategy provides higher returns (23.9% versus 10.2% for market), though at higher risk (24.8% versus 9.5% for market). In the end, Sharpe ratio is higher for the market than for 6 by 12 MV strategy (0.96 versus 1.08).

Table 12: Risk versus return of 6 by 12 months holding strategy versus the market

Avg. return, strategy	*Avg. return, market*	*Avg. st. dev., startegy*	*Avg. st. dev., market*	*Sharpe, strategy*	*Sharpe, market*
23.9%	10.2%	24.8%	9.5%	0.96	1.08

To conclude, 6 by 12 MV strategy earned on average 23.9% in annual nominal return. While return over the market was 13.7%. However, higher nominal return would be achieved by taking higher risks. MV strategy risk was more than double higher than risk of the market (24.8% versus 9.5%).

In the end, Sharpe ratio of the market was higher than of MV strategy, which means that from the return-risk perspective 6 by 12 MV strategy is not preferable for investors. Passive investing in the market in that case would be more efficient.

Comparison of Momentum and Mean-Variance passive strategies

Within this thesis, momentum strategy was based on investments on an equal-weighted manner in the portfolio of winners from the historical period. Unlike momentum strategy, MV strategy algorithm was estimating the risk of an equal-weighted portfolio in the past. Thereafter, it calculated the optimal weights for each of the assets through the mean-variance optimization approach. Those weights were used to build the portfolio to be kept in holding period. The fundamental difference between those two strategies was in the use of weights in order to build portfolio for the holding period.

Summary results for both of the strategies can be found in Appendix. However, the main differences are the following:

- 3 by 9 MV and momentum strategies provided the same nominal returns. For all the other combinations of historical and holding periods momentum strategies outperformed MV strategies before and over the market returns;
- Standard deviation of MV strategies was higher, than of momentum strategies. 9 by 3 was the only exception out of 16 strategies;
- Market outperformed only 3 by 12 momentum strategy;
- Market outperformed 3 by 12, 6 by 12, 9 by 9, 9 by 12, 12 by 12, 12 by 9 and 12 by 12 MV strategies;
- Sharpe ratios of momentum strategies are higher than those of MV strategies;
- 10 percentile returns before and after the market were mainly higher for momentum strategies than for MV strategies.

In conclusion, by comparing nominal returns before and after subtracting the market and 10 percentiles returns, it is to be noted, that momentum strategies provided higher returns. At the same time, momentum strategies were in most of the time less risky. Thus, in general, Sharpe ratio was superior for momentum strategies. Based on the results in this thesis, momentum strategies are preferred for use rather than MV strategies. 9 by 3 strategy provided the highest returns (nominal return 52.3% and 39.2% over the market). However, according to Sharpe ratio, 6 by 12 strategy was the best one (momentum Sharpe of 1.19, while MV Sharpe of 0.96).

4.3 MACD

MACD momentum strategy was implemented for every half-month and one-month holding periods. Due to the fact that MACD uses 26-day moving average and signal line is 9-day moving average of MACD the investment scores were calculated only from thirty forth trading day. The results for each of the holding period strategies will be presented below.

Half-month holding period strategy

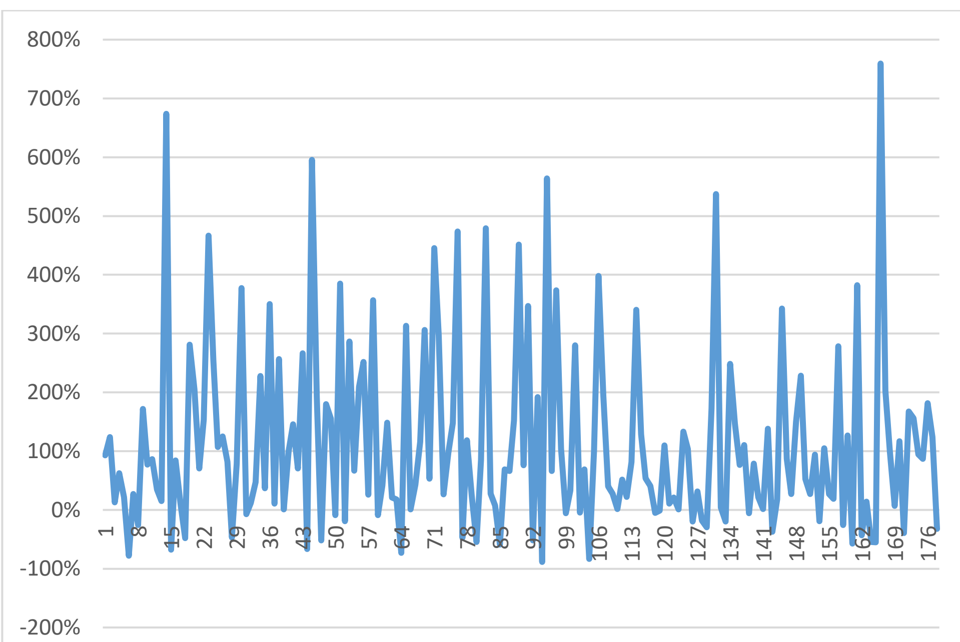
This strategy intended to choose 10 stocks with the highest investment scores on the first day of the first half of the month. Then, the gain of that portfolio during holding period in annual terms was calculated. On the first day of the second half of the month, new portfolio based on investment scores was created. The gain of portfolio for the second part of the month was calculated respectively. In total, the strategy ended with 178 trading periods from Jan 2012 to Jul 2019. Summary statistic for returns before and after the market is presented in table 13.

Table 13: Summary, MACD strategy, half-month strategy

Count	*Mean return*	*Median return*	*St. deviation of return*	*Mean return over market*	*Median return over market*	*St. deviation of return over market*
178	113.0%	73.2%	155.4%	71.2%	44.3%	122.6%

Mean return and standard deviation of MACD strategy are much higher than of passive management strategies, considered in this thesis. Portfolio returns for all the 178 periods in annual terms were presented in figure 5. OY axis shows return in annual terms, while OX axis corresponds to count of periods. The picture shows that portfolios returns for half-month MACD strategy are highly volatile.

Figure 5: Portfolio returns in annual terms. MACD, half-month strategy



According to the figure 5, it can be concluded that at some periods portfolio returns were comparatively high on annual terms. That typically is the result of strong positive short-term momentum captured by the strategy. For example, the first big spike (over 600% in annual term) was experienced in the first half of Sep 2012. Financial instruments and daily gains based on the first half of Sep 2012 are in table 14.

Table 14: Portfolio, first half Sep 2012, MACD

RBREW	SAAB-B	NZYM-B	AAK	FORTUM	TOP	ROCK-B	VITR	AMEAS	ROCK-A
1.001	1.009	0.999	1.006	1.006	1.003	1.012	1.000	1.010	1.012

ROCK-A and AMEAS, for instance, generated 1.2% and 1.0% of daily return based on the period considered. Those increase dramatically, while bringing to annual terms. Thus, they move the total annual return of portfolio for the period and mean return for the strategy upwards. Thus, spikes like observed on the figure 5 mean high positive momentum at least in short-term, that was captured by half-month MACD strategy.

The Sharpe ratio for half-month MACD strategy was 0.73. That is lower than for passive momentum strategies, but higher than for some of the mean-variance strategies.

One-month holding period strategy

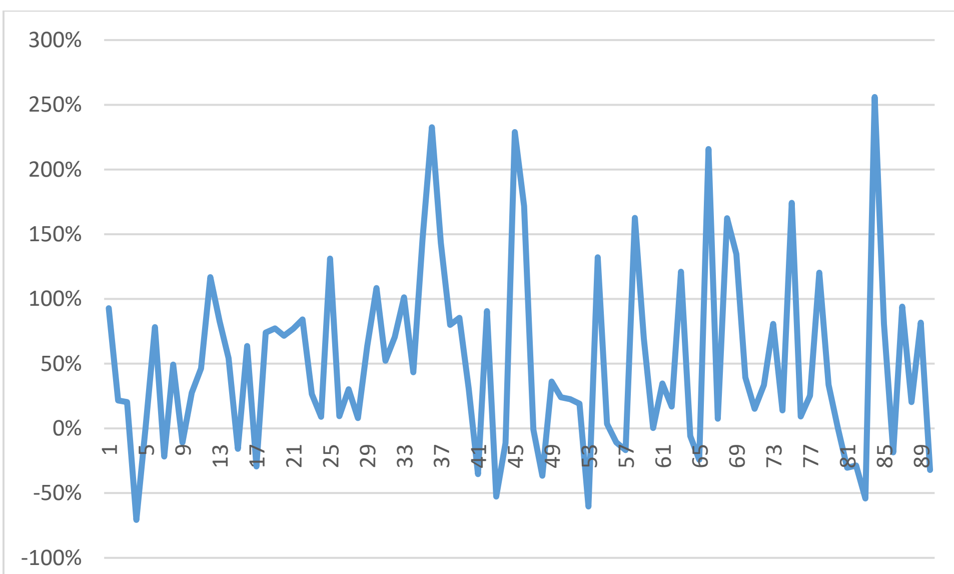
This strategy intended to choose 10 stocks with the highest investment scores on the first day of the month. Then, the gain of that portfolio during holding period in annual terms was calculated. In the first day of the next month, stocks are revised based on investment scores. The gains of portfolio for the second, third and up to the last month were calculated respectively. In total, the strategy ended with 90 trading periods from Jan 2012 to Jul 2019. Summary statistic for returns before and after the market is presented in table 15.

Table 15: Summary, MACD strategy, one-month strategy

Count	*Mean return*	*Median return*	*St. deviation of return*	*Mean return over market*	*Median return over market*	*St. deviation of return over market*
90	50.8%	34.1%	69.2%	31.6%	20.7%	53.4%

Mean return and standard deviation are a way lower than in half-month MACD strategy. Though mean return can be comparable to passive strategies, standard deviation of return is higher. In figure 6, portfolio returns for all the 90 periods in annual terms were presented. Returns on annual terms are less volatile and mainly positive. Short-term momentum seems to have been better captured by half-month MACD strategy. The Sharpe ratio was also 0.73 as in half-month strategy.

Figure 6: Portfolio returns in annual terms. MACD, one-month strategy



4.4 Chaikin

Chaikin strategy was implemented on the same holding periods as MACD strategy. The results for both holding periods will be presented below. Thereafter, the efficiency of MACD and Chaikin strategies will be compared.

Twice per month holding period strategy

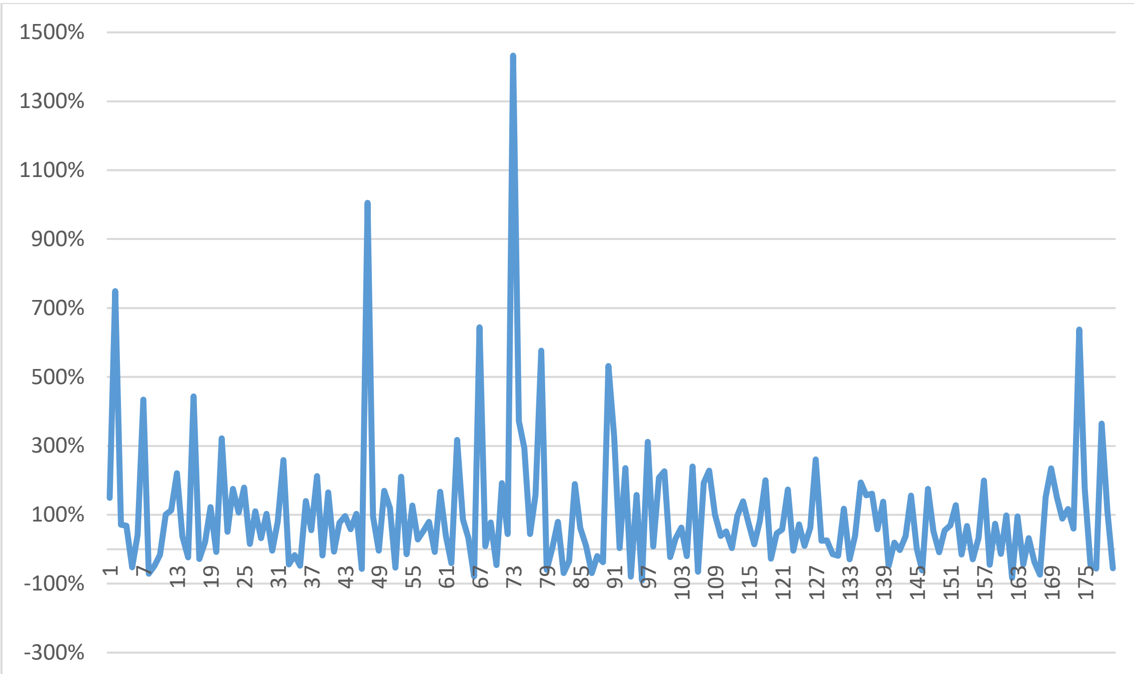
This strategy, in analogy to MACD strategy, chose 10 stocks with the highest investment scores on the first day of the holding period. Thereafter, the gain of that portfolio during holding period in annual terms was calculated. As soon as new holding period started all the stocks were revised based on investment scores. In total, the strategy ended with 180 trading periods from Jan 2012 to Jul 2019. Summary statistic for returns before and after the market is presented in table 16.

Table 16: Summary, Chaikin strategy, half-month strategy

Count	*Mean return*	*Median return*	*St. deviation of return*	*Mean return over market*	*Median return over market*	*St. deviation of return over market*
180	101.1%	59.1%	185.4%	57.6%	28.9%	120.3%

Half-month Chaikin strategy was less profitable, but more risky than half-month MACD strategy. Thus, the Sharpe ratio was predictably lower (0.55). In terms of efficiency, half-month Chaikin is the worst strategy so far considered in the thesis. In figure 7, portfolio returns for all the 180 periods in annual terms were presented.

Figure 7: Portfolio returns in annual terms. Chaikin, half-month strategy



One-month holding period strategy

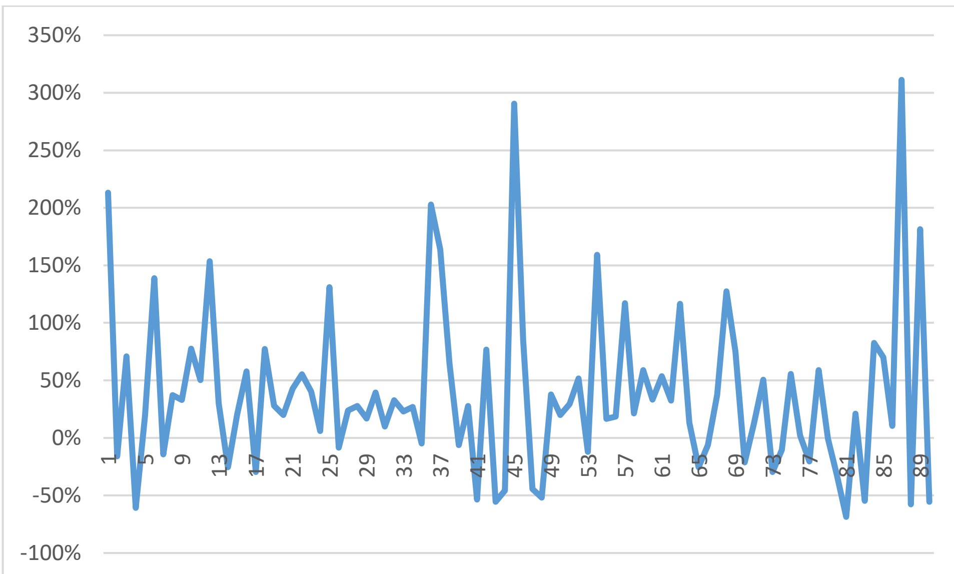
The logic is the same as in the Chaikin strategy above, however, the holding period is one month. In total, the strategy ended with 90 holding periods. Summary statistic for returns before and after the market is presented in table 17.

Table 17: Summary, Chaikin strategy, one-month strategy

Count	*Mean return*	*Median return*	*St. deviation of return*	*Mean return over market*	*Median return over market*	*St. deviation of return over market*
90	38.7%	27.9%	71.9%	18.2%	11.0%	47.6%

Mean return is lower, while standard deviation is higher comparing with analogical MACD strategy. Sharpe ratio (0.54) is the lowest in the thesis.

Figure 8: Portfolio returns in annual terms. Chaikin, one-month strategy



Comparison of MACD and Chaikin active strategies

Both MACD and Chaikin strategies are more rewarding and risky in shorter term rather than in a longer term. Comparatively big outliers in terms of return were the signals of short-term momentum captured. MACD was more rewarding in terms of return than Chaikin strategy. The reason might come from the better ability of MACD oscillator to capture short-term momentum. MACD strategies were also less risky. Thus according to Sharpe ratio MACD strategies are preferable.

5 Conclusions

In this thesis, passive strategies (momentum and mean-variance optimization) and active strategies (MACD and Chaikin) were developed and back tested on more than one hundred Nordic stocks. The period, used for back testing was from Jan 2012 up to July 2019 included. The main goal was to define whether those strategies worked for the Nordic stocks and which one from active and passive performed better.

Momentum strategy was investing in the portfolio of top performers form the historical period. The portfolio was kept during the holding period without any updates made to it. Historical and holding periods used in that strategy were 3, 6, 9 and 12 months. Thus, 16 strategies in total were considered. The algorithm developed within this thesis was running each strategy multiple of times, by skipping the first and adding one recent month to both historical and holding periods. For 3 by 12 strategy, for example, momentum algorithm was run 76 times. The number of runs depended on the length of historical and holding periods. Summary statistics and Sharpe ratio were calculated. The minimum nominal return (23.6%) on annual basis was provided by 12 by 12 strategy, with standard deviation of 22.9%. While the highest return (52.3%) was contributed by 9 by 3 strategy, with standard deviation of 54.4%. The 6 by 12 strategy got the highest return-risk measure of Sharpe at 1.19. The return of 6 by 12 strategy was 26.3% at the risk of 22.1%. All the strategies outperformed the market based on Sharpe ratio, except of 3 by 12 strategy (strategy Sharpe 1.04, while market Sharpe 1.11).

An alternative passive strategy was based on mean-variance optimization approach. The strategy was the same as in momentum but for weights used for holding period portfolio. Historical period equal-weighted portfolio risk of “top” performing stocks was used as the target risk in order to find the optimal weights for portfolio in holding period. Those optimal weights would provide the highest return for the given level of risk historically for “top” performers. The minimum nominal return (22.9%) on annual basis was provided by 9 by 9 strategy, with standard deviation of 28.5%. While the highest return (43.1%) was contributed by 6 by 3 strategy, with standard deviation of 50.2%. The 6 by 12 strategy got the highest return-risk measure of Sharpe at 0.96. The return of 6 by 12 strategy was 23.9% at the risk of 24.8%. Even though all the strategies had positive nominal returns, only ten of them outperformed the market based on Sharpe ratio.

In conclusion, pure momentum strategy with portfolio built from the historical “winners” on an equal weight basis was superior to mean-variance strategy. Both mean returns and standard deviation were mainly higher for momentum strategies. Based on the return-risk measure of Shape momentum strategy outperformed mean-variance in all the 16 strategies.

Strategy based on MACD oscillator was the first among active strategies considered within the thesis. The algorithm was choosing “top” performers at the first day of each holding period. Thereafter, the returns of each period were calculated. Investment score, which was the basis for choosing the best performing stocks, was based on MACD over average price of the share in the same period. Thus, it was treated as an indicator of momentum in relative terms. For the holding period of one-month, the strategy mean return was 50.8% at standard deviation of 69.2%. While return is comparable to passive strategies, the risk is higher. Sharpe ratio of one-month holding was 0.73, which might be comparable to mean-variance passive strategies. However, all the pure momentum passive strategies outperformed one-month MACD. Half-month MACD strategy was more risky and rewarding, however, the return-risk ration was the same as in the one-month strategy.

An alternative strategy to MACD considered in the thesis was based on Chaikin oscillator. That indicator apart from price change, used volume traded in calculation of momentum oscillator. Thereafter, the stocks with the highest Chaikin scores were chosen to be kept during the holding periods. All the other procedures were in analogy to MACD strategy. Chaikin mean return was lower, while standard deviation higher for appropriate with MACD periods. Thus, it might be concluded, that MACD indicator within this thesis was more preferable.

By comparing active and passive management strategies, it is to be noted, that pure momentum strategies of passive character won in terms of return-risk efficiency. However, those aiming to capture short-term momentum while tolerating comparatively high risks might consider MACD as a possible indicator for choosing stocks.

References

Back (2010). Asset Pricing and Portfolio Choice theory. Oxford University Press

Chan, Jagadeesh & Lakonishok (1996). Momentum Strategies. The journal of Finance. 51 (5)

Chan, Hameed & Tong (2000). Profitability of Momentum Strategies in the International Equity Markets. Journal of Finance and Quantitative Analysis. 35(2). 153-172.

Conrad & Kaul (1998). An Anatomy of Trading Strategies. The Review of Financial Studies. 11(3). 489-519.

Daniel, Hirshleifer & Subrahmanyam (1998). Investor Psychology and Security Market Under- and Overreactions. The Journal of Finance. 53(6). 1839-1885.

De Bondt &Thaler (1985). Does the Stock Market Overreact? The Journal of Finance. 40(3). 793-805.

Dijk & Huibers (2002). European Price Momentum and Analyst Behavior. Financial Analysts Journal. 58(2)

Fama (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance. 25(2). 383-417.

Fama & French (1996). Multifactor explanations of Asset Pricing Anomalies. The Journal of Finance. 51(1). 55-84.

Hong & Stein (1997). A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets. Cambridge: National Bureau of Economics

Jegadeesh & Titman. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance. 48(1). 65-91.

Jegadeesh & Titman (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. The journal of Finance. 56 (2)

Jensen (1967). The Performance of Mutual Funds in the Period 1945-1964. The journal of Finance. 23(2). 389-416

Lee & Swaminthan (2002). Price Momentum and Trading Volume. The Journal of Finance. 55(5). 2017-2069.

Markowitz (1952). Portfolio Selection. The journal of Finance 7(1). 77-91.

Merton (1972). An analytical derivation of the Efficient Portfolio Frontier. The Journal of Financial and Quantitative Analysis. 7(4). 1851-1872

Moskowitz & Grinblatt (1999). Do Industry Explain Momentum? The Journal of Finance. 54(4). 1249-1290.

Park & Irwin (2007). What do we know about the profitability of technical analysis? Journal of Economic Surveys. 21(4).786–826

Pedersen (2015). Efficiently Inefficient. Princeton University Press

Pennacchi (2008). Theory of Asset Pricing. Pearson/Addison-Wesley

Ratner & Leal (1999). Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. Banking & Finance. 23(12).1887–1905

Rouwenhorst (1998). International Momentum Strategies. The Journal of Finance. 53(1). 267-284.

Rouwenhorst (1999). Local Return Factors and Turnover in Emerging Stock Markets.The Journal of Finance. 54(4). 1439-1464.

Statman (1987). How Many Stocks Make a Diversified Portfolio? Journal of Financial and Quantitative Analysis. 353-363.

Swinkels (2002). International Industry Momentum. Journal of Asset Management. 3(2). 124-141.

Tharavanij, Siraprapasiri & Rajchamaha (2015). Performance of technical trading rules: evidence from Southeast Asian stock markets. SpringerPlus. 4(1). 1-40.

Yu, Nartea, Gan, Yao (2013). Predictive ability and profitability of simple technical trading rules: recent evidence from Southeast Asian stock markets. International Review of Economics and Finance 25. 356–371

Appendix

Table 18: Abbreviations of 155 stocks used in passive strategies

AAK	ABB	ADDT-B	AF-B	ALFA	ALIV-SDB	ALK-B	ALMB
AMBU-B	AMEAS	ASSA-B	ATCO-A	ATCO-B	ATRLJ-B	AXFO	AZA
AZN	BALD-B	BEIJ-B	BETS-B	BILL	BOL	CARL-A	CARL-B
CAST	CGCBV	CHR	COLO-B	CTY1S	DANSKE	DEMANT	DFDS
DSV	EKTA-B	ELISA	ELUX-B	ERIC-A	ERIC-B	FABG	FIA1S
FLS	FORTUM	FSKRS	G4S	GEN	GETI-B	GN	HEXA-B
HM-B	HOLM-B	HPOL-B	HUFV-A	HUH1V	HUSQ-A	HUSQ-B	ICA
INDT	INDU-A	INDU-C	INTRUM	INVE-A	INVE-B	JDAN	JM
JYSK	KBHL	KCR	KEMIRA	KESKOA	KESKOB	KIND-SDB	KINV-A
KINV-B	KLED	KLOV-A	KNEBV	LATO-B	LOOM-B	LUMI	LUN
LUND-B	LUPE	MAERSK-A	MAERSK-B	METSB	METSO	MTG-B	NCC-A
NCC-B	NDA-DK	NDA-FI	NDA-SE	NESTE	NET-B	NIBE-B	NOBI
NOKIA	NOKIA-SEK	NOLA-B	NOVO-B	NZYM-B	ORNAV	ORNBV	OSSR
OUT1V	PEAB-B	PNDORA	RATO-A	RATO-B	RBREW	RILBA	ROCK-A
ROCK-B	SAA1V	SAAB-B	SAMPO	SAND	SCA-A	SCA-B	SCHO
SEB-A	SEB-C	SECU-B	SHB-A	SHB-B	SIM	SKA-B	SKF-A
SKF-B	SOBI	SPNO	SWEC-B	SWED-A	SWMA	SYDB	TEL2-B
TELIA	TELIA1	TIETO	TIETOS	TIGO-SDB	TOP	TREL-B	TRYG
TYRES	UPM	UPONOR	VITR	VOLV-A	VOLV-B	VWS	WALL-B
WIHL	WRT1V	YIT					

Table 19: Abbreviations of 119 stocks used in active strategies

AAK	ABB	ADDT-B	AF-B	ALFA	ALIV-SDB	ALK-B	ALMB	AMEAS
ASSA-B	ATCO-A	ATCO-B	ATRLJ-B	AXFO	AZA	AZN	BALD-B	BILL
BOL	CARL-A	CARL-B	CAST	CGCBV	CHR	COLO-B	CTY1S	DANSKE
DEMANT	DSV	EKTA-B	ELISA	ERIC-A	FABG	FORTUM	FSKRS	G4S
GETI-B	HEXA-B	HPOL-B	HUFV-A	HUH1V	HUSQ-A	HUSQ-B	INDT	INDU-A
INDU-C	INTRUM	INVE-A	INVE-B	JDAN	JM	JYSK	KEMIRA	KESKOA
KESKOB	KIND-SDB	KLED	KNEBV	LATO-B	LOOM-B	LUMI	LUND-B	METSB
MTG-B	NCC-A	NCC-B	NDA-DK	NDA-FI	NDA-SE	NET-B	NIBE-B	NOBI
NOLA-B	NOVO-B	NZYM-B	ORNAV	OSSR	PEAB-B	RATO-B	RBREW	RILBA
ROCK-A	ROCK-B	SAA1V	SAAB-B	SAMPO	SAND	SCA-A	SCA-B	SCHO
SEB-A	SEB-C	SHB-A	SHB-B	SKA-B	SKF-A	SKF-B	SPNO	SWEC-B
SWED-A	SWMA	SYDB	TEL2-B	TELIA	TELIA1	TIETO	TIETOS	TIGO-SDB
TOP	TREL-B	TRYG	TYRES	UPM	UPONOR	VITR	VOLV-A	WALL-B
WIHL	WRT1V							

Table 20: Summary statistic of momentum strategy before the market

Strategy	*Count*	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
3 by 3	85	-53,8%	323,9%	44,9%	36,5%	57,9%	-6,0%	106,3%
3 by 6	82	-39,2%	128,6%	28,9%	23,8%	31,9%	-4,6%	69,6%
3 by 9	79	-23,3%	95,4%	26,4%	20,2%	26,4%	0,1%	70,6%
3 by 12	76	-14,5%	87,2%	25,0%	21,6%	24,1%	-2,8%	63,7%
6 by 3	82	-69,9%	264,1%	46,1%	38,9%	49,8%	-7,5%	106,1%
6 by 6	79	-36,1%	121,1%	32,8%	29,6%	32,4%	-2,6%	75,5%
6 by 9	76	-19,2%	92,2%	28,7%	26,9%	26,1%	-6,0%	64,8%
6 by 12	73	-12,3%	83,0%	26,3%	25,3%	22,1%	-0,4%	56,7%
9 by 3	79	-67,9%	270,7%	52,3%	43,5%	54,4%	1,1%	124,7%
9 by 6	76	-35,5%	132,1%	33,7%	31,3%	32,7%	-5,9%	70,8%
9 by 9	73	-23,9%	97,9%	27,3%	28,0%	26,2%	-7,8%	61,7%
9 by 12	70	-16,6%	79,1%	25,1%	25,1%	22,4%	-2,8%	57,6%
12 by 3	76	-64,8%	238,5%	44,0%	33,9%	54,4%	-13,1%	120,8%
12 by 6	73	-38,3%	131,6%	28,4%	27,5%	32,0%	-8,2%	66,8%
12 by 9	70	-22,8%	97,2%	24,6%	24,0%	26,6%	-7,0%	61,0%
12 by 12	67	-16,7%	77,1%	23,6%	22,9%	23,0%	-7,0%	51,7%

Table 21: Summary statistic of momentum strategy over the market

Strategy	*Count*	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
3 by 3	85	-39,7%	314,3%	31,4%	21,5%	53,9%	-11,5%	83,6%
3 by 6	82	-26,8%	117,9%	17,3%	15,3%	26,7%	-16,1%	46,9%
3 by 9	79	-26,7%	83,2%	15,7%	12,1%	22,4%	-11,9%	46,7%
3 by 12	76	-17,4%	69,7%	14,2%	12,9%	19,8%	-6,7%	44,4%
6 by 3	82	-42,4%	260,0%	32,9%	27,2%	42,9%	-10,7%	81,9%
6 by 6	79	-27,8%	107,7%	21,4%	21,8%	26,9%	-10,6%	55,5%
6 by 9	76	-21,4%	80,0%	18,4%	18,9%	21,9%	-11,2%	47,8%
6 by 12	73	-13,1%	65,5%	16,1%	14,2%	17,2%	-6,2%	38,7%
9 by 3	79	-40,3%	266,6%	39,2%	27,4%	47,9%	-9,3%	97,6%
9 by 6	76	-27,8%	114,1%	22,8%	21,2%	27,2%	-14,2%	61,4%
9 by 9	73	-18,8%	85,7%	17,6%	17,3%	21,7%	-9,6%	43,5%
9 by 12	70	-16,6%	61,7%	15,1%	13,6%	18,0%	-5,4%	37,7%
12 by 3	76	-37,3%	190,1%	31,8%	23,7%	46,7%	-15,5%	85,8%
12 by 6	73	-25,1%	95,7%	18,4%	17,5%	26,7%	-17,5%	50,5%
12 by 9	70	-23,6%	65,5%	15,2%	10,9%	21,5%	-11,7%	41,6%
12 by 12	67	-18,2%	49,3%	14,1%	13,8%	18,7%	-10,4%	42,3%

Table 22: Mean return, risk and Sharpe ration of momentum strategies

Strategy	*Avg. return, strategy*	*Avg. return, market*	*Avg. st. dev., strategy*	*Avg. st. dev., market*	*Sharpe, strategy*	*Sharpe, market*
3 by 3	44,9%	13,5%	57,9%	25,6%	0,78	0,53
3 by 6	28,9%	11,6%	31,9%	15,3%	0,91	0,76
3 by 9	26,4%	10,8%	26,4%	11,5%	1,00	0,93
3 by 12	25,0%	10,7%	24,1%	9,7%	1,04	1,11
6 by 3	46,1%	13,3%	49,8%	25,3%	0,93	0,52
6 by 6	32,8%	11,4%	32,4%	15,4%	1,01	0,74
6 by 9	28,7%	10,3%	26,1%	11,2%	1,10	0,92
6 by 12	26,3%	10,2%	22,1%	9,5%	1,19	1,08
9 by 3	52,3%	13,1%	54,4%	25,5%	0,96	0,51
9 by 6	33,7%	10,8%	32,7%	15,4%	1,03	0,70
9 by 9	27,3%	9,7%	26,2%	11,0%	1,04	0,88
9 by 12	25,1%	10,0%	22,4%	9,6%	1,12	1,04
12 by 3	44,0%	12,2%	54,4%	25,3%	0,81	0,48
12 by 6	28,4%	10,0%	32,0%	15,2%	0,89	0,66
12 by 9	24,6%	9,4%	26,6%	11,0%	0,93	0,85
12 by 12	23,6%	9,5%	23,0%	9,5%	1,03	1,00

Table 23: Summary statistic of MV strategy before the market

Strategy	*Count*	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
3 by 3	85	-65,3%	343,1%	43,0%	32,4%	65,6%	-14,0%	111,8%
3 by 6	82	-38,7%	138,9%	26,9%	24,6%	32,5%	-10,2%	68,5%
3 by 9	79	-26,9%	100,0%	26,4%	22,4%	27,6%	-5,0%	65,4%
3 by 12	76	-16,8%	88,8%	23,8%	18,4%	25,1%	-2,9%	63,6%
6 by 3	82	-67,9%	293,6%	43,1%	42,0%	50,2%	-2,0%	94,7%
6 by 6	79	-36,4%	128,8%	30,5%	25,7%	33,9%	-13,8%	79,7%
6 by 9	76	-24,3%	96,2%	26,4%	26,4%	28,6%	-10,1%	64,8%
6 by 12	73	-21,4%	77,9%	23,9%	19,3%	24,8%	-5,5%	60,0%
9 by 3	79	-64,0%	223,7%	40,6%	36,2%	48,3%	-16,3%	103,3%
9 by 6	76	-55,7%	148,1%	27,2%	27,4%	36,7%	-18,1%	70,8%
9 by 9	73	-43,3%	82,0%	22,9%	21,4%	28,5%	-11,8%	61,4%
9 by 12	70	-40,7%	72,5%	23,3%	22,2%	24,9%	-11,1%	53,9%
12 by 3	76	-67,2%	285,4%	41,3%	29,9%	58,8%	-22,7%	110,5%
12 by 6	73	-45,2%	98,7%	25,3%	22,8%	34,4%	-21,6%	70,9%
12 by 9	70	-41,0%	93,3%	23,4%	19,0%	29,2%	-12,8%	61,7%
12 by 12	67	-40,5%	75,3%	23,5%	26,5%	26,2%	-11,1%	54,9%

Table 24: Summary statistic of MV strategy over the market

Strategy	*Count*	*Min. return*	*Max. return*	*Mean return*	*Median return*	*St. deviation of return*	*Percentile 10*	*Percentile 90*
3 by 3	85	-44,0%	333,5%	29,5%	18,8%	59,1%	-21,1%	70,9%
3 by 6	82	-31,3%	137,7%	15,3%	13,5%	28,3%	-16,6%	51,8%
3 by 9	79	-23,9%	78,0%	15,6%	14,1%	24,2%	-11,3%	47,4%
3 by 12	76	-23,2%	73,6%	13,1%	9,9%	21,2%	-12,4%	43,3%
6 by 3	82	-44,4%	281,1%	29,8%	28,5%	46,0%	-20,8%	73,8%
6 by 6	79	-26,4%	110,6%	19,2%	20,0%	30,2%	-18,9%	54,4%
6 by 9	76	-29,0%	69,5%	16,2%	16,7%	25,1%	-15,5%	49,1%
6 by 12	73	-24,5%	62,7%	13,7%	10,2%	21,1%	-9,7%	41,4%
9 by 3	79	-58,9%	214,2%	27,5%	23,0%	43,3%	-20,5%	78,5%
9 by 6	76	-54,0%	117,9%	16,4%	15,7%	31,9%	-23,0%	56,0%
9 by 9	73	-43,4%	65,3%	13,2%	15,9%	24,4%	-18,4%	40,8%
9 by 12	70	-42,7%	50,2%	13,4%	11,3%	21,0%	-11,5%	39,4%
12 by 3	76	-71,3%	275,8%	29,1%	21,9%	53,9%	-30,9%	92,8%
12 by 6	73	-43,5%	89,4%	15,3%	16,5%	29,9%	-24,4%	51,3%
12 by 9	70	-41,0%	71,8%	14,0%	13,5%	24,8%	-16,5%	44,8%
12 by 12	67	-42,5%	53,9%	14,0%	15,8%	22,2%	-13,0%	42,2%

Table 25: Mean return, risk and Sharpe ration of MV strategies

Strategy	*Avg. return, strategy*	*Avg. return, market*	*Avg. st. dev., strategy*	*Avg. st. dev., market*	*Sharpe, strategy*	*Sharpe, market*
3 by 3	43,0%	13,5%	65,6%	25,6%	0,66	0,53
3 by 6	26,9%	11,6%	32,5%	15,3%	0,83	0,76
3 by 9	26,4%	10,8%	27,6%	11,5%	0,96	0,93
3 by 12	23,8%	10,7%	25,1%	9,7%	0,95	1,11
6 by 3	43,1%	13,3%	50,2%	25,3%	0,86	0,52
6 by 6	30,5%	11,4%	33,9%	15,4%	0,90	0,74
6 by 9	26,4%	10,3%	28,6%	11,2%	0,92	0,92
6 by 12	23,9%	10,2%	24,8%	9,5%	0,96	1,08
9 by 3	40,6%	13,1%	48,3%	25,5%	0,84	0,51
9 by 6	27,2%	10,8%	36,7%	15,4%	0,74	0,70
9 by 9	22,9%	9,7%	28,5%	11,0%	0,80	0,88
9 by 12	23,3%	10,0%	24,9%	9,6%	0,94	1,04
12 by 3	41,3%	12,2%	58,8%	25,3%	0,70	0,48
12 by 6	25,3%	10,0%	34,4%	15,2%	0,74	0,66
12 by 9	23,4%	9,4%	29,2%	11,0%	0,80	0,85
12 by 12	23,5%	9,5%	26,2%	9,5%	0,90	1,00

Table 26: Abbreviations of the first 8 stocks, for the first 40 periods (out of 79) of 9 by 3 momentum strategy

SOBI	GEN	GN	ALMB	METSB	KCR	COLO-B	ELUX-B
SOBI	GEN	GN	ALMB	COLO-B	SIM	RBREW	HPOL-B
SOBI	GEN	PNDORA	COLO-B	SIM	HPOL-B	TRYG	CHR
PNDORA	SOBI	GEN	HPOL-B	ORNBV	ORNAV	COLO-B	GN
PNDORA	GEN	SOBI	ALMB	SCA-A	SCA-B	SEB-A	HPOL-B
PNDORA	GEN	ICA	SOBI	SEB-A	SEB-C	NOLA-B	ORNBV
PNDORA	GEN	SOBI	SCHO	ALMB	ICA	NOBI	HPOL-B
PNDORA	GEN	SOBI	VWS	ALMB	SPNO	SIM	ICA
GEN	PNDORA	VWS	ICA	SIM	NOBI	HPOL-B	SOBI
PNDORA	GEN	VWS	ICA	HPOL-B	NOLA-B	NOBI	ROCK-A
VWS	PNDORA	GEN	NOBI	INTRUM	ICA	ROCK-A	ROCK-B
VWS	GEN	VITR	ICA	NOBI	INTRUM	PNDORA	KINV-A
VWS	GEN	NOBI	PNDORA	ICA	INTRUM	VITR	SOBI
VWS	GEN	VITR	NOKIA-SEK	PNDORA	NOKIA	JYSK	SPNO
VWS	NOKIA-SEK	GEN	NOKIA	VITR	PNDORA	SOBI	KINV-B
VWS	NOKIA-SEK	NOKIA	KINV-B	KINV-A	PNDORA	VITR	SOBI
VWS	NOKIA-SEK	NOKIA	SOBI	PNDORA	ALK-B	AZA	AMBU-B
VWS	NOKIA-SEK	NOKIA	SOBI	PNDORA	ALK-B	AMBU-B	AZA
VWS	AMBU-B	NOKIA-SEK	NOKIA	PNDORA	AZA	SOBI	RBREW
VWS	NOKIA-SEK	NOKIA	AMBU-B	SAAB-B	NIBE-B	AZA	VITR
VWS	NOKIA-SEK	NOKIA	PNDORA	SOBI	AMBU-B	ALK-B	BALD-B
VWS	PNDORA	AMBU-B	BALD-B	NIBE-B	OUT1V	ALK-B	SAAB-B
VWS	OUT1V	AMBU-B	OSSR	BALD-B	ALK-B	AZN	NIBE-B
OUT1V	BALD-B	AMBU-B	OSSR	ORNBV	ORNAV	VWS	PNDORA
PNDORA	OUT1V	VITR	ORNBV	ORNAV	VWS	OSSR	AMBU-B
VITR	PNDORA	NET-B	OSSR	ELUX-B	ICA	AXFO	HUSQ-B
OSSR	NET-B	VITR	PNDORA	ELUX-B	KIND-SDB	LOOM-B	AMBU-B
VITR	NET-B	AMBU-B	ELUX-B	GEN	KIND-SDB	OSSR	BALD-B
GEN	NET-B	NESTE	OSSR	METSB	AMBU-B	VITR	TRYG
GEN	BOL	METSB	OSSR	NET-B	BALD-B	ELUX-B	DFDS
GEN	NET-B	BOL	NESTE	METSB	ALMB	AMBU-B	BALD-B

GEN	PNDORA	NET-B	NESTE	NOBI	AMBU-B	BALD-B	DFDS
GEN	AMBU-B	NET-B	NOBI	METSB	BOL	DFDS	PNDORA
GEN	DFDS	AMBU-B	NET-B	METSB	PNDORA	SIM	OSSR
GEN	DFDS	VWS	METSB	NET-B	AMBU-B	AMEAS	NOBI
GEN	DFDS	SIM	AMBU-B	BETS-B	NET-B	VWS	NOBI
SIM	DFDS	NET-B	GEN	PNDORA	BETS-B	VWS	LUN
NET-B	SIM	PNDORA	DFDS	TYRES	VWS	GEN	KIND-SDB
NET-B	DFDS	GEN	KIND-SDB	SIM	VWS	LUN	VITR
KIND-SDB	DFDS	VITR	GEN	FIA1S	SIM	VWS	NET-B

Script for 3 by 3 momentum strategy

```
load MomentumInput
start=4
finish=88
for k=start:finish
 IndexFirstHist=find(Date==(k-3));
 shi(1,k-3)=IndexFirstHist(1);
 IndexLastHist = find(Date==(k-1));
 ehi(1,k-3)=IndexLastHist(end);
end;
for k=1:length(shi)
HistRet=Gains(shi(k):ehi(k),1:end);
GeomRetHisDaily(k,:)=geomean(HistRet,1);
  for i=1:length(Assets)
   GeomGainHisAnn(k,i)=GeomGainHisDaily(k,i)^(250);
  end;
 GeomPureRetHisAnn=GeomRetHisAnn-1;
 TopPerf(k,:)=sort(GeomPureRetHisAnn(k,:),'descend')
 for i=1:10
     IndexMomentum (k,i)= find(GeomPureRetHisAnn(k,:)==TopPerf(k,i));
 end;
end;
 Winners=Assets(IndexMomentum);
for k=start:finish
 IndexFirstHold=find(Date==k)
 sho(1,k-3)=IndexFirstHold(1)
IndexLastHold = find(Date==k+3-1)
eho(1,k-3)=IndexLastHold(end)
 end
 for k=1:length(sho)
 GainsHold=Gains(sho(k):eho(k),IndexMomentum(k,:))
 MarketHoldGains=MarketGains(sho(k):eho(k),1)
 MarketGainsHolDaily(k,1)=geomean(MarketHoldGains,1)
GeomGainsHolDaily(k,:)=geomean(GainsHold,1)
for i=1:10
   GeomRetHoldAnn(k,i)=GeomGainsHolDaily(k,i)^(250)
end
RetPortfolio(k,1)=sum(GeomRetHoldAnn(k,:))/10-1
 Rf=0
 NetReturnsHist=GainsHold-1
 PortfolioVariance(k,1)=portvar(NetReturnsHist)   PortfolioRisk(k,1)=sqrt(PortfolioVariance(k,1))
 AnnualPortfolioRisk(k,1)=PortfolioRisk(k,1)*sqrt(250)
 AnnualSharpe(k,1)=(RetPortfolio(k,1)-Rf)/AnnualPortfolioRisk(k,1)
 end
  MarketRetHolAnnual=MarketRetHolDaily.^250-1;
  RetPortfolioMinusMarket=RetPortfolio-MarketRetHolAnnual;
```

```
 Nobs=size(sho,2)
 MinHold=min(RetPortfolio)
 MaxHold=max(RetPortfolio)
 MeanHold=mean(RetPortfolio)
 StDvHold=std(RetPortfolio)
 Percent10Hold=prctile(RetPortfolio,10)
 Percent90Hold=prctile(RetPortfolio,90)
 MedianHold=median(RetPortfolio)


 MinAM=min(RetPortfolioMinusMarket)
 MaxAM=max(RetPortfolioMinusMarket)
 MeanAM=mean(RetPortfolioMinusMarket)
 StDvAM=std(RetPortfolioMinusMarket)
 Percent10AM=prctile(RetPortfolioMinusMarket,10)
 Percent90AM=prctile(RetPortfolioMinusMarket,90)
 MedianAM=median(RetPortfolioMinusMarket)
 MeanHold;
 StDvHold;
 AvgSharpePortfolio=MeanHold/StDvHold
 MeanMarket=mean(MarketRetHolAnnual);
 AvgMarketRisk=std(MarketRetHolAnnual);
 AvgSharpeMarketPortfolio=MeanMarket/AvgMarketRisk
```

Script for 3 by 3 MV strategy

```
load MomentumInput
start=4
finish=88
AssetList=Assets(1,1:end);
for k=start:finish
 IndexFirstHist=find(Date==(k-3));
 shi(1,k-3)=IndexFirstHist(1);
 IndexLastHist = find(Date==(k-1));
 ehi(1,k-3)=IndexLastHist(end);
end;
for k=1:length(shi)
HistRet=Gains(shi(k):ehi(k),1:end);
GeomRetHisDaily(k,:)=geomean(HistRet,1);
  for i=1:length(Assets)
   GeomRetHisAnn(k,i)=GeomRetHisDaily(k,i)^(250);
  end;
 GeomPureRetHisAnn=GeomRetHisAnn-1;
 TopPerf(k,:)=sort(GeomPureRetHisAnn(k,:),'descend')
 for i=1:10
    IndexMomentum (k,i)= find(GeomPureRetHisAnn(k,:)==TopPerf(k,i));
 end ;
```

```
end;
Winners=Assets(IndexMomentum)
ReturnsAll=Gains-1;
for k=1:length(shi);
  ReturnsHistWinnersMatrix=ReturnsAll(shi(k):ehi(k),IndexMomentum(k,:));
  PortfolioVarianceHistWinners(1,k)=portvar(ReturnsHistWinnersMatrix);
  PortfolioRiskHist(1,k)=sqrt(PortfolioVarianceHistWinners(1,k));
  AnnualPortfolioRiskHist(1,k)=PortfolioRiskHist(1,k)*sqrt(250);
     Rf=0;
   p = Portfolio('AssetList', Assets(1,IndexMomentum(k,:)),'RiskFreeRate', Rf);
   p = p.estimateAssetMoments(ReturnsHistWinnersMatrix);
   p = setDefaultConstraints(p);
   portffrontier= p.estimateFrontier(300);
   [portrisk(:,k), portret(:,k)] = p.estimatePortMoments(portffrontier);
   portriskannual(:,k)=portrisk(:,k)*sqrt(250);
   [val(1,k),idx(1,k)]=min(abs(portriskannual(:,k)-AnnualPortfolioRiskHist(1,k)));
   OptimalHistWeights(:,k)=portffrontier(:,idx(1,k));
end
for k=start:finish
 IndexFirstHold=find(Date==k);
 sho(1,k-3)=IndexFirstHold(1); %
IndexLastHold = find(Date==k+3-1);
eho(1,k-3)=IndexLastHold(end);
 end ;
 for k=1:length(sho)
 GainsHold=Gains(sho(k):eho(k),IndexMomentum(k,:));
 MarketHoldGains=MarketGains(sho(k):eho(k),1);
 MarketGainHolDaily(k,1)=geomean(MarketHoldGains,1);
 GeomGainHolDaily(k,:)=geomean(GainsHold,1);
for i=1:10
   GeomRetHoldAnn(k,i)=GeomGainsHolDaily(k,i)^(250);
end
 RetPortfolio(k,1)=GeomGainHoldAnn(k,:)*OptimalHistWeights(:,k)-1;
 end
  MarketRetHolAnnual=MarketRetHolDaily.^250-1
  RetPortfolioMinusMarket=RetPortfolio-MarketRetHolAnnual
  %%HoldingReport
  Nobs=size(sho,2)
  MinHold=min(RetPortfolio)
  MaxHold=max(RetPortfolio)
  MeanHold=mean(RetPortfolio)
  StDvHold=std(RetPortfolio)
  Percent10Hold=prctile(RetPortfolio,10)
  Percent90Hold=prctile(RetPortfolio,90)
  MedianHold=median(RetPortfolio)
  %%%%GivenMarketReturn
  MinAM=min(RetPortfolioMinusMarket);
  MaxAM=max(RetPortfolioMinusMarket);
  MeanAM=mean(RetPortfolioMinusMarket);
```

```
  StDvAM=std(RetPortfolioMinusMarket);
  Percent10AM=prctile(RetPortfolioMinusMarket,10);
  Percent90AM=prctile(RetPortfolioMinusMarket,90);
  MedianAM=median(RetPortfolioMinusMarket);
  MeanHold;
  StDvHold;
  AvgSharpePortfolio=MeanHold/StDvHold
  MeanMarket=mean(MarketRetHolAnnual);
  AvgMarketRisk=std(MarketRetHolAnnual);
  AvgSharpeMarketPortfolio=MeanMarket/AvgMarketRisk;
```

Script for MACD strategy (once per month)

```
load Input2
[MACDLine,SignalLine] = macd(Prices);
MACDcr=MACDLine(34:end,:);
Signalcr=SignalLine(34:end,:);
Pricescr=Prices(34:end,:);
Datecr=Date(34:end,:);
Gainscr=Gains(34:end,:);
MarketGainscr=MarketGains(34:end,:);
start=2
finish=91
for k=start:finish
 IndexFirst=find(Datecr==k);
 shi(1,(k-1))=IndexFirst(1);
 IndexLast = find(Datecr==k);
 ehi(1,(k-1))=IndexLast(end);
end;
for i=1:length(shi)
for p=1:length(Assets)
            InvScore(i,p)=(MACDcr(shi(i),p)-Signalcr(shi(i),p))/Pricescr(shi(i),p);
end
 TopPerf(i,:)=sort(InvScore(i,:),'descend');
for p=1:10
     IndexMomentum(i,p)=find(InvScore(i,:)==TopPerf(i,p));
 end;
end
for i=1:length(shi)
    GainsDailyMatrix=Gainscr(shi(i):ehi(i),IndexMomentum(i,:));
    GeomGainsDaily(i,:)=geomean(GainsMonthMatrix,1);
    GeomGainsDailyPor(i,:)=GeomGainsDaily(i,:).^250
    GeomGainsAnnual(i,:)=(sum(GeomGainsDailyPor(i,:)))/10
    MarketHoldGains=MarketGainscr(shi(i):ehi(i),1)
    MarketRetHolDaily(i,1)=geomean(MarketHoldGains,1)
end
```

```
Returns=GeomGainsAnnual-1
  Nobs=size(shi,2);
  MinHold=min(Returns);
  MaxHold=max(Returns);
  MeanHold=mean(Returns);
  StDvHold=std(Returns);
  Percent10Hold=prctile(Returns,10);
  Percent90Hold=prctile(Returns,90);
  MedianHold=median(Returns);
Rf=0
Sharpe=(MeanHold-Rf)/StDvHold
MarketRetHolAnnual=MarketRetHolDaily.^250-1;
MarketReturnAnn=mean(MarketRetHolDaily.^250)
MarketRisk=std(MarketRetHolDaily.^250)
SharpeMarket=(MarketReturnAnn-1)/MarketRisk
RetPortfolioMinusMarket=Returns-MarketRetHolAnnual;
 MinAM=min(RetPortfolioMinusMarket);
  MaxAM=max(RetPortfolioMinusMarket);
  MeanAM=mean(RetPortfolioMinusMarket);
  StDvAM=std(RetPortfolioMinusMarket);
  Percent10AM=prctile(RetPortfolioMinusMarket,10);
  Percent90AM=prctile(RetPortfolioMinusMarket,90);
  MedianAM=median(RetPortfolioMinusMarket);
 SharpeAM=(MeanAM)/StDvAM
```

Script for Chaikin strategy (once per month)

```
load DataInput2
 for i=1:length(Assets);
  MoneyFlowMultuplier(1,i)=(Close(1,i)-Low(1,i))-(High(1,i)-Close(1,i))/(High(1,i)-Low(1,i));
  MoneyFlowVolume(1,i)=MoneyFlowMultuplier(1,i)*Volume(1,i);
  AD(1,i)=MoneyFlowVolume(1,i);
 end;
  for k=1:length(Assets);
  for i=2:length(Close);
  MoneyFlowMultuplier(i,k)=(Close(i,k)-Low(i,k))-(High(i,k)-Close(i,k))/(High(i,k)-Low(i,k));
  MoneyFlowVolume(i,k)=MoneyFlowMultuplier(i,k)*Volume(i,k);
  AD(i,k)=AD(i-1,k)+MoneyFlowVolume(i,k);
  end;
  end;
start=2
finish=91
for k=start:finish;
 IndexFirst=find(Date==k);
 shi(1,(k-1))=IndexFirst(1);
 IndexLast = find(Date==k);
 ehi(1,(k-1))=IndexLast(end);
end;
```

```
EMA3=tsmovavg(AD,'e',3,1);
EMA10=tsmovavg(AD,'e',10,1);
ChaikinOsc=EMA3-EMA10;
for i=1:length(shi);
for p=1:length(Assets);
        InvScore(i,p)=ChaikinOsc(shi(i),p);
end
TopPerf(i,:)=sort(InvScore(i,:),'descend');
end
for i=1:length(shi);
for p=1:10
     IndexMomentum(i,p)=find(InvScore(i,:)==TopPerf(i,p));
 end ;
end
for i=1:length(shi)
    GainsMonthMatrix=Gains(shi(i):ehi(i),IndexMomentum(i,:));
    GeomGainsDaily(i,:)=geomean(GainsMonthMatrix,1);
    GeomGainsDailyPor(i,:)=GeomGainsDaily(i,:).^250
    GeomGainsAnnual(i,:)=(sum(GeomGainsDailyPor(i,:)))/10
    MarketHoldGains=MarketGains(shi(i):ehi(i),1)
    MarketRetHolDaily(i,1)=geomean(MarketHoldGains,1)
end
  Returns=GeomGainsAnnual-1
  Nobs=size(shi,2);
  MinHold=min(Returns);
  MaxHold=max(Returns);
  MeanHold=mean(Returns);
  StDvHold=std(Returns);
  MedianHold=median(Returns)
Rf=0
Sharpe=(MeanHold-Rf)/StDvHold
MarketRetHolAnnual=MarketRetHolDaily.^250-1;
MarketReturnAnn=mean(MarketRetHolDaily.^250)
MarketRisk=std(MarketRetHolDaily.^250)
SharpeMarket=(MarketReturnAnn-1)/MarketRisk
RetPortfolioMinusMarket=Returns-MarketRetHolAnnual;
  MinAM=min(RetPortfolioMinusMarket);
  MaxAM=max(RetPortfolioMinusMarket);
  MeanAM=mean(RetPortfolioMinusMarket);
  StDvAM=std(RetPortfolioMinusMarket);
  Percent10AM=prctile(RetPortfolioMinusMarket,10);
  Percent90AM=prctile(RetPortfolioMinusMarket,90);
  MedianAM=median(RetPortfolioMinusMarket)
```