BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Master in Finance

Quantitative Momentum in the Nordic Markets

Navn: Felipe Pasquotto de Andrade, Lars Iver Strand

Start: 01.01.2018 09.00

Finish: 15.01.2018 12.00

TABLE OF CONTENTS

ABSTRACT

This research aims to discover if momentum strategies built on empirical evidence from academic research yield better returns than the market for a Norwegian investor. We study the performance of two different momentum strategies applied to the Norwegian, Swedish, Danish, Finnish and Nordic stock markets from 29 December 1995 to 29 December 2017: (i) buy winners derived from the method of Jegadeesh & Titman (1993); and (ii) buy high-quality winners derived from the method of Gray & Vogel (2016). On each strategy, we analyse the returns obtained from the combination of four formation periods *J* (3, 6, 9 and 12 months) with four holding periods *K* (3, 6, 9 and 12 months).

Keywords: momentum, quantitative momentum, asset pricing, relative strength strategy

1 INTRODUCTION

Throughout history, the main goal of investors has been to beat the market by predicting the market direction. Though an endless number of strategies exists, most of them can be gathered into two main categories; fundamental- and technical analysis. Fundamentalists are often referred to as value investors, and their strategy basically involves buying stocks trading at a low price versus various fundamentals. For a value investor, fundamentals lead and prices follow. Technical analysts on the other hand often described to as speculators due to their short-term focus, buy securities because they “act” well and sell when they do not. This strategy, generally labelled as “momentum”, is with other words so straightforward that even your grandmother would understand it - buy the winners.

Can it be this simple? Does this strategy really work? Many successful and highly qualified investors within the art of finance have most certainly argued against its existence. The famous value-investor guru, Benjamin Graham, expressed his thoughts about the topic in his reputable book “The Intelligent Investor”:

> The one principle that applies to nearly all these so-called “technical approaches” is that one should buy because a stock or the market has gone up and one should sell because it has declined. This is the exact opposite of sound business sense everywhere else, and it is most unlikely that it can lead to lasting success on Wall Street. (Graham & Zweig, 2006, p. 2-3)

However, today the momentum-effect is seen as one of the most important documented anomalies (Novy-Marx, 2015) and has even been acknowledged as the premier anomaly by no other than the father of Efficient Market Hypothesis (EMH), Eugene Fama. In this thesis, we explore the very existence of this anomaly in the Nordics and determine if momentum strategies built on the publications of Jegadeesh & Titman (1993) and Gray & Vogel (2016) outperform the market. Going forward, we will dig into the intriguing universe of momentum investing.

Momentum literature contains two contradictory phenomena which are argued to have a long-term prevalence in time series data of asset prices. The first is the above mentioned momentum-effect, which was documented by Jegadeesh & Titman's groundbreaking study in 1993. The latter, known as the "contrarian"-effect, relies on price reversals in assets and had its breakthrough with research done by De Bondt & Thaler (1985) and Lehman (1990). Jegadeesh & Titman confirmed that their previous findings still existed through an updated study in 2001, and Geczy & Samonov (2016) found evidence that these effects appear to hold over long time periods. Rouwenhorst (1998), Rouwenhorst (1999), and Asness, Moskowitz & Pedersen (2013) concluded the effects exist on different stock markets and across various asset classes such as bonds, commodities and currencies.

From an investor's perspective, both effects can be exploited by constructing long-only, short-only or self-financing portfolios. To create the latter one need to buy winners and sell past losers (momentum effect), or buy past losers and sell past winners (contrarian effect). Given the contradictory nature of the effects, only one of them can prevail at the same time. This leaves the investor with two critical decisions: (i) which strategy to invest according to, and (ii) how to time the investments.

Researchers debate over different explanations of these effects. Most of the discussion revolves around the question whether the results are consistent with a risk-based explanation or due to behavioural bias from the investors. This leads to the discussion of market efficiency and the viability of the EMH. Though this thesis hopefully can contribute and add value to the extensive topic and discussion of the EMH, the main goal is to discover if a quantitative momentum strategy is a profitable choice for investors.

We are puzzled by the fact that even though momentum strategies have proven its profitability over and over historically, it does not seem to have convinced Norwegian investors to a large extent. Our aim is to develop and study the effect of a practical long-only momentum-strategy which is accessible for the average investor. We want to determine if this momentum strategy can beat the market in each separate country and combined in a Nordic portfolio, using the returns of the companies listed on Oslo Børs, Stockholm Stock Exchange, Copenhagen Stock Exchange and Helsinki Stock Exchange between January 1996 and December 2017. The main contribution to existing literature is an updated study on momentum effect for the Nordic markets, with the addition of a new strategy which, to our best knowledge, has not been tested before in the Nordic markets.

Specifically, this research addresses the following questions:

1. *Are the "Conventional Momentum Strategy*[1]*" and "Quantitative Momentum Strategy*[2]*" profitable?*
2. *Is the "Quantitative Momentum Strategy" more profitable than the "Conventional Momentum Strategy"?*
3. *Does the more profitable strategy yield abnormal returns (alpha) after adjusting for asset pricing models such as the CAPM and Fama & French 3-factor model?*

The thesis is organized as follows: Chapter 2 reviews the relevant literature; Chapter 3 describes the data; Chapter 4 presents the methods applied; Chapter 5 gives the schedule for the coming tasks related to the master thesis; Chapter 6 lists the references used in the development of this research.

[1] Built on Jegadeesh & Titman (1993)
[2] Built on Gray & Vogel (2016)

2 LITERATURE REVIEW

Relative strength strategies, which assume that past winners (losers) tend to be future winners (losers), have been around for a long time. Robert Levy (1967, p. 602) concluded that "the profits attainable by purchasing the historically strongest stocks are superior to the profits from random selection". Despite Levy's early contribution on relative strength strategies, further research on the topic went dormant for a couple of decades. The main reason for this was the development and increasingly dominating position of the Efficient Market Hypothesis (EMH).

The EMH is one of the most debated topics in financial theory. The foundation of the EMH is that the price of an asset reflects all available information, making it impossible for investors to obtain any abnormal return, i.e. any return greater than the risk-adjusted return of the determined asset. This concept of market efficiency was created by Fama (1970) and quickly flourished across academia. Consequently, most of the academic research done during the 70s and 80s suggested that the market was efficient.

However, the development of technology and computers in the mid-80s allowed researchers to intensify their studies, and they found evidence of the existence of abnormal behaviour in asset returns. These abnormal behaviours began to challenge some of the elementary circumstances of the efficient market hypothesis. It was within this scenario, where several studies pointed out the existence of anomalies in the market, that the theory of behavioural finance arose.

Behavioural finance incorporates concepts from psychology, sociology and other sciences, with the objective to approximate the financial theory to the reality of the financial markets. In other words, behavioural finance uses psychology-based theories to analyse stock market anomalies and investment decisions. The theory takes into consideration that investors may show irrational behaviour, hence affecting the stock prices.

The vast majority of behavioural finance literature attributes the momentum effect to either an underreaction or overreaction to information (Hong, Lim, & Stein, 2000, and Jegadeesh & Titman, 2001). To illustrate the reaction to information, consider the story of a frog placed in a pot of water. If the water is boiling, the frog will immediately jump out. However, if the water holds room temperature, and is gradually heated to the boiling point, the frog will remain still in the pot until it is fully cooked. The story serves as a good analogy to how investors react to stock price changes. A stock with an immediate 100% gain would quickly attract investor attention and the new stock price would typically reflect approximately fair value. However, if a stock slowly achieves a 100% return, it would attract less attention and would be more likely to be priced less than fundamental value. Da, Gurun & Warachka (2014) investigated the limited attention of investors to gradual information diffusion and described their "frog-in-the-pan" hypothesis as follows:

> A series of frequent gradual changes attracts less attention than infrequent dramatic changes. Investors therefore underreact to continuous information. (Da et al., 2014, p. 1)

The researchers concluded that momentum strategies that focus on the path-dependency of momentum generate a much stronger momentum effect. This goes in line with the findings of Barberis, Shleifer & Vishny (1998), which suggest that the momentum anomaly is due to underreaction to positive news.

The resurrection of Robert Levy's relative strength strategy, later renamed as "momentum", was formalized in the early 1990s through Jegadeesh & Titman's publication "Returns to Buying Winners and Selling Losers: Implications for Market Efficiency." In this paper, the authors demonstrated statistical evidence for a trading strategy, with a lookback period in the range between one to four quarters, that outperformed their peers in comparative future periods. The strategy was to buy equities that had performed well in the past and to sell equities that had performed poorly. They attributed the excess returns to an investor underreaction to firm-specific information. Since Jegadeesh & Titman's publication, academia has searched for the answer of whether the prevalence of momentum implies that markets are inefficient at processing information, or if the premium is reasonable compensation for bearing systematic risk. While the theoretical explanations regarding why the existence of the momentum-effect persist remain heavily debated, the existence itself is considered one of the main anomalies observed in stock markets around the world, even referred to as the "premier anomaly" by Fama himself (Fama & French, 2008).

The momentum anomaly has been thoroughly researched the last decades and as a result of that the list of studies that document the momentum effect is extensive. The bulk of the existing literature suggests that momentum and contrarian effects are widely present both geographically and across asset classes.

Rouwenhorst (1998) examined the momentum effect in 12 European countries with data ranging from 1980-1995. With the use of Jegadeesh & Titman's methodology, he found the presence of the momentum effect on a 3-12 month horizon in all countries. In 2001, Jegadeesh & Titman verified their previous findings and documented that their strategy still works, suggesting that the results did not suffer from bias in the database. Fuertes, Miffre & Tan (2009) showed that the momentum strategy features a negatively skewed leptokurtic return distribution that leaves investors with irregular but severe losses. Daniel & Moskowitz (2016) found that both momentum and contrarian strategies yield abnormal returns, however, the strategies feature overhanging downside risk exposures. Asness et al. (2013) found consistent return premiums in both the value and momentum investments across 8 different markets. In addition, they found that value and momentum are negatively correlated, suggesting that momentum (long-only) strategies are highly desirable in a portfolio context when they are pooled with value strategies.

Twenty years after the discovery by Jegadeesh & Titman (1993), Asness, Frazzini, Israel & Moskowitz (2014) clarified a big part of what is known about the momentum effect and refuted some of their myths, using results of several academic works and public information available about the topic. Geczy & Samonov (2015) analysed several asset classes between 1800 and 2014, including 47 stock indexes from different countries, 43 bond indexes, 76 commodities, 301 global sectors indexes, 34795 American stocks. The data of this study confirmed the momentum significance in these assets in the long term, but with an increase in the risk of this strategy.

In recent years researchers have explored alternative methods of exploiting the momentum anomaly. Gray & Vogel (2016) developed the quantitative momentum strategy based on several empirical evidences from the academic literature, with ties back to behavioural finance in a coherent and logical way. Their approach is inspired by Jegadeesh & Titman (1993) and Da et al. (2014) and it can be summarized as a strategy that seeks to buy stocks with the highest quality momentum. Antonacci (2017) apply a strategy called "dual momentum" where he combines both cross-sectional and time-series momentum using only stocks. The rationale for the combination is to avoid the large drawdowns of the cross-sectional momentum long-only strategy. The author claims that this strategy substantially outperforms both cross-sectional and time-series used on a stand-alone basis. Blitz, Hanauer & Vidojevic (2017) claim that sorting stocks into portfolios based on their idiosyncratic returns generate comparable average returns, with half the volatility of the conventional momentum strategy. Their empirical results support the underreaction hypothesis for the idiosyncratic premium, and they document significant idiosyncratic momentum profits in international equity markets.

3 DATA

3.1 Data Source

All data used in this research are exported from Datastream for the period from 29 December 1995 to 29 December 2017.

3.2 Sample "Investable Universe"

The dataset comprises all listed and delisted stocks on Oslo Stock Exchange (Norway), Stockholm Stock Exchange (Sweden), Copenhagen Stock Exchange (Denmark) and Helsinki Stock Exchange (Finland). For each stock, we collect its daily total index return (RI)[3], monthly market capitalisation (MCap) and monthly market-to-book ratio (MTBV). All values are in Norwegian krone (NOK).

To create the sample "Investable Universe" for each market, we rank the stocks by market capitalisation at the end of each month and add only the 30% largest companies[4] to the sample. For instance, the Norwegian "Investable Universe" comprises the largest companies listed on Oslo Stock Exchange, while the Nordic "Investable Universe" comprises the largest companies listed on all four Nordic markets together. Table 3-1 shows the size of the "Investable Universes". The sample covers many business cycles, e.g. the "dot-com" bubble in the late 1990s and the global financial crisis of 2007-2008.

	Norway	Sweden	Denmark	Finland	Nordics
Min	TBC	TBC	TBC	TBC	TBC
Max	TBC	TBC	TBC	TBC	TBC
Mean	TBC	TBC	TBC	TBC	TBC
Median	TBC	TBC	TBC	TBC	TBC

Table 3-1: Summary statistics for the number of stocks in each "Investable Universe" from 29 December 1995 to 29 December 2017.

3.3 Market Returns

Table 3-2 shows the proxies for the market returns $r_{m.}$ We use the Morgan Stanley International Capital (MSCI) Indices' monthly RI in NOK.

[3] The total index return (RI) is used instead of the price level because RI considers reinvestment of dividends over the holding period.
[4] The use of large and mid-caps suggests that an investor will not face liquidity issues nor be able to affect the price of the shares when purchasing them.

Market Proxy	Description
MSCI Norway Index	With 10 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in Norway
MSCI Sweden Index	With 31 constituents, the index covers about 85% of the equity universe in Sweden.
MSCI Denmark Index	With 18 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in Denmark.
MSCI Finland Index	With 12 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in Finland.
MSCI Nordic Countries Index	With 71 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country.

Table 3-2: Description of the MSCI indices (MSCI, 2017)

3.4 Risk-free Rate

Since the aim of this research is to analyse the performance of momentum strategies for an investor who is resident (or domiciled) in Norway, the chosen proxy for the risk-free rate r_f is the Norwegian Interbank Offered Rate (Nibor)[5]. We collect monthly Nibor 3-month rates.

[5] "Nibor - the Norwegian Interbank Offered Rate - is a collective term for Norwegian money market rates at different maturities. Nibor is intended to reflect the interest rate level a bank require for unsecured money market lending in NOK to another bank." (Finans Norge, 2017). Its quotes are issued by Oslo Børs.

4 METHODOLOGY

4.1 Calculation of Logarithmic Returns

We choose to use continuously compounded returns (i.e. logarithmic returns) for modelling and statistical purposes because the additivity property of multiperiod continuously compounded returns makes it more convenient (Campbell, Lo & MacKinlay, 1997)

To calculate the continuously compounded monthly return on each stock *i* from month *t-1* to month *t*, we use the following equation:

$$r_{i,t} = ln\left(\frac{RI_{i,t}}{RI_{i,t-1}}\right) \tag{1}$$

where $r_{i,t}$ is the continuously compounded monthly return on stock *i* at end of month *t* and $RI_{i,t}$ is the total return index of stock *i* at end of month *t*

The continuously compounded monthly return on each portfolio *p* from month *t-1* to month *t* is calculated as follows:

$$r_{p,t} = ln\left(1 + \sum_{i=1}^{n} w_i \cdot R_{i,t}\right) \tag{2}$$

$$R_{i,t} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1 \tag{3}$$

where $r_{p,t}$ is the continuously compounded monthly return on portfolio *p* at end of month *t,* w_i is the weight of stock *i* in portfolio *p* and $R_{i,t}$ is the one-month simple net return of stock *i* at end of month *t*.

4.2 Construction of Momentum Portfolios

Empirical evidence suggests that past winners in the intermediate-term[6] are more likely to be future winners. We analyse, therefore, two different long-only

[6] Lookback period between 3-month and 12-month. See Jegadeesh & Titman (1993)

momentum strategies that buy past winners: the "Conventional Momentum Strategy" and the "Quantitative Momentum Strategy".

4.2.1 "Conventional Momentum Strategy": Construction of Portfolios

The construction of portfolios of the "Conventional Momentum Strategy" follows the method introduced by Jegadeesh & Titman (1993). First, at the end of each month *t*, we rank the stocks in the "Investable Universe" in ascending order based on their cumulative returns over the past *J* months (formation period). Then, we divide the ranked stocks into deciles and construct an equal weighted portfolio with the stocks belonging to the bottom decile, i.e. with the winners of month *t*. Finally, we hold this portfolio over *K* months (holding period) as shown in Figure 4-1.

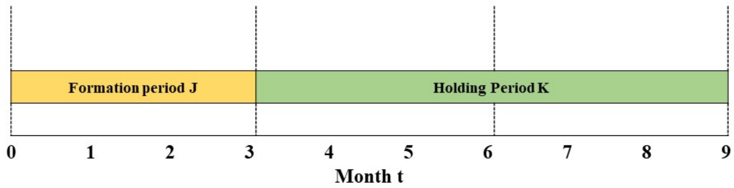

Figure 4-1: Example of a momentum portfolio constructed according to the "Conventional Momentum Strategy". At the end of month t=3, a portfolio is formed with the stocks that had the best past 3-months performance (formation period J=3). Then, this portfolio is held over 6 months (holding period K=6).

4.2.2 "Quantitative Momentum Strategy": Construction of Portfolios

The construction of portfolios of the "Quantitative Momentum Strategy" follows the method described by Gray & Vogel (2016). First, at the end of each month *t*, we rank the stocks in the "Investable Universe" in ascending order based on their cumulative returns over the past *J* months (formation period), without considering the most recent month. As shown in Figure 4-2, we skip the most recent month return to remove the short-term reversal effect addressed by Jegadeesh (1990) and Lehmann (1990).

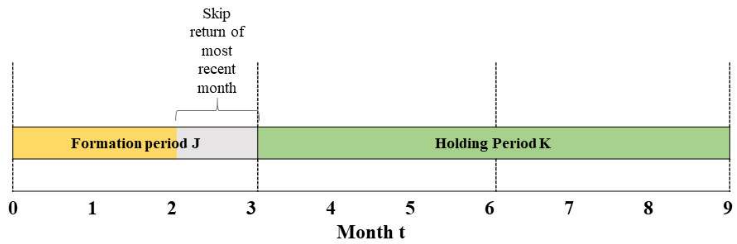

Figure 4-2: Construction of momentum portfolios using Gray & Vogel (2016), "Quantitative Momentum Strategy". Even though we skip the most recent month when calculating the cumulative compounded return over the formation period, we still refer the formation period as J. For example, when J=3 months, it means that we calculate the cumulative return from t-3 to t-1, i.e. we skip the return the stock had between t-1 and t.

Then, we divide the ranked stocks into deciles and select the ones in the bottom decile (stocks with best past performance). After that, we rank the winning stocks based on their "momentum quality" and divide them into "High-Quality Momentum" and "Low-Quality Momentum" stocks, as shown in Figure 4-3.

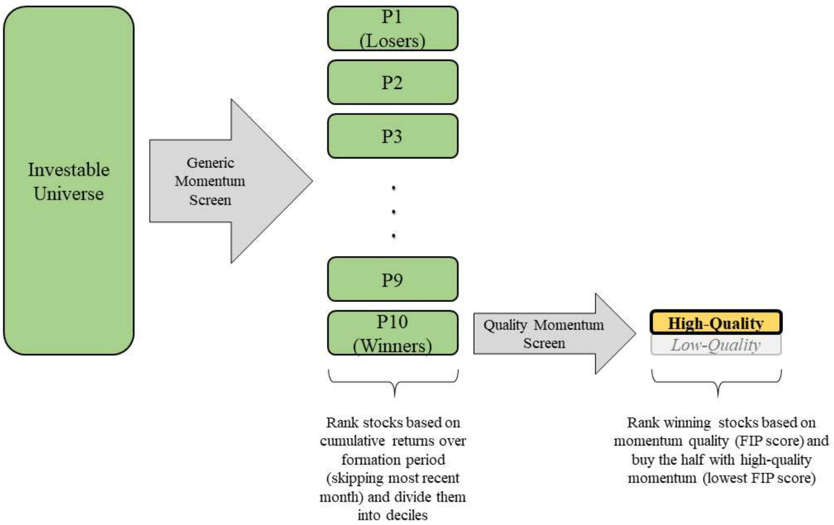

Figure 4-3: Overview of the stock screening process for constructing the winner portfolio of the "Quantitative Momentum Strategy" at the end of month t. First, the stocks in the "Investable Universe" are screened based on their past J months (formation period) returns. Then, the stocks in the winning decile P10 are screened based on their "momentum quality": the stocks are ranked based on their "Frog-in-the-pan" score (FIP score). Finally, an equal weighted portfolio is formed with the winning stocks that had the lowest FIP scores (high quality momentum).

To measure the "momentum quality" of each winning stock, we calculate its "Frog-in-the-pan" score (FIP score)[7].

$$FIP = sign\,(Past\ return) * [\%\,negative\ returns - \%\,positive\ returns] \quad (4)$$

The FIP score views the trading days in the past J-months of a stock and counts the percentage of trading days with negative and positive returns. The difference between these percentages is multiplied by the sign of the cumulative return over the formation period *J*[8]. For example, if a high momentum stock has a low (negative) FIP score, this stock will have a high momentum quality, i.e. a more continuous price path that shows a slow diffusion of gradual information elements. Therefore, the winning stocks with the lowest FIP scores are placed in the "High Quality Momentum" group.

After the "Quality Momentum Screening" is performed, we select the high-quality momentum stocks and construct an equal weighted portfolio with them. Finally, we hold this portfolio over *K* months (holding period) as shown in Figure 4-2.

4.3 Analysis of the Momentum Strategies' Returns

For each type of momentum strategy, we analyse 16 cases by combining four formation periods *J* (3, 6, 9 and 12 months) with four holding periods *K* (3, 6, 9 and 12 months). To test each case, we use overlapping sub-portfolios because it increases the number of observations and the power of the statistical tests (Jegadeesh & Titman 1993). Figure 4-4 shows the overlapping sub-portfolios technique. At the end of each month *t*, we re-balance the weights of *1/K* of the stocks in the whole portfolio and carry over all the other stock positions. In effect, we hold K sub-portfolios on each month *t*.

[7] The FIP score (Da et al., 2014) attempts to quantify the path of a high momentum stock. It separates high momentum stocks into those that have more continuous price paths (i.e. smooth, with a slow diffusion of gradual information elements) versus those high momentum stocks that have more discrete price paths (i.e. jumpy, with immediate information elements).
[8] The return on the most recent month is skipped when calculating the cumulative return over the formation period J.

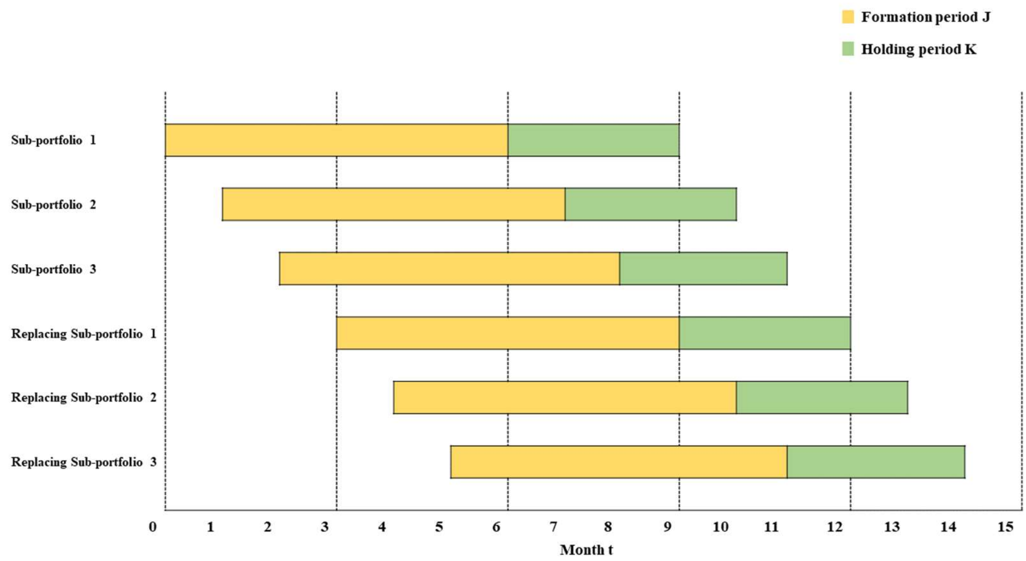

Figure 4-4: Illustration of the overlapping sub-portfolios technique with formation period J equal to 6 months and holding period K equal to 3 months. For example, on June 30, 2015 (t=6) we use one-third of our cash to buy stocks with high momentum (sub-portfolio 1). We hold these stocks until September 30, 2015 (t=9). On July 31,2015 (t=7), we use another one-third of our cash to buy stocks with high momentum (sub-portfolio 2). We hold these stocks until October 30,2015 (t=10). On August 31, 2015 (t=8) we use another one-third of our cash to buy stocks with high momentum (sub-portfolio 3). We hold these stocks until November 30, 2015 (t=11). We repeat the process every end of month t. Therefore, the return to the portfolio from August 31,2015 (t=8) to September 30, 2015 (t=9) is the returns to the stocks in the sub-portfolios originally formed on June 30,2015 (sub-portfolio 1), July 31,20125 (sub-portfolio 2) and August 31,2015 (sub-portfolio 3).

To test the momentum strategies, we perform hypothesis tests using the monthly returns of all sub-portfolios from 31 January 1997[9] to 29 December 2017. First, we test if the momentum strategies are profitable.

$$\begin{cases} H_0: \mu_{conventional(J,K)} = 0 \\ H_1: \mu_{conventional(J,K)} > 0 \end{cases} \tag{5}$$

$$\begin{cases} H_0: \mu_{quantitative(J,K)} = 0 \\ H_1: \mu_{quantitative(J,K)} > 0 \end{cases} \tag{6}$$

Then, we test if the "Quantitative Momentum Strategy" is more profitable than the "Conventional Momentum Strategy".

[9] The longest formation period analysed is 12 months. Hence, the first portfolio can be created on 31 December 1996.

$$\begin{cases} H_0: \mu_{quantitative(J,K)} = \mu_{conventional(J,K)} \\ H_1: \mu_{quantitative(J,K)} > \mu_{conventional(J,K)} \end{cases} \tag{7}$$

To calculate the t-statistics for the mean monthly returns, we use the autocorrelation-consistent Newey-West standard errors (Newey & West, 1987) because the returns are autocorrelated and dependent (overlapping portfolios).

4.4 Analysis of the Momentum Strategies' Alphas

To analyse the alpha (abnormal return) of each momentum strategy, we apply first the Capital Asset Pricing Model (CAPM).

$$r_{p,[t-K,t]} - r_{f,[t-K,t]} = \alpha_p + \beta_p \cdot \left(r_{m,[t-K,t]} - r_{f,[t-K,t]}\right) + \varepsilon_p \tag{8}$$

where $r_{p,[t-K,t]}$ is the continuously compounded return of portfolio p, $r_{f,[t-K,t]}$ is the continuously compounded return of the risk-free rate, and $r_{m,[t-K,t]}$ is the continuously compounded return of the market; all for the period between $t\text{-}K$ and t.

Then, we calculate the alpha of each momentum strategy using the Fama and French 3-factors regression model.

$$r_{p,[t-K,t]} - r_{f,[t-K,t]} = \alpha_p + \beta_p \cdot \left(r_{m,[t-K,t]} - r_{f,[t-K,t]}\right) + \gamma_p \cdot SMB_{[t-K,t]} + \delta_p \cdot HML_{[t-K,t]} + \varepsilon_p \tag{9}$$

where $r_{p,[t-K,t]}$, $r_{f,[t-K,t]}$, $r_{m,[t-K,t]}$ are the same variables as the ones defined above for the CAPM regression, $SMB_{[t-K,t]}$ is the "Small Minus Big" factor that explains the returns due to firm size characteristics and $HML_{[t-K,t]}$ is the "High Minus Low" factor that explains the returns due to firm value characteristics; all for the period between $t\text{-}K$ and t. We use Fama & French (1993) to derive the factors $SMB_{[t-K,t]}$ and $HML_{[t-K,t]}$ from our data[10].

[10] Book equity (BE) is the COMPUSTAT book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. (Fama & French, 1993). We do not perform these adjustments because it is time consuming and outside the scope of our thesis. Therefore, we use the market-to-book (MTB) ratios provided by Datastream. MTB is defined as the market value of the common equity divided by the balance sheet value of the common equity in the company.

In both regressions, the autocorrelation-consistent Newey-West standard errors Newey-West estimators (Newey & West, 1987) are used to compute the t-statistics of the regression coefficients.

4.5 Test of Seasonality Effects

Once the momentum strategies with best returns are found, we test them for seasonality effects as well. Based on the K-month holding period, we create *K* portfolios starting at different months *t* and rebalance them after *K* months (non-overlapping portfolios), as shown in Figure 4-5. Afterwards, we compare the returns of these non-overlapping portfolios with the returns from the overlapping portfolios to verify if timing the rebalancing affects the strategy performance.

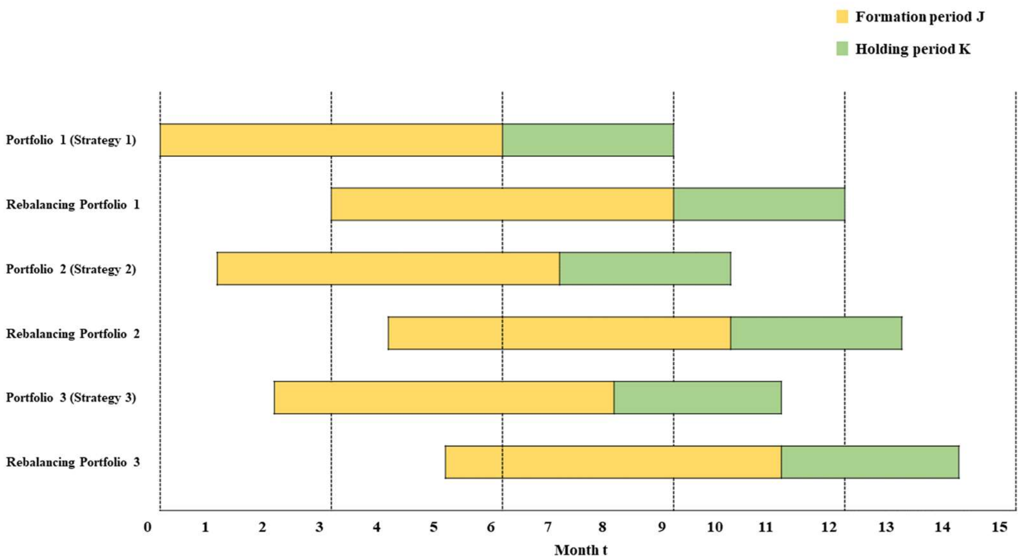

Figure 4-5: Illustration of the non-overlapping portfolios technique to study seasonality effects. For example, if we want to examine the seasonality effect in a momentum strategy with 3-months holding period, we can examine 3 different strategies using nonoverlapping portfolios formed in different months. First, we can trade the nonoverlapping seasonal momentum portfolio 1 (Strategy 1) at the end of June (t=6), September (t=9), December (t=12), etc. We hold this nonoverlapping portfolio for three months, which means there are four rebalances per year. Second, we can trade the nonoverlapping seasonal momentum portfolio 2 (Strategy 2) at the end of July (t=7), October (t=10), January in the following year(t=13), etc. Third, we can trade the nonoverlapping seasonal momentum portfolio 3 (Strategy 3) at the end of month August (t=8), November (t=11), February in the following year (t=14), etc. Then, we can compare the performance of the three portfolios against each other and verify if any of them performs better than the overlapping portfolio constructed with 3-months holding period (with no seasonality effect).

5 NEXT MILESTONES

Table 5-1 presents our next milestones for the master thesis assignment.

Milestone	Planned date of completion
Development of Python script to run required calculations of momentum strategies	End of March 2018
Analysis of the results	End of April 2018
Submission of final thesis to supervisor for comments	June 1st, 2018
Implementation of supervisor's comments and final submission of master thesis	September 1st, 2018

Table 5-1: Next milestones

6 REFERENCES

Antonacci, G. (2017). Risk Premia Harvesting Through Dual Momentum. *Journal of Management & Entrepreneurship*, *2*(1), 27-55. doi:10.2139/ssrn.2042750

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, *68*(3), 929-985. doi:10.1111/jofi.12021

Asness, C., Frazzini, A., Israel, R., & Moskowitz, T. (2014). Fact, fiction, and momentum investing. *The Journal of Portfolio Management*, *40*(5), 75-92. doi:10.3905/jpm.2014.40.5.075

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307-343. doi:10.1016/S0304-405X(98)00027-0

Blitz, D., Hanauer, M. X., & Vidojevic, M. (2017). The Idiosyncratic Momentum Anomaly. Retrieved from https://ssrn.com/abstract=2947044

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The Econometrics of Financial Markets* (2nd ed.). Princeton, NJ.: Princeton University Press.

Da, Z., Gurun, U. G., & Warachka, M. (2014). Frog in the pan: Continuous information and momentum. *The Review of Financial Studies*, *27*(7), 2171-2218. doi:10.1093/rfs/hhu003

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, *122*(2), 221-247. doi:10.1016/j.jfineco.2015.12.002

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact?. *The Journal of Finance*, *40*(3), 793-805. doi:10.1111/j.1540-6261.1985.tb05004.x

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383-417. doi:10.2307/2325486

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56. doi:10.1016/0304-405x(93)90023-5

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, *63*(4), 1653-1678. doi:10.1111/j.1540-6261.2008.01371.x

Fuertes, A. M., Miffre, J., & Tan, W. H. (2009). Momentum profits, nonnormality risks and the business cycle. *Applied Financial Economics*, *19*(12), 935-953. doi:10.1080/09603100802167304

Finans Norge. (2017). Nibor – the Norwegian Interbank Offered Rate. Retrieved from https://www.finansnorge.no/en/interest-rates/nibor---the-norwegian-interbank-offered-rate/

Geczy, C., & Samonov, M. (2015). 215 Years of global multi-asset momentum: 1800-2014 (equities, sectors, currencies, bonds, commodities and stocks). Retrieved from https://ssrn.com/abstract=2607730

Geczy, C. C., & Samonov, M. (2016). Two centuries of price-return momentum. *Financial Analysts Journal*, *72*(5), 32-56. doi:10.2469/faj.v72.n5.1

Graham, B. & Zweig, J. (2006). *The Intelligent Investor* (revised ed.). New York, NY.: Harper Collins

Gray, W. R., & Vogel, J. R. (2016). *Quantitative Momentum a Practitioner's Guide to Building a Momentum-Based Stock Selection System* (1st ed.). Hoboken, NJ.: Wiley.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, *55*(1), 265-295. doi:10.1111/0022-1082.00206

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance*, *45*(3), 881-898. doi: 10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65-91. doi: 10.1111/j.1540-6261.1993.tb04702.x

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, *105*(1), 1-28. doi: 10.2307/2937816

Levy, R. A. (1967). Relative strength as a criterion for investment selection. *The Journal of Finance*, *22*(4), 595-610. doi: 10.1111/j.1540-6261.1967.tb00295.x

MSCI. (2017). MSCI DENMARK INDEX (USD). Retrieved from https://www.msci.com/documents/10199/5db4fa3f-1775-4d39-8838-e260a97d2b94

MSCI. (2017). MSCI FINLAND INDEX (USD). Retrieved from https://www.msci.com/documents/10199/464722b4-4bfd-403c-bfba-ce3322ca1b85

MSCI. (2017). MSCI NORDIC COUNTRIES INDEX (USD). Retrieved from https://www.msci.com/documents/10199/6bd9ad54-61be-4bdf-afcd-7465994bcb95

MSCI. (2017). MSCI NORWAY INDEX (USD). Retrieved from https://www.msci.com/documents/10199/9d0f5852-2652-4307-9f60-9fe2724c6e22

MSCI. (2017). MSCI SWEDEN INDEX (USD). Retrieved from https://www.msci.com/documents/10199/5b5d91b7-505a-4d4d-b060-51a3af6be160

Newey, W., & West, K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703-708. doi:10.2307/1913610

Novy-Marx, R. (2015). *Fundamentally, momentum is fundamental momentum* (No. w20984). National Bureau of Economic Research. doi:10.3386/w20984

Rouwenhorst, K. G. (1998). International momentum strategies. *The Journal of Finance*, *53*(1), 267-284. doi: 10.1111/0022-1082.95722

Rouwenhorst, K. G. (1999). Local return factors and turnover in emerging stock markets. *The Journal of Finance*, *54*(4), 1439-1464. doi: 10.1111/0022-1082.00151