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Master's Thesis

The Price Momentum Effect

- An Empirical Study of the Danish Stock Market

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Abstract

This paper investigates and confirms previous findings related to the price momentum effect. By applying the momentum strategy framework by Jegadeesh and Titman (1993) to the stocks in the Danish OMXC index from 2000-2017, this paper is able to find significant results, confirming that price momentum exists. The results are strikingly similar to many previous studies. Consequently, the paper finds that the 12/3-winner strategy and the 9/3-zero-cost strategy are the best performing strategies, generating average monthly returns of 1.98% and 1.85% respectively. In addition, these strategies, along multiple others, significantly outperform the OMXC index benchmark.

The statistically significantly positive returns generated in this paper contradict the efficient market hypothesis, which serves as a central part of the conventional financial theory. To explain this anomaly, the relationship between risk and return proposed by the conventional theory is investigated in relation to the momentum strategies, but without any success. In search of alternative explanations, the field of behavioral finance is introduced.

Consequently, the dynamic confidence model by Daniel et al. (1998) provides the most substantial explanation. Having taken the cultural context of the markets investigated into account, the model is seemingly able to explain the short-term price momentum documented in this paper, the subsequent long-term price reversal found in multiple previous studies, and the lack of price momentum in Japan as documented by Liu and Lee (2001). Thus, when the assumption of self-attribution bias in the dynamic confidence model is related to the cultural context of the markets in question, the model provides an explanation. It thereby explains why the momentum effect is predominant in the Western markets, and absent in the Japanese stock market where self-criticism prevails self-enhancement, as opposed to the American market where the opposite is proven to be true.

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1. Introduction

For decades, both academics and practitioners have been debating the dynamics that rule the financial markets. One of the biggest controversies surrounds the assumption that financial markets are efficient. The assumption is deeply embedded in the conventional financial theory and is based on the Efficient Market Hypothesis developed by Eugene Fama (1970). Efficient markets refer to the concept that financial asset prices fully reflect all available information, thereby making them unpredictable, and implying that technical trading is not able to produce positive returns consistently.

However, in the 1980's studies began to present evidence suggesting markets were not necessarily efficient as otherwise presumed. De Bondt and Thaler (1985) proved that contrarian strategies, buying past losers and selling past winners, earned an abnormal return on the stock market when using a holding period of 3 to 5 years. Amid this talk about long-term price reversal, Jegadeesh and Titman (1993) published what would become the first seminal study of price momentum, showing that for holding periods of 3 to 12 months US stocks show price momentum rather than price reversal. Price momentum refers to the concept of financial assets that have earned a high return in the past and continue to do so in the short-term, while those that have earned a low return continue to underperform. In the following decade, various studies confirmed the momentum effect for various markets but none could fully explain the phenomenon. However, a further study by Liu and Lee (2001) would go on to show that surprisingly the effect did not exist in Japan.

The anomaly of price momentum is puzzling and conventional financial theory would suggest that market dynamics had eliminated it two decades later, due to the assumption of rational investors and no arbitrage. Therefore, the primary purpose of this paper's empirical research is to investigate whether the price momentum effect observed in the majority of the literature exists in the Danish stock market in more recent times. Additionally, this paper seeks to investigate and understand what might drive the momentum effect and why this anomaly has been noticeably absent from certain markets like the Japanese.

2. Problem Statement

To what degree does price momentum exist in the current Danish stock market, how does the current degree of price momentum relate to previous research and what are some possible explanatory factors for price momentum?

Sub-questions:

- What have previously been documented for price momentum strategies?
- What is the current degree of price momentum on the OMXC index?
- How does the empirical results compare to the studies conducted previously?
- To what extent can the empirical results be explained by conventional financial theory?
- How does behavioral finance models offer alternative explanations on the subject?

3. Scope

The scope of the paper is to investigate the current degree of price momentum on the Danish stock market and understand the drivers behind the phenomenon. Throughout the paper, momentum will refer to price momentum unless specifically started otherwise. Even though the scope of the analysis is on the current Danish market, it is unconceivable to produce a proper analysis without including studies and findings from previous periods and other markets. Therefore, this paper will not limit itself to only use certain literature.

Furthermore, the paper should be relevant to all investors. That said, institutional and private investors do not have the same options and resources and therefore the applicability of the momentum strategies for private investors will be kept in mind throughout.

4. Delimitation

Previous studies have not been confined to price momentum. A topic such as earnings momentum, among others, has also been covered, but mainly as an additional analysis to illuminate other aspects closely related to price momentum. However, given the sole intend of investigating and ultimately understanding price momentum, earnings momentum and other types of momentum has been excluded from this study.

Had the purpose of this paper been to investigate current price momentum across the financial markets on a global scale, then the more markets analyzed in the empirical research, the better. However, as this is not within the scope, and as it is not deemed feasible to conduct a meaningful and thorough study on more than one market with the resources and time available, all other markets than the Danish stock market has been excluded from the empirical research. At the same time, this also means that the equity market is the focus, excluding other assets such as debt and currency. Additionally, due to limited historical data availability for stocks currently listed on the OMXC index, the empirical research excludes the years prior to 2000.

In the second part of the paper the theoretical field of behavioral finance is introduced. The area is fairly new but has already developed in many different directions. The most cited behavioral aspects related to price momentum have been those of over- and underreaction. Although some previous studies have suggested underreaction as a cause for price momentum, overreaction has been deemed the more relevant of the two by the authors of this paper, due to a lack of fit between the empirical results and the underreaction models, as evident later in the analysis. Therefore, the focus in the last part of the paper will be on behavioral models related to overreaction among investors.

5. Structure

Traditional financial theory: The paper starts by outlining the traditional financial theory in the first section, as this provides the backdrop for any stock market analysis and sets up the premise for the analysis and discussion.

Literature review: The next section clarifies what has previously been established throughout the financial literature regarding price momentum. As such, the article by Jegadeesh and Titman (1993) will be used as a focal point throughout the paper. The remainder of the literature review will serve to illustrate differences in methodology and findings as well as support the significance of the original work by Jegadeesh and Titman (1993).

Methodology: This section develops the methodology adopted for the paper's empirical research and presents arguments throughout as to why the given methodology has been chosen. The method chosen is closely related to the momentum strategies developed by Jegadeesh and Titman (1993).

Empirical results: Following the methodology, the next section presents the empirical results obtained for the price momentum strategies and the related sub-analyses.

Analysis of empirical results: This section compares the empirical results to the literature presented earlier and tries to explain the phenomenon through the conventional theory.

Behavioral Finance: Given the conclusions reached in the previous section, this section looks for alternative explanations, which leads to the introduction of behavioral finance and two behavioral models: The positive feedback trading model and the confidence model. This section investigates how the two behavioral models can help explain the results obtained in this paper as well as those in previous studies.

Discussion: This section considers the findings of the paper and comments on their implication, and goes on to suggest relevant areas for further research.

6. Traditional Investment Theory

This section seeks to outline the relevant theory regarding traditional investment practises. The theory will be used throughout the paper as a reference-point and will be used for practical and theoretical considerations. Further, the momentum strategy approach and the results obtained throughout the literature as well as those of this paper will be compared with the traditional investment theory. This section will start by outlining the modern portfolio theory associated with Harry Markowitz, proceed to the Capital Asset Pricing Model and the arbitrage pricing theory. Finally, the Efficient Market Hypothesis by Eugene Fama will be introduced and related to the theoretical profitability of momentum strategies.

6.1 Modern Portfolio Theory

Modern portfolio theory is basically a theorem of how the return and risk of an asset influences the expected return of a portfolio, and how the risk associated with a portfolio can be mitigated through diversification. Harry Markowitz mentioned the theory for the first time back in 1952[1], and his theoretical framework has since constituted the foundation for many of the theories within the academic area of finance theory[2].

Return and risk are the two fundamental components in portfolio theory. The return is an indicator of the profit or loss associated with a financial asset, such as a stock of equity. The mathematical expression for an asset's return at time t is provided below[3]:

$$R_t = \frac{P_t - P_{t-1} + Div_t}{P_{t-1}} \qquad (1)$$

Where P_t is the price of the financial asset at time t and Div_t is the dividends paid at time t.
The risk of an asset is a much more complex component as this can be expressed in various ways. However, the most common measures of risk are the variance and the standard deviation, which are expressed mathematically below[4]:

[1] Markowitz, 1952, p. 77
[2] Markowitz, 1999, p. 5
[3] Berk & DeMarzo, 2014, p. 319
[4] Berk & DeMarzo, 2014, pp. 317 and 323

$$Var(R) = \frac{1}{T-1} \cdot \sum_{t=1}^{T} (R_t - \bar{R})^2 \qquad (2)$$

$$SD(R) = \sqrt{Var(R)} \qquad (3)$$

Where T is the number of observations, R_t is the return of the asset at time t and $\bar{R}$ is the average return over T observations. As such, these risk-measures describe a single financial asset's return, but modern portfolio theory focuses much more on portfolios of assets rather than single assets. Therefore, portfolio theory investigates the link between the return of a portfolio and the composition of assets in the portfolio. The return on a portfolio is given as the sum of each asset multiplied by its weight in the portfolio, and the expression can be seen below[5]:

$$R_p = \sum x_i \cdot R_i \qquad (4)$$

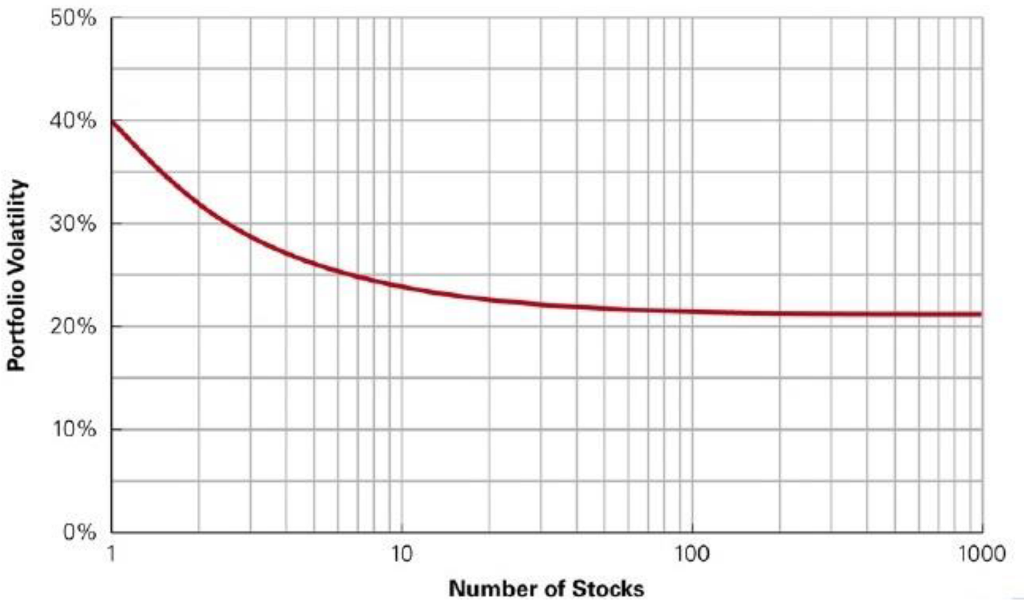
Where x_i is the weight of the *i*'th asset in the portfolio and R_i is the return of the *i*'th asset. As shown, the calculation of the portfolio return is straightforward once the weights of the assets are known. However, it's a different story for the portfolio's risk measures. The asset returns of the portfolio do not necessarily behave identically; that is, the return of one asset might be positive while it's negative for another asset in the portfolio. The fact that a portfolio's components are not necessarily correlated is extremely important in portfolio theory because it makes it possible to reduce the risk of the investment by diversifying the portfolio[6].

To illustrate the effect from simply increasing the number of assets in a portfolio, we assume an equally weighted portfolio of assets. The link between the number of assets and risk can be illustrated by figure 6.1 below[7] [8]. As it is shown, the risk falls exponentially as the number of assets in the portfolio increases. Further, the illustration shows that the effect of diversifying is larger for small portfolios than for large ones as the slope's absolute value decreases as the number of stocks increases.

[5] Berk & DeMarzo, 2014, p. 352
[6] Markowitz, 1952, p. 79
[7] Berk & DeMarzo, 2014, p. 360
[8] The illustration assumes a constant stock volatility of 40% and a constant correlation of 28% between stocks.

Figure 6.1: The benefits of diversification

The figure shows the benefits of diversification as more stocks are added to a given portfolio, but also that the marginal benefits of adding more share decrease as the number of stocks in the portfolio increases.



Source: Berk and DeMarzo, 2013, p. 360

The degree to which the risk can be reduced depends on the joint variability of the portfolio's stocks. This is measured by the covariance. This measure describes the sum-product of the volatility of two return time-series. However, the numerical value of the covariance is difficult to interpret, thus the correlation is used instead. The correlation takes a value between -1 and 1 depending on how correlated the two time-series are. If two time-series are perfectly correlated in the same direction, the correlation will be equal to 1. Further, if they are perfectly correlated in opposite directions, the correlation will equal -1, while 0 indicate no correlation. The expressions for the correlation and the covariance between asset *i* and asset *j* are given below[9]:

$$Corr(R_i, R_j) = \frac{Cov(R_i, R_j)}{SD(R_i) \cdot SD(R_j)} \qquad (5)$$

$$Cov(R_i, R_j) = \frac{1}{T-1} \cdot \sum_{t=1}^{T} (R_{i,t} - \bar{R}_i) \cdot (R_{j,t} - \bar{R}_j) \qquad (6)$$

Where $Corr(R_i, R_j)$ is the correlation between the *i*'th and the *j*'th asset and $Cov(R_i, R_j)$ is the covariance between the *i*'th and the *j*'th asset.

[9] Berk & DeMarzo, 2014, pp. 354-355

By the logic outlined above, the total risk related to a portfolio's return depends on the volatility of the portfolio's components and the degree of correlation between these. Below is given the mathematical expression for the variance of a multi-asset portfolio's return[10]:

$$Var(R_p) = \sum_i \sum_j x_i x_j Cov(R_i, R_j) \qquad (7)$$

In other words, the volatility of a portfolio's return is given as the sum of the covariance of all the various pairing combinations of stocks in the portfolio, multiplied by the weights of said assets. As such, the total volatility of the portfolio depends on the co-movement of the stocks within it.

Combining formula (5), (6) and (7) results in the variability expressed in terms of the correlation[11]:

$$Var(R_p) = \sum_i x_i SD(R_i) SD(R_p) Corr(R_i, R_p) \qquad (8)$$

Dividing with the standard deviation on each side yields[12]:

$$SD(R_p) = \sum_i x_i SD(R_i) Corr(R_i, R_p) \qquad (9)$$

This indicates that each stock contributes to the portfolio standard deviation with the product of the risk of the particular asset and the fraction of risk that is common to the portfolio risk. As such, unless the last term, the correlation, is indicating perfect correlation of 1, the portfolio will have less risk than the average asset. Further, the risk associated with a portfolio can be reduced and even terminated if the correlation is equal to -1. However, it can never be terminated fully as returns from stocks are too inter-correlated[13].

From what has been shown above, it seems clear that the risk can be split into two components. An idiosyncratic component that can be mitigated by diversification, and a systematic component, which cannot be diversified away, even with a large number of assets. The last component is often referred to as the market risk, which implies the level of risk for a portfolio consisting of all financial assets on the market. In other words, the systematic risk represents the fact that stocks are inter-correlated. For a given stock, the volatility related to the overall market is the systematic risk and the component of the volatility unrelated to the market is referred to as

[10] Berk & DeMarzo, 2014, p. 359
[11] Ibid, p. 363
[12] Ibid, p. 363
[13] Markowitz, 1952, p. 79

the idiosyncratic or the firm-specific component. The latter is thus related entirely to the given asset and can be mitigated completely by diversification[14].

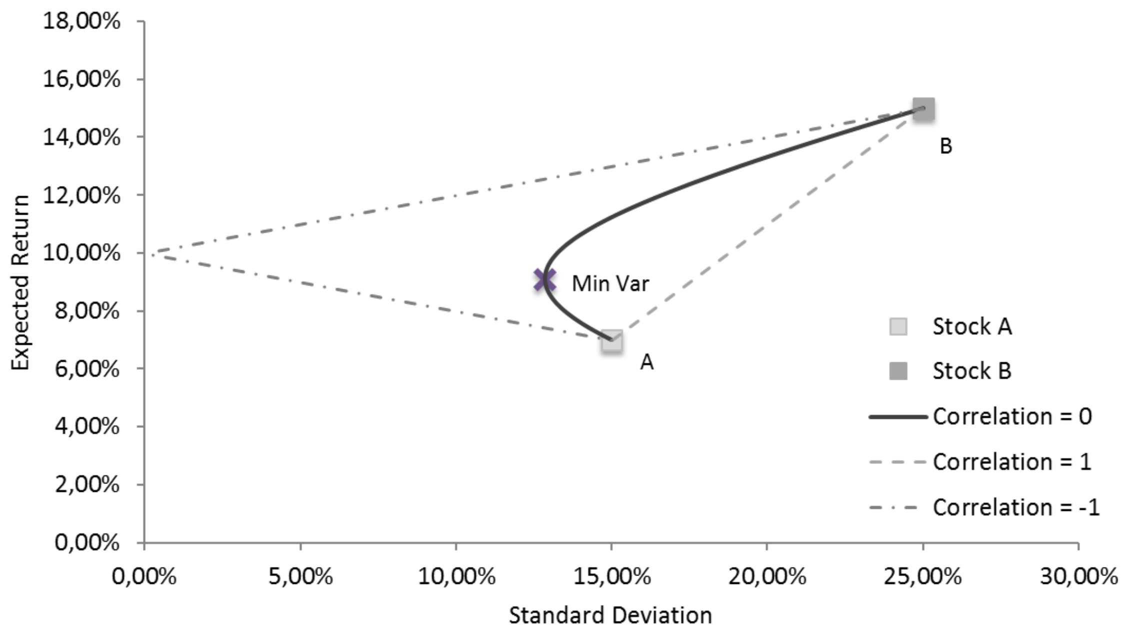
The asset's component of systematic risk is known as the asset's market beta. This variable is usually defined as the expected percentage change of the return given a change in the return of the market portfolio of 1%. The beta of an asset can be estimated by regression analysis, regressing the return time-series of the asset on the return time-series of the market portfolio, or by using the formula below[15]:

$$\beta_i = \frac{SD(R_i) \cdot Corr\left(R_i, R_p\right)}{SD\left(R_p\right)} \qquad (10)$$

Having introduced all the basic concepts and variables relevant for the modern portfolio theory, the focus turns towards the portfolio formation. For illustrative purposes, a two-stock portfolio is regarded at first. Stock *A* has an expected return of 7% and a standard deviation of 15%, while stock *B* has an expected return of 15% and a standard deviation of 25%. Using formula (4) and formula (9), the various weights of stock *A* and *B* result in the various portfolios shown in figure 6.2 below. From the figure, it is evident that the level of correlation matters.

Figure 6.2: The effect of correlation on a two-stock portfolio

The figure shows the effect that the correlation between two stocks has on the possibilities of diversification.



Source: Own creation

[14] Berk & DeMarzo, 2014, p. 332
[15]Ibid, p. 382

The most important takeaway from figure 6.2 is, that unless the stocks are perfectly and positively correlated, diversification will allow the investor to obtain a lower level of risk. Assuming a correlation of 0, investing 84% in stock A and 16% in stock B will yield an expected return of 10.8% with a standard deviation of 13.8%. This is an improvement of expected return (higher) and the standard deviation (lower) relative to simply investing in stock A. The line representing a correlation of 0 has a mark (X) at the point indicating the minimum volatility that can be obtained. The line above this mark is called the efficient frontier. This frontier indicates the highest obtainable expected return given the standard deviation for the portfolio.

So far, the investor has only been able to trade two stocks. But let's introduce a risk-free asset and the possibility of trading on margin. By doing so it is possible for the investor to form new portfolios outside the efficient frontier of risky assets, and consequently form a new efficient frontier. This new efficient frontier is obtained by combining the risk-free asset with the tangent portfolio. The tangent portfolio is found at the point of tangency from the risk-free asset to the efficient frontier of risky asset. This point indicates the optimal portfolio of risky assets for the investor to hold in combination with the risk-free asset. This is because the tangent line has the highest slope, thus proving the highest expected return per unit of risk taken, as seen in figure 6.3. The slope of this line is referred to as the Sharpe Ratio and describes the trade-off between risk and return. The Sharpe Ratio is mathematically expressed as follows[16]:

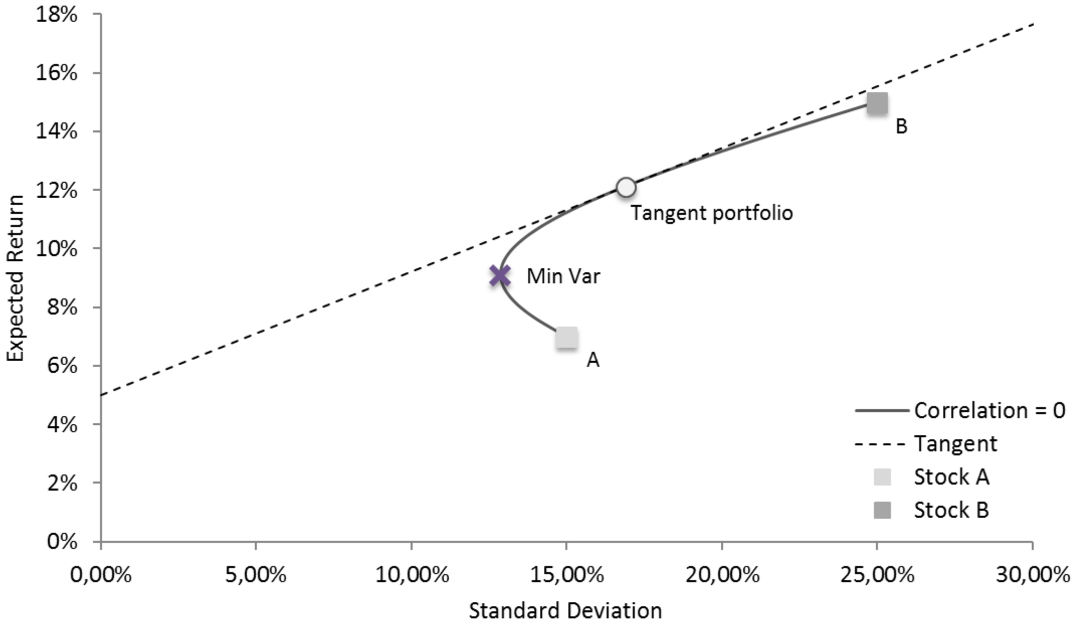
$$Sharpe\ Ratio = \frac{E(R_p) - r_f}{SD(R_p)} \qquad (11)$$

Since the various combinations of the risk-free asset and the tangent portfolio will provide the highest return-to-risk trade-off for the investor, all investors should always invest in this tangent portfolio, regardless of the investor's risk-profile. To obtain a higher expected return, additional risk will have to be held, but instead of altering the risky investment weights, the investor now has the possibility to buy the risky portfolio on margin. As seen in figure 6.3 below, the line with the highest Sharpe Ratio extends beyond the tangent portfolio. This is to illustrate the possibility of buying the tangent portfolio on margin, thus adding risk to earn a higher expected return.

[16] Berk & DeMarzo, 2014, p. 376

Figure 6.3: The tangent portfolio and efficient frontier with risk-free asset

The figure shows how the addition of a risk-free asset enables the investor to create portfolios outside the space of risky assets. Note how the tangent portfolio and tangent line represents the new efficient frontier.



Source: Own creation

Having established the optimal investment strategy as a combination of the risk-free asset and the tangent portfolio, we now turn to the portfolio composition. As previously shown, the idiosyncratic risk component of a stock can be mitigated by diversification, but the added volatility from the systematic component could increase the portfolio risk. Therefore, the required return of a stock in a portfolio should only compensate for the risk the stock adds to the portfolio. This required return is expressed mathematically below[17], showing that the required return is equal to the risk-free rate plus the risk premium of the portfolio multiplied with the asset's portfolio beta. This beta represents the sensitivity of the asset *i* to changes in the portfolio returns.

$$r_i = r_f + \beta_i^P \cdot \left(E\left(R_p\right) - r_f\right) \qquad (12)$$

If the expected return of asset *i* is larger than the required return stated above, including the asset in the portfolio will increase the portfolio's performance. Furthermore, including asset *i* in the portfolio will result in a higher correlation of the asset with the portfolio, which causes the beta in formula (12) to increase, thus yielding a higher required return. When the required return of the

[17] Berk & DeMarzo, 2014, p. 376

asset is equal to the expected return of the asset, the optimal position in asset *i* has been included in the portfolio. This procedure should be repeated until all assets in the portfolio have a required return equal to its expected return. This relationship between the expected return, the required return and the assets beta can be expressed mathematically as[18]:

$$E(R_i) = r_i = r_f + \beta_i^{eff} \cdot \left(E\left(R_{eff}\right) - r_f\right) \qquad (13)$$

Where β_i^{eff} is the asset beta with respect to the efficient portfolio and $E\left(R_{eff}\right)$ is the expected return of the efficient portfolio. Thus, when the asset beta represents the optimal level of correlation with the return of the efficient portfolio, the expected return of an asset is equal to the required return of said asset.

As such, this equation can be used to calculate the expected return of an asset based on its beta with respect to the efficient portfolio. However, the practical implementation of formula (13) is not as straightforward as it might seem. The biggest issue revolves around the efficient portfolio. This portfolio is said to be the one with the highest Sharpe Ratio in the market and should represent a benchmark that indicates the systemic risk in the economy. However, the question remains: How to identify the efficient portfolio? In order to mitigate this problem, the Capital Asset Pricing Model is introduced next.

6.2 Capital Asset Pricing Model

The Capital Asset Pricing Model, or the CAPM, is a model which, when the underlying assumptions hold, can identify the efficient portfolio and thus describe the relationship between the expected return and the systematic risk for stocks in a manner that can be applied in practice. The CAPM relies on three assumptions of investor behavior[19] [20]:

1. *"Investors can buy and sell all securities at competitive market prices (without incurring taxes or transactions costs) and can borrow and lend at the risk-free interest rate."*
2. *"Investors hold only efficient portfolios of traded securities – portfolios that yield the maximum expected return for a given level of volatility."*

[18] Berk & DeMarzo, 2014, p. 376
[19] Sharpe, 1964, p. 433
[20] Berk & DeMarzo, 2014, p. 379

3. *“Investors have homogeneous expectations regarding the volatilities, correlations, and expected returns of securities.”*

These assumptions are basically in line with the modern portfolio theory previously described. The first assumption allows an investor to move freely on the new efficient frontier. Thus, the investor can use leverage to increase the expected return and volatility. The assumption of a market without taxes and transaction costs are rather fundamental but it should still be noted that this is a simplified version of reality and therefore not a perfect description of real markets. The second assumption relies on all investors being rational, thereby investing in the combination of the risk-free asset and the tangent portfolio previously outlined. The third is the most debatable assumption. If all investors base their expectations on the same set of information, they should all arrive at a similar result. However, this paper will go on to show that this might not always be the case and therefore the third assumption might not be a perfect description of reality, but is included as a simplifying and somewhat reasonable assumption.

Now, if all the investors have homogeneous expectations, then everyone will identify the tangent portfolio as the efficient portfolio. If this is the case, then the combined portfolio of all investors’ portfolios must also be equal to the tangent portfolio, and as investors own all stocks, the tangent portfolio must also be equal to the market portfolio. Given the assumptions of the CAPM, the market portfolio is efficient and thus represents the tangent portfolio previously introduced. The tangent line from the risk-free asset through the tangent portfolio is referred to as the Capital Market Line. The CAPM suggests that any investor should invest in some combination of the risk-free asset and the market portfolio on the Capital Market Line, as this will grant the investor with the highest return-to-risk trade-off. Based on this, it is possible to rewriting formula (13), which yields the final CAPM formula used to price financial assets under the CAPM assumptions[21]-:

$$E(R_i) = r_i = r_f + \beta_i \cdot \left(E(R_{Mkt}) - r_f\right) \qquad (14)$$

Where $E(R_{Mkt})$ is the expected return of the market portfolio and β_i is the beta of stock *i* with respect to the market portfolio. The beta of *i* is determined using formula (10), substituting R_p with R_{Mkt}. The formula above states that in an efficient market, stocks with a similar level of

[21] Berk & DeMarzo, 2014, p. 381

systematic risk must have the same level of expected return. As the idiosyncratic risk can be eliminated by diversification, only the systematic risk, the beta with respect to the market portfolio, should be determining the level of expected return.

6.3 Arbitrage Pricing Theory

The CAPM above is a one-factor model, meaning that the expected return on any given stock is given by just one factor. In the CAPM model the beta-value, which supposedly captures all the systematic risk on a given stock, is the one and only factor explaining differences in the expected return. However, since the CAPM was first publicized it has been both praised and criticized for its simplicity. Some of the critique eventually manifested itself in a new theoretical direction called Arbitrage Pricing Theory (APT). Supporters of the APT claim that the market portfolio is not always efficient, and thereby implying that the market beta is not able to properly explain differences in the expected return on its own, because all systematic risk cannot be confined to a single factor. Stephen A. Ross is the originator of the Arbitrage Pricing Theory. In his paper from 1976 he suggests that it is not actually necessary to identify the efficient portfolio itself, but that instead it is possible to construct an efficient portfolio from a collection of well-diversified portfolios, which are called factor portfolios[22]. Just like the market portfolio and the related beta, which measures the return sensitivity on a given stock with respect to the market portfolio, there are factor portfolios and factor betas that measure the return sensitivity on a given stock with respect to the factor portfolio. The factor betas all capture different components of the systematic risk, but when they are implemented into the same model they will collectively capture all the systematic risk. Thus, when the proper factor portfolios are identified, it is possible to create a pricing model based on multiple risk factors, which incorporates multiple factor betas which, when combined, can explain differences in expected return on different stocks, in a somewhat similar manner to the CAPM[23]. Due to the no arbitrage mechanism embedded in the model[24], two stocks with identical factor betas must also have identical expected returns, hence the name Arbitrage Pricing Theory. In the APT, the expected return on an asset *i* is given by[25]:

[22] Ross, 1976, p. 341
[23] Bodie et al., 2011, pp. 435-463
[24] The law of one price
[25] Berk & DeMarzo, 2014, p. 462

$$E(R_i) = r_f + \sum_{n=1}^{n} \beta_i^{F_n} \cdot \left(E\left(R_{F_n} - r_f\right)\right) \qquad (15)$$

Where $\beta_i^{F_n}$ is the *n*'th beta factor for stock *i* and $E\left(R_{F_n} - r_f\right)$ is the expected risk premium on the *n*'th factor.

Ross (1976) did a good job creating an intuitive and fairly simple model, but didn't quite answer the question of which factor portfolios to include for an optimal model. Chen, Roll & Ross (1986) came up with a model focusing on macroeconomic factors, which for many years served as the most predominate APT multifactor model. However, in 1992 and 1993, Fama and French published what would become the most famous multifactor model to date. Instead of looking at macroeconomic factors, they put forth strong empirical evidence that suggested that certain firm characteristics where good proxies for the stock's exposure to systematic risk (Fama & French, 1992) (Fama & French, 1993). The Fama & French Three Factor Model marks their most noteworthy contribution to the APT literature. As the name implies it consists of three factors; the market factor, the size factor and the book-to-market factor. These three factors were chosen on the grounds that they proved to be good predictors of differences in stock return over longer periods of time. The Fama & French Three Factor model is given by[26]:

$$E(R_{it}) = r_f + \beta_{iM} \cdot R_{Mt} + \beta_{iSMB} \cdot SMB_t + \beta_{iHML} \cdot HML_t + \epsilon_i t \qquad (16)$$

Where SMB is the return of a portfolio of small stock in excess of the return on a portfolio of large stocks, and where HML is the return of a portfolio of stocks with high book-to-market values in excess of the return on a portfolio of stocks with low book-to-market values. Since its publication, the Fama & French Three Factor Model has been debated as to whether the factors identified reflect an APT model or a multi ICAPM[27], but this discussion is beyond the scope of this paper. The important takeaway is, that the arbitrage pricing theory suggests that there are multiple risk factors that can explain differences in the return on stocks.

[26] Fama and French, 1996, p. 56

[27] '*Intertemporal Capital Asset Pricing Model*' as described by Merton, 1973.

6.4 Efficient Market Hypothesis

The previous sections regarding the modern portfolio theory, the CAPM and APT rely on an efficient market. This phenomenon however was not formalized until 1970. Back then, Eugene Fama provided the foundation for the Efficient Market Hypothesis. In general, the main concern of the theory is whether prices fully reflect available information at any point in time. If so, a market is considered "*efficient*"[28].

However, Fama believes that the statement that prices fully reflect available information has no empirically testable implications in this general form. Therefore, the concept of "*fully reflecting*" is specified further, leading to three testable subsets of the efficient market hypothesis: Strong form efficiency, semi-strong form efficiency and weak form efficiency[29]. The strong form efficiency concerns testing the possibility of someone having monopolistic access to information, which could be relevant for the formation of prices. As such, if the market is efficient in its strong form, all information of any kind will be reflected in the prices and insider information will not exist[30] [31]. As this seems highly unlikely, the semi-strong form efficiency hypothesis relaxed these extreme assumptions. It concerns testing the speed of price adjustments to publicly available information[32]. If the market was to be efficient in its semi-strong form, all publicly available information will be fully reflected in the share price[33]. This hypothesis allows for companies to have inside information, but would require instant price changes at the time of publication, thereby fully reflecting the new public information. The third form, the weak form efficiency, simply concerns testing for historical prices[34]. This would mean that the current share price at all times simply reflects the equity's past prices[35].

While the weak form efficient market implies that looking at historical stock returns would be meaningless, the semi-strong form indicates that a thorough knowledge and detailed analysis of publicly available information of a given company would not generate profit for the investor either. The weak form efficiency is, all else equal, the easiest obtainable and testable

[28] Fama, 1970, p. 383
[29] Ibid, pp. 383-384
[30] Ibid, p. 388
[31] Hillier et al., 2011, p. 335
[32] Fama, 1970, p. 388
[33] Hillier et al., 2011, p. 336
[34] Fama, 1970, p. 388
[35] Hillier et al., 2011, p. 336

kind of market efficiency. As such, it is also the most coveted and in an article from 1991, Fama states[36]: "*There is a resurgence of interesting research on the predictability of stock returns from past returns and other variables. Controversy about market efficiency centres largely on this work.*"

6.5 Implications

The traditional investment theory presented above would indicate that momentum strategies would not be profitable over time. However, it does not imply that the strategies would not be able to perform positive returns on occasion. In such a scenario, the theory states that the opportunity to create a positive return from a momentum strategy would be due to chance, and further that it would be public knowledge. Therefore, all investors would seek to exploit this opportunity, thus causing the positive returns to be temporary. In summary, the traditional investment theory suggests that sporadic positive returns may be generated, but continuous positive returns should not occur.

[36] Fama, 1991, p. 1609

7 Literature Review

The overall purpose of this section is to cover the previous studies related to price momentum strategies in order to support decision made later in the methodology and analysis of the empirical results. In doing so, methodologies, results and the various sub-samples as well as the robustness tests from previous studies will be covered. The methodologies do not vary a lot across the studies but the various options for splitting up the overall sample and for testing the significance levels through robustness checks do. Some are persistent in much of the literature while others are only used sporadically. It seems that the many possible sub-studies regarding the momentum strategies have required previous research to delimitate itself, and therefore, a review of previous literature on the subject is pivotal when deciding how the empirical research should be conducted in this paper. Throughout the following section, the main focus will be on the pioneering work of Jegadeesh and Titman from 1993, before turning to the similarities and deviations observed in other studies of price momentum strategies.

7.1 Methodologies

7.1.1 The Original Approach

Jegadeesh & Titman, 1993

The period leading up to 1993 had been dominated by research on price contrarian strategies, which buys past losers and sell past winners with an expectation of mean reversals[37]. In 1993 however, Jegadeesh and Titman provided the pioneering work on price momentum strategies and their methodology has been used extensively in studies on the subject ever since, either by a full or a partial replication. The contrarian strategies had proved successful in the short and long term respectively, but practitioners at the time, mutual funds especially, also used what was known as the momentum approach. Jegadeesh and Titman (1993) report anecdotal evidence suggesting that these practitioners based selections on price movements over the past 3 to 12 months[38]. They go on to implement this anecdotal evidence into their momentum strategies. In short, the strategies are based on historical returns over the past 3, 6, 9 and 12 months respectively. This is

[37] Jegadeesh and Titman, 1993, p. 66
[38] Ibid, p. 67

called the formation period and is referred to by *J*. Further, the strategy implies holding the portfolio based on past returns in 3, 6, 9 and 12 months respectively. This is called the holding period and is referred to by *K*. The various combinations of these formation and holding periods lead to 16 distinct *J*/*K*-strategies. The portfolios are sorted and ranked based on the past *J*-month returns. A decile approach is used to create a winner and a loser portfolio consisting of the top and bottom 10% of the stocks respectively. The approach then buys ("*long*") the winner portfolio and sells ("*short*") the loser portfolio for the following *K* months. This yields a strategy consisting of the previous winners (the winner strategy), a strategy consisting of the previous losers (the loser strategy) and a combined strategy consisting of both portfolios, buying winners and selling losers. The latter is referred to as the *zero-cost portfolio*[39]. Thus, by examining whether the previous high performing stocks are outperforming the previous worst preforming stocks in the following period, they determine whether price momentum exists. This process is repeated monthly, giving the investor a total of *K* portfolios at a given point in time for the respective strategy.

Thus, at the time of formation, the momentum strategy terminates the position initiated at month $t - K$. So each month, the strategy revises the weights on $1/K$ of the stocks of the total portfolio at time *t*, and carries the remaining positions over to the next month, $t + 1$. In other words, the strategy implements a partial rebalancing approach, where multiple winner and loser portfolios are held at the same time. For a *J*/*K*-strategy where $K = 6$, a total of 6 distinct winner and loser portfolios are held at the same time. Moving forward in time by one month then buys/sells a new winner/loser portfolio while closing the positions initiated at time $t - 6$[40]. Jegadeesh and Titman (1993) applied this approach on historic data of NYSE and AMEX stocks from 1965 to 1989[41].

Jegadeesh and Titman, 2001

In 2001, Jegadeesh and Titman made a follow-up study to their 1993 research. An important aspect of this was, that they performed an out-of-sample test, covering a period extending from 1990 through 1998. This was done to address the criticism arising related to data mining[42]. They applied an identical approach as to their previous work. However, they only investigate the 6/6-

[39] Jegadeesh and Titman, 1993, p. 69
[40] Ibid, p. 68
[41] Ibid, pp. 67-68
[42] Jegadeesh and Titman, 2001, p. 699

strategy and furthermore chose to include Nasdaq stocks as well as to exclude small stocks and low-priced stocks[43].

7.1.2 Replications and alterations to the original methodology

Chan, Jegadeesh and Lakonishok, 1996

Following the research by Jegadeesh and Titman of the US stock market in 1993, Chan, Jegadeesh and Lakonishok collaborated in 1996 on a study addressing the "*woeful shortage of potential explanations for momentum*"[44]. Their main hypothesis was, that the profitability of momentum strategies is entirely due to earnings-related news[45]. The methodology applied to the momentum strategies is in accordance with the one by Jegadeesh and Titman, using formation and holding periods, a decile ranking approach to winner and loser portfolios and equally weighted portfolios. However, the extent of the various strategies is different. They only investigate momentum strategies with a formation period of 6 months, and focuses on holding periods of 6, 12, 24 and 36 months respectively. Thus, the study addresses both momentum and contrarian strategies. The literature does not offer an explicit statement as to whether full or partial rebalancing have been used.

The study investigates the period from 1977 to 1993 and focuses on the NYSE, AMEX and Nasdaq stock markets. Further, the article specifies that "*closed-end funds, real estate investment trusts, trusts and American depository receipts*" are excluded from the sample of stocks[46].

Rouwenhorst, 1998

While the original study from 1993 and the follow-up by Chan, Jegadeesh and Lakonishok focused on US stock markets, Rouwenhorst (1998) studies the European stock markets. He argued that, if the international markets did not experience return continuation, then the US momentum strategy success might simply have been an unusual case. Therefore, the study was extremely important, as it went a long way to confirm the profitability of return continuation on a wider sample of indices, and further addressed the issue of data mining. In addition to confirming the

[43] Jegadeesh and Titman, 2001, p. 703
[44] Chan, Jegadeesh and Lakonishok, 1996, p. 1682
[45] Ibid, p. 1682
[46] Ibid, p. 1684

findings by Jegadeesh and Titman, he also suggests that the European and US momentum strategies have a common explanatory proponent. This could be some common factor driving the profitability of the strategies in question, but no further examination of possible explanatory factors are included in the study[47].

Regarding the methodology, he replicates the one laid out by Jegadeesh and Titman[48], and thus also investigates momentum strategies based on formation and holding periods of 3, 6, 9 and 12 months respectively (16 distinct strategies in total). Similarly he also employs the decile ranking approach and the equally weighted winner and loser portfolios. Finally, the zero-cost portfolio is investigated as well. The full replication of the original study's methodology, applied to new data, makes it for great comparison of results. Rouwenhorst conducts his research on 12 different European stock markets, covering a period from 1978 through 1995[49].

Schiereck, De Bondt and Weber, 1999

One year later, in 1999, Schiereck, De Bondt and Weber conducted a similar study on the Frankfurt Stock Exchange from 1961-1991. The idea was again to crosscheck in a second market for the results established somewhere else. The main difference between this study and the one conducted by Rouwenhorst is that the one by Schiereck et al. (1999) also examines contrarian strategies. Like Rouwenhorst however, they address one of the common accusations in financial research regarding data mining[50]. The methodology was a close replica of the original price momentum methodology by Jegadeesh and Titman (1993). Again, the *J/K*-strategy approach with formation and holding periods was adopted, but instead of a decile approach to rank the stocks, the authors chose a top 10, 20 and 40 approach to create winner and loser portfolios[51]. The entire sample consisted of 357 distinct stocks, but these stocks were not necessarily all available throughout the entire sample period. For instance, for the 12/12-strategy, only 183 stocks were included in 1973. The 12/12-strategy is based on an average of 206 stocks and this number is said

[47] Rouwenhorst, 1998, p. 268
[48] Ibid, p. 269
[49] Ibid, p. 268
[50] Schiereck, De Bondt and Weber, 1999, p. 104
[51] Ibid, p. 107

to be representative[52]. Therefore, the top 20 and 40 rankings represent a fraction of the total stocks included, somewhat similar to the decile and quintile approach. Furthermore, instead of the partial rebalancing scheme applied by Jegadeesh and Titman and Rouwenhorst, this article applies a full rebalancing approach. That is, at the end of each holding period, only one new winner and one new loser portfolio are formed, thus implying that the investor at all times hold one zero-cost portfolio instead of *K* distinct portfolios. The full rebalancing approach drastically decreases the number of observations. For the 12/12-strategy, only 30 observations are accessible. The argument for the deviation from the original partial rebalancing approach was, that "*this technique avoided overlapping rank periods and thereby guaranteed the independence of return observations*"[53]. The methodology presented investigates formation periods of 1, 3, 6 and 12 months but only a holding period of 12 months – thus a total of 4 distinct strategies[54].

Chan, Hameed and Tong, 2000

Chan, Hameed and Tong conducted the first research study covering the existence of price momentum in global equity markets in 2000 and cover the period from 1980-1995[55]. In contrast to previous studies, which consider individual stocks in one or multiple stock indices, Chan et al. (2000) look at momentum strategies based on stock market indices instead of individual stocks[56]. Furthermore, the authors choose not to use a winner and loser portfolio set-up as applied in previous literature. Instead, the portfolio consist of all market indices (the assets bought or sold) and the portfolio weights are determined by the past performance of the index relative to the average performance of all the indices in question[57]. As they argue, this methodology is consistent with the one applied by Jegadeesh and Titman (1993), as it also buys the best performers and sells the previous losers. However, the portfolio weights are proportional and not equal as previously applied in the literature, which could indicate that if past winners/losers deviates highly from the average performance, they will obtain an excessive weight in the portfolio[58]. Their approach is similar to previous research in their overall purpose, but quite different in the implementation, as

[52] Schiereck, De Bondt and Weber, 1999, pp. 105 and 107
[53] Ibid, p. 107
[54] Ibid, p. 107
[55] Chan, Hameed and Tong, 2000, p. 158
[56] Ibid, p. 154
[57] Ibid, p. 155
[58] Chan, Hameed and Tong, 2000, p. 156

all indices are included in the portfolio. However, this technique was a necessity, given that the analysis only included 23 distinct countries and their respective stock market index. A decile approach would only have led to approximately 2 indices in the winner and loser portfolios respectively. Even though the weighting scheme is quite different from the original approach, the idea remains the same. Just as the zero-cost portfolio, the weights sum to zero.

They do however address the possibility of excessive weights toward individual stock markets. To avoid small markets to obtain a large weight, the weights are revised in a separate sample. For this sample, the market-capitalization are taken into account and the new weights are computed as the stock market's excess return compared to the average stock market return, multiplied by the market capitalization weight of the stock market in question. This way, the investor avoids taking a large position, long or short, in a small market that outperformed or underperformed the average significantly during the formation period[59]. Both methodologies are used throughout their article.

Liu and Lee, 2001

The last study included in this literature review is the study of Liu & and Lee (2001). Their study focuses on the Japanese market from 1975 to 1997[60] and use an exact replica of the methodology applied by Jegadeesh and Titman (1993), although they do not disclose information regarding whether they use a full- or partial approach to rebalancing[61].

Every study investigated has thus adopted the main framework presented Jegadeesh and Titman's (1993) methodology. Although few replicate the approach fully, the majority uses the idea of *J*/*K*-strategies. Deviations occur regarding the ranking and rebalancing approaches but the overall methodology has always been connected to that of Jegadeesh and Titman (1993).

[59] Chan, Hameed and Tong, 2000, p. 157
[60] Liu and Lee, 2001, p. 322
[61] Ibid, p. 323

7.2 Sub-samples

Jegadeesh and Titman, 1993

Metghalchi et al. (2012) addressed the issue of data snooping. This phenomenon occurs whenever the same set of data is used several times with the purpose of inference or model selection. The main issue is, that reusing the same data set might imply the resulting conclusions to be down to pure luck, rather than any real merit of the particular model[62]. Previously, researchers have tried to test their models on different but comparable data in order to avoid this bias. Sometimes such data is not available, and instead, if the original data sample is sufficiently large, sub-samples of the data has been created to see if the obtained results are persistent throughout sub-samples[63]. Therefore, one of the main reasons for using sub-samples is to check whether or not the existence of a given pattern is persistent throughout the available data. Furthermore, another important feature of using sub-samples is presented. As abnormal returns are observed in the price momentum strategies, this could be explained by the conventional financial theory linking returns to risk factors.

They use what they refer to as a simple return-generating model to decompose the excess returns and identify sources of price momentum profits[64]. The chosen model decomposes the profits into two components related to systematic risk, which they argue would exist in an efficient market, and a final and third element related to the firm-specific returns, which would only explain the momentum profits if the market was inefficient. The return-generating model used is a one-factor model consisting of three components: The unconditional expected return on the individual stock, the dependency of the chosen factor and the firm-specific component of return[65]. This model is then linked with the expectation that both future profits and previous profits are larger than the corresponding index values. The exact deduction of the formulas used are beyond the scope of this study, but their final formula describes the three components of potential sources of the price momentum profits[66]:

$$E\{(r_{it}-\bar{r}_t)(r_{it-1}-\bar{r}_{t-1})\} = \sigma_\mu^2 + \sigma_b^2 Cov(f_t, f_{t-1}) + \overline{Cov}_i(e_{it}, e_{it-1}) \qquad (17)$$

[62] Metghalchi, Marcucci and Chang, 2012, p. 1540
[63] Ibid, p. 1543
[64] Jegadeesh and Titman, 1993, p. 69
[65] Ibid, p. 71
[66] Ibid, p. 72

Where the two σ^2 components on the right-hand side are the cross-sectional variances of the expected returns and factor sensitivity respectively. For a full understanding of how to get to this point, the article by Jegadeesh and Titman (1993) is recommended. However, the formula above is the one of importance for this study. When momentum profits can be obtained, the expression on the left-hand side has a value greater than zero. This indicates that at least one of the three components on the right-hand side must be as well. The first component represents the cross-sectional dispersion in expected returns, and the third component is the average serial covariance of the idiosyncratic components of stock returns. The second component has a less intuitive interpretation. The expression states that the extent to which the momentum strategy is able to generate profits due to the serial correlation of the factor portfolio is a function of the cross sectional variance of the factor sensitivities.

If the profit obtained is due to any one of the first two components, then they may represent compensation to bearing systematic risk and might not indicate market inefficiency. If however the profits were due to the third component, then it would indicate market inefficiency[67].

The considerations and the model outlined above lead Jegadeesh and Titman to turn to an analysis of sub-samples. To investigate the first component, they investigate "*the two most common indicators of systematic risk*": the betas of the winner and loser portfolios and the average capitalizations of the stocks in the mentioned portfolios[68]. Further, they relate the second component to the in-sample serial covariance of the equally weighted index return, which has to be positive for the second component to carry explanatory power[69]. The last component is addressed by investigating the serial covariance of market model residuals for individual stocks on average. Beside the mentioned decomposition of momentum returns, they look into the possibility that the profits arise from a lead-lag relationship in stock prices[70].

They go on to investigate the profitability of their 6/6-strategy on sub-samples for betas and firm size. As such, they split the total sample into a small, medium and a large segment, doing this for betas and firm size respectively. This is done in order to test whether or not the profitability is confined to certain sub-samples of stocks[71]. Their final sections are devoted to a

[67] Jegadeesh and Titman, 1993, p. 72
[68] Ibid, p. 72
[69] Ibid, p. 73
[70] Ibid, p. 74
[71] Ibid, p. 76

look at the effect of transactions costs, sub-periods of 5-year horizons, an event study of the average portfolio return in the 36 months following the formation period and finally the link to earning announcement dates[72].

Jegadeesh and Titman, 2001

As mentioned, Jegadeesh and Titman published an out-of-sample test of their original results in 2001. The main motivation was to evaluate various suggested explanations to momentum profits. As such, this study does not include new sub-analysis per se, but rather focuses on the behavioral aspect of the strategies.

Chan, Jegadeesh and Lakonishok, 1996

Chan, Jegadeesh and Lakonishok (1996) focused primarily on the link between price momentum and earnings momentum. This is an important study as it covers a lot of previously uncovered ground on this link, and creates a foundation for later research to investigate different areas of the price momentum strategies. They do however briefly look into other aspects. First off, they look only at large stocks, as they believe this would "*alleviate potential problems of survivor bias in the sample, and problems with low-priced stocks*"[73]. As such, they believe that the large stocks have a lesser tendency to default and therefore that none of the included stocks would default over the sample period. In this study, the large stock segment is defined as stocks whose market capitalization is above the market median. Finally, they take a closer look at a three-factor model as they believe the predictive power of price and earnings momentum may be related to the effects of book-to-market or firm size[74].

Rouwenhorst, 1998

Rouwenhorst (1998) was, as mentioned previously, the first to conduct a large study of price momentum on the European stock markets. As the study was carried out for 12 distinct countries, he hypothesized that the effect may be confined only to some countries. Thus, he chose to

[72] Jegadeesh and Titman, 1993, pp. 77, 82-83 and 86
[73] Chan, Jegadeesh and Lakonishok, 1996 – p. 1704
[74] Ibid – p. 1705

investigate whether the overall effect was due to country momentum[75]. Further, as the winner and loser portfolios both had an average market capitalization below the sample average, he further investigated the effect of firm size. As some of the countries included in the overall sample represented a much larger fraction of the large firms, country and firm size might be related. He therefore produced a combination of the two sub-samples: a country- and size-neutral sub-sample[76]. The previous American studies both focused on firm size, but this was the first study to investigate the country effect. As the entire study by Rouwenhorst (1998) is based on testing whether Jegadeesh and Titman's 1993 results were representable for Europe, he checks for risk-adjusted returns by investigating the betas of the winner and loser portfolios and goes on to look at returns in event-time[77]. Furthermore, like Jegadeesh and Titman (1993), he looks into the possible effect of a lead-lag effect. Where Jegadeesh and Titman (1993) looked into a 1-week delay of the portfolio formation, Rouwenhorst (1998) investigated the effect of a 1-month delay from the ranking period to the start of the holding period. Finally, as he finds strikingly similarities between the US results from 1993 and his own European results, he explores the possibility of common components for momentum returns across geographic markets[78].

Schiereck, De Bondt and Weber, 1999

The previously mentioned studies on momentum strategies considered very similar sub-samples. This changed when Schiereck et al. (1999) offered a different perspective to the robustness checks of the observed profitability. They looked into firm size and betas as previously done[79], but instead of simply looking at whether the average monthly return was significantly larger than zero or not, they also looked at how often the strategy provided a net positive performance over the different ranking and holding periods examined[80]. Furthermore, they went on to include the contrarian framework into their analysis by extending the holding period to 2-5 years[81]. Finally, they tried to link the performance of the momentum strategies to the state of the economy. This part of their

[75] Rouwenhorst, 1998, p. 273
[76] Ibid, p. 276
[77] Ibid, pp. 277 and 279
[78] Ibid, p. 282
[79] Schiereck, De Bondt and Weber, 1999, pp. 110-111
[80] Ibid, p. 107
[81] Ibid, p. 110

study is highly relevant as well, as the period examined in this paper includes the subprime crisis.

Chan, Hameed and Tong, 2000

The global study conducted by Chan, Hameed and Tong in 2000, as previously mentioned, is looking at country indices instead of individual stocks. They hypothesize that the profits could be due to market segmentation, as some countries had restrictions on foreign equity ownership in the beginning of the sample. Therefore their first sub-analysis is to exclude the first 5 years of the sample (1980-1985) and instead focus on the remaining 10-year period (1985-1995)[82]. Like previous studies, they look to a beta-based sub-sample to investigate the potential link between risk and abnormal profits. Further, they include a new analysis, investigating the link between momentum profits and trading volume[83]. In accordance with the major studies by Jegadeesh and Titman (1993) and Rouwenhorst (1998) of the US and European stock markets respectively, this paper looks at the effect of a lag between the formation and holding period. In the US study, the implemented lag length was 1 week, for the European counterpart it was 1 month, and for this global study the lag-length used is 1 week[84]. In the remainder of the study they focus on two distinct sub-analysis: 1) A sample excluding emerging markets, as emerging markets have a low liquidity, and 2) an analysis linking the degree of momentum profits to the state of the economy[85]. Regarding the latter, this is an analysis somewhat similar to the one conducted for the Frankfurt Stock Exchange study the previous year by Schiereck et al. (1999).

Liu and Lee, 2001

The Japanese study by Lee and Liu from 2001 starts by looking at the effect of a 1-month lag between the formation and holding period, like Rouwenhorst did in 1998[86]. They go on to look at the performance of the strategies in up- and down markets through sub-periods based on the market tendencies of a bull and a bear market[87]. Furthermore, they look at a small/large sub-sample based on firm size and go on to create size-neutral portfolios[88]. An event-time study like

[82] Chan, Hameed and Tong, 2000, p. 161
[83] Ibid, pp. 161 and 164
[84] Ibid, p. 166
[85] Ibid, pp. 166 and 168
[86] Liu and Lee, 2001, p. 323
[87] Ibid, p. 327
[88] Ibid, p. 328

the one used by Jegadeesh and Titman (1993) and Rouwenhorst (1998) is included as well, although the one used only covers 6 months compared to 36 months by the aforementioned authors[89].

As shown, the majority of the work conducted on momentum strategies was done in the 1990's and the various studies cover different geographic areas, although overlapping in places, and have various alterations to the use of sub-analyses. The most popular areas for sub-analyses have been the study of a lead-lag relationship, the possibility of an explanatory risk factor (mainly market beta and size), the effect of transaction costs and splitting the original data sample into sub-periods. Less predominant are the sub-analyses of the possible influence of the state of the economy, the number of monthly portfolio observations that has a positive return, event studies and geographic splits.

7.3 Results

Jegadeesh and Titman, 1993

The original research conducted by Jegadeesh and Titman in 1993 motivated the majority of the following research. This motivation occurred due to the empirical results they published, in which their main finding was the statistically significant profits of the momentum strategies. Their most profitable zero-cost strategy is the 12/3-strategy, which yields a profit of 1.31% per month, and has a *t*-value of 3.74. All of their *J*/*K*-strategies are profitable and all except the 3/3-strategy are statistically significant at the 95% confidence level. For most of their strategies, they show that the profits can be slightly higher if the one-week lag is introduced[90]. Regarding their three-component model describing the momentum profits, formula (17) above, their evidence suggests that the profits are not due to the first component, σ_μ^2, which would have indicated a strategy systematically picking high-risk stocks[91]. Further, the results show that the second component, $\sigma_b^2 Cov(f_t, f_{t-1})$, which would indicate whether the serial covariance of the factor-portfolio caused the momentum profits, is neither the source. In turn, they conclude that the

[89] Liu and Lee, 2001, p. 329
[90] Jegadeesh and Titman, 1993, p. 70
[91] Ibid, p. 72

profitability is related to market underreaction to firm-specific information[92]. They then turn to their sub-analysis of beta-based and size-based portfolios. The main finding is, that the strategy is profitable and statistically significant at the 95% confidence level in each of the sub-samples. Further, they show that for the zero-cost portfolio, the sub-sample consisting of the largest firms provide the lowest abnormal profits. Regarding the betas, the large beta sub-samples performs the best, while the small beta sub-sample provides the lowest abnormal return[93].

Turning to the sub-period analysis, they look at five 5-year sub-periods. Except for the 1975-1979 period, the strategy results in positive average monthly returns[94]. The event-time study clearly shows positive profits from month 2-12 and negative profits from month 13-36[95]. This indicates a reversal of the momentum profits when a one-year holding period is exceeded.

Chan, Jegadeesh and Lakonishok, 1996

Chan, Jegadeesh and Lakonishok (1996) also study the American market, and like Jegadeesh and Titman (1993) they show the existence of the momentum effect. Their zero-cost strategies with a formation period of 6 month show a total yearly return of 15.4% on average[96]. In addition, they investigate earnings momentum, as they argue that past price performance of the formed portfolios is closely related to the past earnings. Both the price and earnings momentum strategies yield positive results, but the spread between the winner and the loser portfolios' return tend to be larger and persist for a longer period for the price momentum strategies[97]. The authors go on to argue that neither of the momentum exploiting strategies subsumes the other, but rather that they each take advantage of underreaction to different sub-sets of information[98]. In contrast to Jegadeesh and Titman (1993), this study does not find direct evidence of return reversals in the subsequent period, which leads them to question the validity of a behavioral hypothesis of the momentum profits being induced by positive feedback trading[99]. Their investigation into the large stock segment shows that there is evidence that the market adjusts

[92] Jegadeesh and Titman, 1993, p. 75
[93] Ibid, p. 78
[94] Ibid, p. 82
[95] Ibid, p. 84
[96] Chan, Jegadeesh and Lakonishok, 1996, p. 1687
[97] Ibid, p. 1693
[98] Ibid, p. 1697
[99] Ibid, p. 1703

gradually to information regarding earnings and returns[100]. The main takeaway from the remainder of the study is, that adjusting for size and book-to-market factors does not alter the observed pattern of price momentum profits[101]. ‘

Rouwenhorst, 1998

The European replication of the study by Jegadeesh and Titman (1993), conducted by Rouwenhorst (1998), shows strikingly similar results. The best overall price momentum strategy in this study is the 12/3-strategy as well, which yields a monthly average return of 1.35% and has a *t*-stat of 3.97. All of the 16 distinct strategies are profitable and statistically significant at the 95% confidence level. The profits are improved slightly for the shorter ranking periods when a lag effect is introduced, but not for the longer ones[102]. Rouwenhorst (1998) goes on to argue that the market betas of the zero-cost portfolios are not significantly different from zero, thus indicating that the profitability is not due to its covariance with the market[103]. When looking at the effect of firm size, the average loser is smaller than the average winner, but both are below the overall average[104]. When investigating the differences between countries, the results show that the average country profits are only slightly lower than for the overall sample, 0.93% per month compared to 1.16% per month. Furthermore, as winners outperform losers in every country, the idea of price momentum being confined to certain countries is discarded[105].

Like Jegadeesh and Titman (1993), he shows that by splitting the original sample into a small, medium and large size segment, that past winners outperform past losers in every segment, but that the smaller firms obtain larger profits than the large firms[106]. He goes on to obtain similar findings to those of Jegadeesh and Titman (1993) related to beta as an explanatory risk factor, showing that the average beta of the winner and loser portfolio is very similar[107]. The event-time study is, as well, strikingly similar to the results shown by Jegadeesh and Titman (1993). It is shown that the zero-cost portfolios provides positive profits in month 1 through 11

[100] Chan, Jegadeesh and Lakonishok, 1996, p. 1704
[101] Ibid, pp. 1707-1708
[102] Rouwenhorst, 1998, p. 270
[103] Ibid, p. 271
[104] Ibid, p. 272
[105] Ibid, pp. 274-275
[106] Ibid, p. 276
[107] Ibid, p. 277

and then turns negative in period 12 through 24 with the exception of month 19 where a positive return of 0.1% is observed[108]. Transaction costs are included as well in the analysis, and do not present an obstacle hindering the profitability of the momentum strategies[109]. The final part of his paper looks at the link between US and European profits, and although he does seem to prove a common explanatory component, he also shows an independent component for the European momentum profits[110].

Schiereck, De Bondt and Weber, 1999

The study by Schiereck, De Bondt and Weber on the Frankfurt Stock Exchange (1999) shows that their price momentum strategies are profitable as well. They only look at a 12-month holding period, which proves profitable and statistically significant at the 95% confidence level[111]. Interestingly, they show that the zero-cost strategies are, on average, profitable in roughly 60-80% of the observations.[112]. They also confirm results in previous studies[113], by showing that the beta has no explanatory power when it comes to the momentum profits observed on the German market. Furthermore, they concluded that the state of the economy has no say on the performance of the momentum strategies[114]. Their final remark is, that investors seem to be too optimistic (pessimistic) about past winner (loser) companies.

Chan, Hameed and Tong, 2000

Apart from the studies by Jegadeesh and Titman (1993) and Rouwenhorst (1998), the most significant contribution to the literature was the work conducted by Chan, Hameed and Tong (2000) on international market indices. However, when it comes to the comparability of the study, only the holding period of 12 and 26 weeks are applicable. Although they confirm the market anomaly for short horizons (holding periods up to 4 weeks), they don't confirm it for their 12-week holding period, since the positive average returns are not significant. However, the 26-week

[108] Rouwenhorst, 1998, p. 280
[109] Ibid, pp. 281-282
[110] Ibid, p. 283
[111] Schiereck, De Bondt and Weber, 1999, p. 108
[112] Ibid, p. 109
[113] See Jegadeesh and Titman (1993) and Rouwenhorst (1998)
[114] Schiereck, De Bondt and Weber, 1999, p. 111

holding period strategy is significantly profitable as well[115]. The 12-week holding period has a 12-week formation period, and it should be noted that in Rouwenhorst's study, the 3/3-strategy was the second worst of the 16 distinct strategies investigated. Looking at the same 16 strategies by Jegadeesh and Titman (1993), the 3/3-strategy was also the worst one observed. Thus, the 12-week strategy might not be the best strategy to confirm or reject the profitability of momentum strategies in general. They further investigate whether the exclusion of the first 5 years of the sample or the exclusion of emerging markets might influence the results. Excluding emerging markets does affect the profits obtained, but they remain positive, while the exclusion of 5 years does not affect the results significantly[116]. A simple beta risk adjustment does not explain the profits either[117]. This is the first study to look at market capitalization-weighted portfolios but this implementation does not alter the results significantly either. However, an interesting aspect is, that they show that the price continuation is somewhat stronger following an increase in the trading volume[118]. As others before them, they look at the effect of introducing a one-week lag, but conclude that the profits get smaller[119].

Jegadeesh and Titman, 2001

Like the out-of-sample test conducted by Chan, Jegadeesh and Lakonishok in 1999, Jegadeesh and Titman does the same in 2001 with respect to their original publication from 1993. In this follow-up research, they confirm their previous results for a new period ranging from 1990 through 1998[120]. They conclude that the investment strategies of market participants have not changed in ways which would/could eliminate the momentum profits[121]. Behavioral theories are then studied and the brief conclusion is, that they show return reversals from year 2-5 after the formation period, and that this leans towards a model expecting post-holding return reversals.

[115] Chan, Hameed and Tong, 2000, p. 160
[116] Ibid, pp. 161 and 166
[117] Ibid, p. 162
[118] Ibid, p. 164
[119] Ibid, p. 166
[120] Jegadeesh and Titman, 2001, pp. 704 and 707-709.
[121] Ibid, p. 718

Liu and Lee, 2001

As mentioned earlier, the study by Lee and Liu (2001) of the Japanese market is highly important due to the results. They applied the exact same approach as Jegadeesh and Titman (1993), but instead of showing evidence of price momentum, their results show the opposite. As such, every single one of their 16 distinct zero-cost strategies come up with negative returns, all statistically significant at the 95% confidence level[122]. What is especially interesting however is, that both the winner and the loser portfolios contribute with positive profits, but the profits from the loser portfolios are significantly higher than those of the winner portfolios. Even though all of the zero-cost portfolios come up with negative returns, it is striking that the one with the lowest *t*-value is the 12/3-strategy, which is shown to be the best performing strategy in the previous studies by Jegadeesh and Titman (1993) as well as by Rouwenhorst (1998). The introduction of a 1-month lag does not make any of the zero-cost strategies profitable but does improve them[123]. Although the strategies remain unprofitable in all sub-period, they do show a tendency to lose more money in the bear market[124]. Furthermore, Liu and Lee (2001) find smaller stocks to incur higher losses than large stocks, and even after controlling for size through size-neutral portfolios, the strategies remain unprofitable[125]. The event-time study shows that the strategies are only incurring statistically significant losses in the first month[126]. The event-time study by Jegadeesh and Titman (1993) shows a similar tendency, as strategies only start having positive and significant returns from month 2-12. As such, different studies show that the first month is the worst one regarding profits and/or losses. Liu and Lee (2001) take a closer look at the reasons for the losses of the momentum strategies and conclude that time-series predictability in stock returns is a significant contributor to the losses obtained[127].

[122] Liu and Lee, 2001, p. 324
[123] Ibid, p. 324
[124] Ibid, p. 327
[125] Ibid, p. 328
[126] Ibid, p. 331
[127] Ibid, p. 338

7.4 Summing up

The focus towards price momentum has faded since the turn of the millennium. The majority of the work conducted has shown clear evidence of statistically significant profits from the price momentum strategies, but some studies were not able to replicate the profits. As such, the study of the Japanese market is an outlier. As the previous sections points out, a lot of sub-samples have been used to try and explain the market anomaly but none have proven especially successful. Instead, the articles have suggested that further research should be focused on the investors and behavioral models. But at the same time, conventional theory suggests that rational investor would eliminate the abnormal profits in the future. Therefore, it seems highly relevant to conduct a study based the period from 2000 to now, investigating both aspects. One of the interesting aspects of this period is, that investors has had almost two decades to correct the market anomaly. Therefore, if the anomaly has faded with time, then this should be seen in the empirical results in the coming sections. Further, the research will be conducted on data that has not been used previously in any of the cited articles and as such it also includes the financial crisis of 2007-2009. This inclusion allows for a closer look at the effect of momentum strategies in up and down markets.

Table 7.1 below summarizes the sample periods, markets investigated and whether the momentum effect was confirmed for each article mentioned above.

Table 7.1: Literature Summary

The table shows the authors, sample period, market investigated and whether the momentum effect was confirmed for each article outlined above.

Authors	Sample Period	Market	Momentum Effect
Jegadeesh & Titman (1993)	1965-1989	US	Yes
Chan et al. (1996)	1977-1993	US	Yes
Rouwenhorst (1998)	1978-1995	Europe	Yes
Shiereck et al. (1999)	1961-1991	Germany	Yes
Chan et al. (2000)	1980-1995	Global	Yes for 6/6-, no for 3/3-strategy
Jegadeesh & Titman (2001)	1990-1998	US	Yes
Liu & Lee (2001)	1975-1997	Japan	No

Source: Own creation

8. Empirical Methodology

8.1 Data for the Empirical Research

The literature review revealed that several earlier studies have confirmed the momentum effect, and further investigated the effect using various sub-samples. In order to test for the effect on the entire Danish stock market, the OMXC index has been chosen as the sample index. The Copenhagen stock exchange is called Nasdaq Copenhagen and the OMXC index is the exchange's all-share index, which was introduced in 1989[128 129]. Hence, the index includes all small, medium and large cap stocks listed at the Copenhagen stock exchange.

The index is the obvious choice given the totality of stocks included, but it does not come without considerations to be made. As such, the stocks listed on the index have not necessarily been part of the index since the beginning. Companies listed after 1989 have obviously not been within the index for the entire period, while other companies may have defaulted or gone private throughout the years. This could represent a survivorship bias in the data. However, with this in mind, the OMXC index and the stocks currently within it still seem like the obvious choice for the purpose of the study.

8.1.1 Data Source

All of the data used for the empirical research have been extracted from Bloomberg terminals, in order to get as much uniformity in the data as possible.

8.1.2 Data Adjustments

The OMXC index currently consists of 142 stocks[130]. Of these, 4 no longer actively exist in the index as of March 10th 2017, but data have been included up until the last date where data was available. Further, various previous studies have excluded stocks related to real estate investment trusts, real estate development companies, mutual funds and investment funds[131 132]. In

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[128] Borsen, *Fondsbørsen sætter nye regler for bredt indeks*, Published: 7/5 – 2012, (Retrieved: 6/2 - 2017)
[129] NPINVESTOR, *OMXC Indexet*, (Retrieved: 6/2 – 2017)
[130] Euroinvestor, *OMXC PI*, (Retrieved: 6/2 - 2017)
[131] Chan, Jegadeesh and Lakonishok, 1996

accordance with previous studies this criteria have been applied to this data sample as well. None of the previous studies excluding these types of shares provide an explicit explanation for the exclusion, but given how asset management funds' stocks are correlated with the market, thus would explain the exclusion. Therefore, if these stocks were included, they would interfere with the interpretation of the results.

With these stocks excluded, a last selection criterion is applied as well. This criterion relates to the share type: whether it is an *A* or a *B* share. As *A* shares are usually a lot more illiquid, these will be excluded. Furthermore, A shares are strongly correlated with the corresponding *B* shares, which strengthen the argument for excluding these. A full list of excluded companies can be found in appendix A and a full list of included stocks can be found in appendix B. A total of 122 stocks have been included in the final data foundation.

8.1.3 Data Variables

The overall objective of the research is to test for price momentum in the Danish stock market, and therefore the adjusted closing prices for each company listed in appendix 2 has been extracted. The closing prices collected have all been adjusted for dividends and stock splits. That is, the effect of dividend payments and stock splits have been removed from the data, as this would interfere with the results and consequently the validity of the conclusions made upon them. Further, the market-capitalization for each company has been collected as well in order to perform sub-analyses later.

8.2 Timeframe of the Empirical Research

The basis of many studies on price momentum is, as previously stated, the empirical research performed by Jegadeesh & Titman (1993). They looked at a sample period from 1965-1989, thus covering 25 years of historical return data. The following studies by Chan, Jegadeesh and Lakonishok (1996) and Rouwenhorst (1998) covered 1977-1993 and 1978-1995 respectively. The German study by Schiereck, De Bondt and Weber (1999) was based on a period from 1961 to 1991 and the global study by Chan, Hameed and Tong (2000) covered 1980-1995. The Japanese study by Liu and Lee (2001) looks at a period from 1975-1997. As illustrated, much of the research has

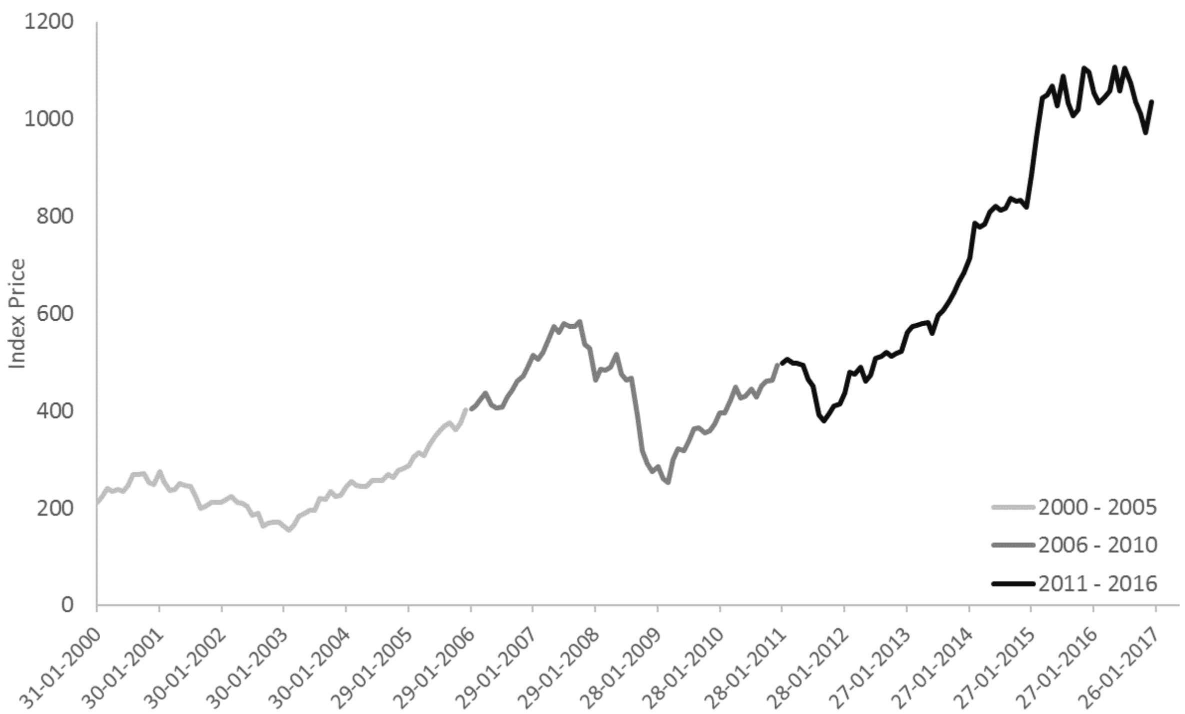
[132] Chan, Jegadeesh and Lakonishok, 1999

been conducted covering roughly the same period. Therefore, this study sets out to investigate a newer and less researched period, which is why the period from January 2000 to January 2017 has been chosen. However, it should be noted that of the 122 stocks for which data was collected, only 90 had a closing price in January 2000. An alternative would be to shorten the timeframe. As such, the timeframe would have to be adjusted forward roughly 6 years to reach a total of 100 of the 122 stocks. However, one of the reasons for choosing a long timeframe in previous studies is to account for the possibility of the momentum effect being a coincidence. Therefore, this paper argues that the addition of 10 stocks does not outweigh the exclusion of 6 years of data.

As the timeframe covers the period beyond 2006, this study includes the subprime crisis. Therefore, it would be of interest to look at sub-samples and investigate the effect of price momentum in the years before, during and following the crisis. Doing so would indicate whether changes in the general market conditions affect the results.

Figure 8.1: Index price of the OMXC from 2000 - 2017

The figure illustrates the development in the index price of the Danish OMXC throughout the 17-year long analysis period. The different nuances in the line color indicate the sub-periods analyzed individually later in the analysis.



Source: Own creation

The overall OMXC index experienced a downturn around 2001-2002 due to the Internet bubble at that time. After this period, the market experienced a long upturn, eventually leading up to the financial crisis. During this period the index more than tripled in value from the end of 2002 and up to the start of the subprime crisis in 2008. The crisis almost reverted the index value back to the level of the start of the millennia, thereby almost neutralizing close to 5 years of economic upturn. The value fell more than 50% from 2008-2009. But since then it has increased steadily until recently, where the progress stagnated for the last couple of years. When considering the entire 17-year period, the index value has increased more than 400%, even though the bubble in 2001-2002 and the crisis in 2008-2009 drove the index value down for long periods of time.

8.3 Data Frequency

The previous studies of price momentum mostly use an approach either identical or similar to the *J*/*K*-strategy approach by Jegadeesh & Titman (1993). In order to compare the obtained results with previous work, this empirical study will follow a similar approach. As the strategies conducted by Jegadeesh & Titman (1993) are all based on monthly intervals of formation and holding periods, this paper uses end-of-month data as the data frequency. Therefore monthly observations for each of the variables have been used for this research.

An alternative to the monthly frequency would be either weekly or daily observations. This would create a much higher amount of portfolio return observations and would ultimately heighten the significance levels of the results. However, the approach with monthly data provides almost 200 observations per strategy, which is considered to be a sufficient amount of data. Finally, from an private investor's perspective, having to adjust the portfolios daily or weekly is deemed unfeasible, thereby further supporting the argument to use monthly data.

8.4 Portfolio Formation

As previously stated, the portfolios are based on monthly data. In the literature, two methodologies dominate regarding the formation of portfolios. The first method is the decile method, which ranks the entire sample of stock returns for a given formation period (3, 6, 9 or 12 months). The top- and bottom 10% of the stocks are then chosen for the winner and loser portfolios. The second method consists of all available stocks. This method gives each stock a weight based on its formation period return relative to the sample average. The decile method is used for the majority of the research[133]. The second method is not used a lot, but is implemented for the global study of market indices[134]. For this study, only 23 market indices were studied and thus, a decile approach would have resulted in approximately 2 indices in the winner and loser portfolios respectively. As such, it seems to be a matter of limited data that has forced Chan, Hameed and Tong (2000) to adapt the second approach.

Each time a portfolio needs to be rebalanced, the purchases and sales come at a cost, which depends on the number of transactions. One aspect is the cost of time, which is an important aspect for especially private investors. Having to buy/sell +100 stocks instead of 10 is obviously much more time-consuming. Another cost is the transaction cost. Some brokers take a percentage fee, which would even out with either method, as the invested amount is assumed constant. However, other brokers require a fixed minimum fee per transaction, and unless the overall investment amount is sufficiently large, this might prove to be costly. The backlash of the decile method however is, that the portfolio is a lot less diversified. In the end, we believe the decile approach is the most appropriate since it allows us to compare our results with the majority of the previous studies. Furthermore, it also seems like the most applicable approach in practice. The decile methodology suggests creating winner and loser portfolios of the top 10% of the sample. As the sample size used for this study varies slightly over the span of 17 years (from 90 to 121 stocks), the numerical top 10 is used across time instead of the top 10%, similar to Schiereck et al. (1999). The numerical top 10 is very close to the top 10%, which ranges from 9 to 12 stocks, and the added stability to the portfolio creation is deemed sufficient to outweigh the slight deviation from the original methodology by Jegadeesh and Titman (1993).

[133] See Jegadeesh and Titman (1993)(2001), Chan, Jegadeesh and Lakonishok (1996), Rouwenhorst (1998), Schiereck et al. (1999) and Liu and Lee (2001)
[134] See Chan, Hameed and Tong (2000)

8.5 Portfolio Weighting Scheme

Having chosen a slightly altered decile methodology for the stock selection, the weighting scheme still needs to be addressed in order to create the portfolios. The most widely used scheme is one applying equal weight to each asset in the portfolio. This scheme does not favor any of the selected stocks and is that sense neutral. Another weighting scheme applies weight the top 10 stocks based on their market capitalization. This way, larger stocks have more weight than smaller stocks. This weighting scheme can create issues if one of the stocks is too large compared to the remaining 9 stocks, as this would more or less eliminate the benefits of diversification. This study will follow the majority of the previous studies and employ the equal weight method as the primary weighting scheme. Nonetheless, although market-capitalization weighting scheme has been used more infrequently, it has been referred to as supporting evidence. Chan, Hameed and Tong (2000) were the only ones to adopt the approach as their primary one, but this was mostly to counteract the possibility of an uneven weighting scheme due to their low number of assets. Therefore, the market-capitalization weighting scheme is also applied later in this paper, in order to investigate whether this method would significantly change the results.

8.6 Rebalancing

The simplest rebalancing approach is to hold a portfolio for *K* months, sell it, and then buy a new portfolio to be held for another *K* months. This is called the full rebalancing approach, as this would imply that the investor only has one portfolio at each point in time. For instance, for a 6/6-strategy, this would only require semi-annual transactions. The second approach is more complicated but would yield more observations and therefore a higher statistical significance. The second approach is based on monthly rebalancing and is called the partial rebalancing approach. Each month a new portfolio of 10 stocks would be purchased and held for *K* months, always based on the previous *J*-month stock returns. This way, the investor would, at all times, possess *K* different portfolios. Each month the portfolio purchased *K* months ago would be sold, and a new portfolio would be purchased to replace the former, thus, $1/K$ percent of the total investment would at all times be placed in each portfolio.

In the previous literature, the issue of rebalancing has not always been addressed, but when it has, the majority has opted for the partial rebalancing approach, due to the larger amount of observations and the consequent significance. In the case of this study, adopting the approach of full rebalancing to the 12/12-strategy would only result in 17 distinct portfolios compared to close to 200 portfolios when adopting the partial rebalancing during the 17-year analysis period. The main reasons for choosing full rebalancing are the increased feasibility of implementing the strategies as well as the reduced costs. However, in order to generate comparable and more significant results, tis paper opts to adopt the partial rebalancing approach.

Figure 8.2: Illustration of Full Rebalancing vs. Partial Rebalancing

The figure illustrates the difference between a full rebalancing approach and a partial rebalancing approach when using a 3/3-strategy. Note how in month 6 the full rebalancing approach only holds 1 portfolio whereas the rebalancing approach holds 3 portfolios at the same time.

Source: Own creation

8.7 Winner, Loser and Zero-cost Portfolios

Much of the previous literature focus on the winner portfolios and the zero-cost portfolios when analyzing their results. The idea of price momentum suggests that stocks which have performed better than the sample average in the recent past will continue to do so, and stocks with a performance below the sample average will continue to perform that way in the near future. This would suggest that the recent winners would be able to outperform the index in the short run.

Furthermore, The loser portfolios are expected to perform worse than the index, but this does not necessarily mean that these portfolios have negative returns.

Following the efficient market hypothesis, the expected return on a stock during the next period should be zero. By this logic, the return of a given stock in the next period should have an even likelihood of increasing and of decreasing. However, if the monthly returns of the zero-cost portfolios are statistically significant and different from zero, then these results would contradict conventional finance theory. Therefore, testing whether the previous high performing stocks are outperforming the previous worst preforming stocks in the following period will highlight whether price momentum exists in the Danish stock market. However, even if the strategies turn out to be profitable, they still might not exceed the market return. Therefore, the testing for price momentum should be supported by whether the winner portfolios outperform the benchmark index or not. If the loser portfolios are experiencing a negative monthly average return, the zero-cost portfolios might even prove more profitable than the pure winner portfolios. Thus, the zero-cost portfolio creation has a two-fold purpose: 1) Testing the price momentum effect on the Danish stock market and 2) attempting to improve the return obtained from the winner portfolios.

8.8 Implementing the *J*/*K*-strategies

As previously stated, this study is following the approach laid out by Jegadeesh & Titman (1993). This approach involves adopting 16 different *J*/*K*-strategies. As mentioned earlier, the *J*/*K*-strategies are based on a *J*-month formation period and a *K*-month holding period. That is, the previous *J*-months stock returns are the data foundation for the upcoming portfolio creation and this portfolio will be held for *K*-months. *J* and *K* will take on lengths of 3, 6, 9 and 12 months in accordance with previous studies.

8.8.1 *J*-month Returns

The first step in implementing a *J*/*K*-strategy is to convert the closing prices into returns. For a given strategy, the return period of interest is equal to the value of *J*. As the return periods are always measured on a monthly basis, time thus moves forward in increments and therefore the discrete compounding seems the obvious choice for compounding the *J*-month returns. The following formula is similar to formula (1), but dividends are excluded from the formula as these have been excluded in the closing prices. Formula (18) have been used to calculate all of the *J*-month returns for each stock in the sample:

$$r_i = \frac{(P_{i,t} - P_{i,t-1})}{P_{i,t-1}} \qquad (18)$$

Where r_i is the return for stock *i*, $P_{i,t}$ is the closing price of stock *i* at time *t* and $P_{i,t-1}$ is the closing price of stock *i* at time $t - 1$.

8.8.2 Ranking the Stocks

When introducing the winner and loser portfolios, the slightly adjusted decile approach requires a ranking of all the *J*-month stock returns at any given month. The previous *J*-month period is used as the data foundation of the stock ranking and the 10 stocks obtaining the highest rate of return go into the winner portfolio. In accordance, the 10 stocks obtaining the lowest rate of return go into the loser portfolio. Having chosen the partial rebalancing approach, this means that a winner and a loser portfolio have been created each month based on the previous *J*-month formation period.

8.8.3 Portfolio Returns

By ranking the stocks, the 10 best and worst stocks based on previous *J*-month returns are then selected for a winner and a loser portfolio respectively. These portfolios are held for *K* months and returns thus have to be computed for each of the portfolios during the holding period.
As an approach using equal weights to each individual stock in each portfolio has been adopted as the primary weighting scheme in the analysis, the portfolio return for the first month is the simple arithmetic mean of each stock's 1-month return. In formula (19) below, *t* indicates the beginning of the portfolio's holding period:

$$R_{PF\,,t+1} = \frac{1}{N}\sum_{i=1}^{N} r_{i,t+1} \qquad (19)$$

Where $R_{PF,t+1}$ indicates the portfolio return for a 1-month period, *N* is the number of stocks in the portfolio, and $r_{i,t+1}$ is the individual 1-month stock return.

However, when the holding period extends beyond the 1-month horizon, individual stock returns have to be compounded. The easy way would be to replicate formula (19), but instead of using the individual 1-month stock returns, the individual stock returns from period $t+1$ to period $t+2$ would be used. The portfolio return for period $t+1$ to $t+2$ would then be multiplied with the 1-month portfolio return to obtain a 2-month accumulated return for the portfolio. This would create some issues though. If this methodology had been applied, it would not account for the initial investment being in individual stocks. Suppose one of the stocks in the portfolio had a high return in the first period and that it happened to experience another high rate of return in the subsequent period. This would increase the invested value in the portfolio more than if it occurred to a stock performing less well in the first period. In other words: As the initial decision to pursue an equal investment in each stock no longer persists after the first period, the simple arithmetic mean of returns from $t+1$ to $t+2$ no longer yields the desired results. Therefore, in order to account for the initial equal investments placed in each stock in the portfolio, the compounded returns for each stock will be used to determine the compounded portfolio return at a given point in time. The compounded return of each stock is calculated using formula (20) below:

$$acc, r_{i,t+h} = \left(1 + r_{i,t+1}\right) \cdot \left(1 + r_{i,t+2}\right) \cdot \ldots \cdot \left(1 + r_{i,t+h}\right) - 1, \qquad for\ h = 1, 2, 3 \ldots K \quad (20)$$

Where $acc, r_{i,t+h}$ is the accumulated stock return of the individual stock *i* at time $t+h$, where *h* is the *h*'th month during the *K*-month holding period.

These accumulated stock returns calculated above are then used for calculating the compounded portfolio returns each month for the winner- and loser portfolios:

$$acc, R_{PF,t+h} = \frac{1}{N} \sum_{i=1}^{N} acc, r_{i,t+h} \qquad (21)$$

Where $acc, R_{PF,t+h}$ is the accumulated portfolio return at time $t+h$, hence h is *h* is the *h*'th months during the *K*-month holding period.

8.8.4 Market Capitalization Weights

When calculating the portfolio returns using market capitalization weights some adjustments have to be made. For the equally weighted portfolio returns described above, the arithmetic mean was used. The accumulated stock returns for the individual stocks calculated with formula (20) are still applicable, but the new portfolio returns are found by applying new weights. These weights are found by dividing the individual stock's market capitalization at time $t+h$ with the sum of the portfolios stocks market capitalization. The formula used to derive the weights for the individual stocks, *i*, is:

$$w_i = \frac{Cap_{i,t+h}}{\sum_{i=1}^{N} Cap_{i,t+h}} \qquad (22)$$

Where $Cap_{i,t+h}$is the market capitalization for stock i at time $t + h$ and w_i is the weight of the initial investment put into stock *i*. From here, replacing the equally weighted portfolios with the market capitalization weighted ones simply requires a slight change to formula (21). The arithmetic mean is replaced by the sum of the accumulated stock returns multiplied by the respective stock's weight, which leads us to formula (23) calculating compounded portfolio returns for the market capitalization weighted 10-stock winner and loser portfolios:

$$acc, R_{PF,t+h} = \sum_{i=1}^{N} w_i \cdot acc, r_{i,t+h} \qquad (23)$$

8.8.5 Monthly Strategy Returns

At any point in time the given strategy consists of *K* different portfolios. These portfolios are naturally at different point in their holding period cycle. Formula (21) only computes accumulated returns for the portfolio at any given time, and therefore the actual 1-month returns for each portfolio must be found in order to arrive at the monthly strategy returns.

The individual monthly portfolio return, accounting for the initial investment split amongst the stocks, is therefore:

$$R_{PF,t+h} = \frac{\left(1 + acc, R_{PF,t+h}\right) - \left(1 + acc, R_{PF,t+h-1}\right)}{\left(1 + acc, R_{PF,t+h-1}\right)} \qquad (24)$$

Where $R_{PF,t+h}$is the 1-month portfolio return at time $t + h$.

Having calculated the monthly portfolio returns for each month, we can simply take the arithmetic average of the monthly portfolio returns generated in each month, to finally end up with the monthly return for the given *J*/*K*-strategy as seen in formula (25) below:

$$R_{Strategy\,,t} = \frac{1}{K}\sum_{i=1}^{K} R_{PF_i\,,t} \qquad (25)$$

Where $R_{Strategy,t}$ is the strategy return at time *t* and $R_{PF_i\,,t}$ is the individual portfolio returns.

8.8.6 Total Returns for Winner, Loser and Zero-cost Strategies

When calculating the total return over the entire sample period for the various *J*/*K*-strategies, the main concern is the starting point. The data stretches back to January 2000. For a $J = K$ strategy, *K* months of historic data has to be available for creating the first portfolio. After *K* months, only 1 portfolio exists and the investor then faces the issue of how much to invest in this portfolio. One option is to invest $1/K$ of the initial investment into this portfolio. The investor could also wait until data is available for creating *K* distinct portfolios. In this way, the first portfolio created will now only be held for 1 month when the strategy is implemented like this. Hence, for a 3/3-strategy the investor will first begin the strategy in the beginning of the 6th month, as illustrated in figure 8.2. With this in mind, when investors choose to adopt a *J*/*K*-strategy, they will most likely have at least $J + K$ months of data available. Therefore, the approach establishing *K* portfolios at once is used. This imply that the $J = K$ strategy start when *K* different winner and loser portfolios can be formed at the same time, each based on *J* months of data. Once the strategy has been initialized, the total investment amount is multiplied with one plus the strategy return each month. This process is replicated throughout the sample period until the last point in time where *K* distinct portfolios are available at the same time.

8.8.7 Average

Having computed monthly returns for strategies, these returns will be translated into an average monthly return in accordance with previous studies. The dominant methodology for calculating average returns is the method of an arithmetic mean. This is calculated as the sum of all the observations divided by the number of observations, similar to formula (19). However, this result may be somewhat misleading. A strategy may experience a negative compounded return over the entire sample period and still end up with a positive average monthly return.

8.8.8 Standard Deviation

In order to test for the statistical significance levels of the average monthly returns of each strategy, the standard deviation of the monthly return time series must be obtained first.

The standard deviation is a number describing the volatility of a given average return. The formula used for computing the standard deviations of each strategy's monthly returns is similar to formula (3):

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i - \bar{r})^2} \qquad (26)$$

Where σ represents the standard deviation and $\bar{r}$ is the average return.

8.8.9 Statistical Significance of the Momentum Returns

When each strategy has been implemented, and the average monthly returns and standard deviations have been calculated, the next step is to investigate whether the obtained results are statistically significant or not. The objective for this test is to see if the returns obtained are significantly above zero. As such, the test applied will be one-sided. The null-hypothesis will be that the given strategy's true monthly average return is equal to- or less than zero, with the alternative hypothesis being that it is higher than zero. Therefore, the *t*-test applied to check if the true average is equal to or less than zero is[135]:

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{N}} \qquad (27)$$

Where $\bar{x}$ is the observed monthly average return, $\mu_0$is the null-hypothesis value, in this instance 0, *s* is the standard deviation observed and *N* is the number of observations. Formula (27) indicates that a high standard deviation will lead to a low t-statistic and thereby a low significance level. Further, the formula shows that more observations will increase the significance of the results. When evaluating the *t*-statistics computed with formula (27), they are compared to critical values indicating various significance levels. As the strategy with the fewest portfolios (the 12/12-strategy) has 170 portfolios, the degrees of freedom are well in excess of 100 and are thus approximated by infinite degrees of freedom. This means that the *t*-distributions critical values are identical to the normal distributed critical values.

[135] Stock, 2011, p. 75

8.8.10 Transaction Costs

Even if the strategies are proven profitable and statistically significant, one aspect to be considered is the costs of implementing these. For each strategy, transaction costs occur at the outset, when the investor creates *K* winner and loser portfolios. From this point and throughout, with the partial rebalancing approach, a winner and a loser portfolio will have to be replaced every month, which induces some transaction costs. Before the implementing procedures are outlined, the issue of determining the size of the transaction costs needs to be addressed. Two different types of transaction costs exist: A percentage of the investment or a fixed minimum fee, should the percentage costs be lower than some fixed amount. The usual fixed amount in Denmark is 29kr.[136] [137]. Some brokers have transaction costs, which are only quoted in percentages, and the transaction costs have decreased historically. However, if the initial investment is large enough, the minimum fees will not be relevant. Therefore, the analysis will assume that only percentage fees apply to the conducted transactions. The next aspect is the size of the transaction cost percentage fee and first, the previously described literature is used for clues to the historical price. In 1993, Jegadeesh and Titman (1993) uses a one-way percentage fee of 0.5% which they describe as fairly conservative as Berkowitz, Logue and Noser (1998) reports a 23 basis point fee for institutional investors[138]. Similar transaction costs for institutional investors are reported by various studies from the mid-90s quoted by Metghalchi, Marcucci and Chang (2012)[139]. However, the study from 2001 by Domowitz et al. is by far the largest study on transaction costs and as such they report the one-way transaction costs for 42 countries, Denmark included. The transaction cost percentage fee for Denmark is reported as 0.41% in the article from 2001[140]. Today, the observed fees are closer to 0.1% or even less[141] [142]. Given the lack of information on the transaction costs in the period from 2001 and up to today, a linear interpolation has been used. As such, the level implied by Domowitz et al. of 0.4% (slight adjustment from the 0.41% reported) is applied in the period 2000-2004, 0.3% is applied from 2005-2008, 0.2% is applied from 2009-2012 and 0.1% is applied from 2013-today.

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[136] Danske Bank, Danske *Investering Online,* (Retrieved: 13/2 - 2017)
[137] Nordnet, *Priser for at handle*, (Retrieved: 13/2-2017)
[138] Jegadeesh and Titman, 1993, p. 77
[139] Metghalchi et al., 2012, p. 1554
[140] Domowitz et al.,2001, p. 227
[141] Danske Bank, *Danske Investering Online*, (Retrieved: 13/2 - 2017)
[142] Nordnet, *Priser for at handle,* (Retrieved: 13/2-2017)

The implementation into the *J*/*K*-strategies is fairly simple. The transaction costs are considered a negative return and is as such multiplied with the given portfolio's monthly return in the first and last month of the respective holding period.

8.8.11 Practical Implementation in Excel

The portfolio calculations explained above and in the subsequent sections have been performed in Microsoft Excel. Appendix C presents a guide to the Excel spreadsheets, illustrating how the momentum strategies have been implemented in practice.

8.9 Sub-samples

Much of the literature use just one of their momentum strategies when investigation sub-samples. The most frequently chosen strategy has been the 6/6-strategy[143], and is often followed by a statement suggesting that the results for the chosen strategy are representative for the remaining strategies. However, this study chooses 5 different strategies as the basis for further analysis. The 5 strategies chosen are the ones with the highest *t*-values, testing whether the profits are statistically significant above zero. The chosen strategies include the 6/6-strategy and should reveal if the results observed for this strategy is representable or not. The reason for choosing the best strategies is, that these would be the most attracting to the investor.

Regarding the implementation of the sub-period analysis, the momentum strategy returns for equally weighted portfolios are used. The monthly averages within each period or segment respectively have been used to compute average monthly returns, total return and standard deviation.

8.9.1 Size-neutral Sub-sample

A frequently used approach in the literature has been to check if the price momentum profits are reserved for small firms or if the effect was persistent across firm size. This approach was applied by Jegadeesh and Titman (1993), Rouwenhorst (1998), Liu and Lee (2001) etc. Even though none of these show size matters, this might have changed over the past two decades.

[143] Jegadeesh and Titman, 1993; Chan, Jegadeesh and Lakonishok, 1996; Rouwenhorst, 1998; and Liu and Lee 2001.

The main issue when introducing a size-neutral sub-sample is the split construction. Liu & Lee (2001) only looked at a small and large segment, using the median market capitalization as the splitting point. Rouwenhorst looked at a small, medium and large segment addressing the bottom 30% to the small segment, the middle 40% to the medium segment and the top 30% to the large segment. The small, medium and large segmentations are further deployed by Jegadeesh and Titman (1993) but they provide no explanation as to how the split is conducted. In order to improve the analysis, the medium segment is included in this paper, and to be comparable with previous studies, a simple 33% split is used for the small, medium and large sub-samples.

The implementation starts by ranking all the stocks based on a 3-year moving average of size. Each month, the highest-ranking third of the available firm-sizes are used for the sample of large firms, the second third is used for the sample of medium sized firms and the lowest ranking firms are used for the sample of small firms. The next step is to compute the formation period returns for each of the stocks in each sample - from here, all the computed returns are ranked. The sample size is now down to approximately 30 to 40 firms, which requires a re-visit to the previous numerical top 10 vs. top 10% discussion. The top 10% would create winner and loser portfolios consisting of 3 or 4 firms each. The previous argument for choosing a numerical top 10 approach was to replicate the decile approach as consistently as possible with a fluctuating sample size. However, the opposing argument was, that the decile approach lacks diversification. A 10 stock portfolio was deemed significantly diversified given the equal weights, but a portfolio of 3 stocks would be too small. Instead, a middle-way is chosen. Thus, the winner and loser portfolios will each consist of the numerical top 5 stocks. This way, the amount of stocks in the portfolios are consistent, slightly more diversified than they would be with the decile approach, and are still comparable to the decile approach. The remaining part of the analysis follows the methodology outlined in the section on "*Monthly Strategy Returns*" and "*Total Returns for Winner, Loser and Zero-cost Strategies*".

8.9.2 Beta-neutral Sub-sample

Similar to the size-neutral portfolios, the beta-neutral analysis has been conducted frequently. This analysis investigates whether added risk might explain the profits obtained by the zero-cost strategies. The approach has been carried out by Jegadeesh and Titman (1993), Rouwenhorst (1998), Liu and Lee (2001) etc.

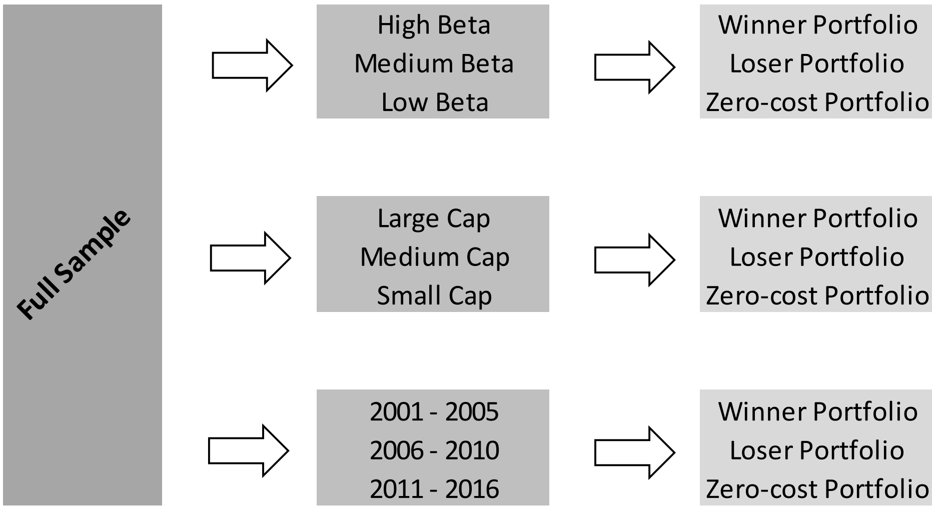
As for the size-neutral sub-samples, the betas are likewise split into a small, medium and large segment with the top third going into the large segment and so forth. Implementing the beta-neutral analysis is basically similar to the implementation of the size-neutral portfolios. Again, the stocks are ranked based on previous 3-year moving betas, and assigned to a high, medium and low segment. Then, for each sub-sample, the stocks are ranked and assigned to a winner and a loser portfolio each consisting of 5 stocks - see the size-neutral portfolio argumentation which is similar to this. Further, as the winner and loser portfolios have been created for each month, the remaining process follows the methodology outlined previously regarding monthly strategy returns, total returns etc.

8.9.3 Sub-periods

Another frequently used analysis is the one of sub-periods. This kind of analysis has previously been used differently as some have used it to see if the momentum effect is fading over time, while others have used it to check if market conditions might lead to varying degrees of momentum profits over time. For this paper, both aspects are of interest. First, as the overall period covers the subprime crisis, this is an obvious opportunity to investigate the profitability of the strategies when the market is in a state of recession. The second purpose of this analysis is to see if the market might have eradicated or somewhat dampened the effect of price momentum strategies over time. The subprime crisis would require a close study of the profitability during the period from 2008 through 2009, while the analysis of the market conditions would go well with an even split of the overall period into 3 sub-periods. However, if more sub-periods were chosen, the time-intervals would get too short, so in accordance with previously conducted sub-period analyses, 3 sub-periods of approximately 5 years each have been chosen. The periods applied thus cover 2001-2005, 2006-2010 and 2011-2016 respectively, which are highlighted in figure 8.1.

Figure 8.3: Overview of Sub-sample Analyses

The figure gives a brief overview the subsamples analyzed in this paper and how these are constructed.



Source: Own creation

8.10 Market Benchmark

Even if the strategy is found profitable, it may not be able to beat the market index, and as such, a simple buy-and-hold strategy purchasing the market would be a better solution compared to the momentum strategies. Therefore, it is relevant to compute returns in excess of the market index. If the strategies' returns in excess of the market index are statistically significant and positive, then the momentum strategy is further indicating a weak form inefficient market.

8.10.1 Benchmark Methodology

The OMXC has been chosen as the market benchmark. In order to compare the OMXC index with the individual strategies, monthly closing prices have been collected from Bloomberg for the index. The monthly returns of the index are calculated using the same methodology as for the individual stocks in the sample, using formula (19). Further, the methodologies for computing the monthly average and the standard deviation for the strategies applies to the OMXC index as well. Formula (19) and (26) have been used for the monthly average and standard deviation respectively.

When comparing the individual strategies with the market index, the monthly observations of the OMXC index are subtracted from the monthly strategy return. This way, a time-series of differences are created illustrating the return obtained in excess of the index by the given strategy. This time-series of monthly returns are then used when investigating the statistical significance of the results, as well as for computing average monthly returns and standard deviations of the benchmark comparing strategies.

8.10.2 Statistical Significance

The returns observed in excess of the index might simply be a coincidence. Therefore, these results, as for the ordinary results, are investigated for statistical significance. The easy way of doing this would be to use the simple *t*-test formula outlined previously in formula (27). This would require that the length of the OMXC return period is adjusted to correspond the period length of the given strategy and then inserting the OMXC average monthly return for the respective period as μ_0. This is done and referred to as the student's t-test. However, this does not take into account that the OMXC monthly average return itself has volatility. Therefore, another *t*-test is used called Welch's *t*-test. This test is a two-sample test used for testing the hypothesis that two samples have equal means. As for the simple *t*-test, the two means are subtracted in the numerator. In the denominator, the volatility and the number of observations of the second sample (the index) is now taken into account[144]:

$$t = \frac{\overline{\mathrm{X_S}} - \overline{\mathrm{X_{OMXC}}}}{(s_S + \mathrm{s_{OMXC}})/\sqrt{N_S + N_{OMXC}}} \qquad (28)$$

Where the subscript S and OMXC refers to the strategy and the index's returns, standard deviations and observations respectively.

This test however, implies no covariance between the index and the given momentum strategy. The index contains all stocks, and the momentum strategy consists of a subset of these stocks. Therefore some correlation is given. To account for this, an adjusted Welch's *t*-test is introduced:

$$t = \frac{\overline{\mathrm{X_S}} - \overline{\mathrm{X_{OMXC}}}}{\sqrt{s_S^2/\mathrm{N_S} + s_{OMXC}^2/N_{OMXC} - 2 \cdot cov(\mathrm{r_S}, \mathrm{r_{OMXC}})/\mathrm{N}}} \qquad (29)$$

Where r_S is the return time series of the momentum strategy and r_{OMXC} is the return time series of the OMXC index. As can be seen, the only adjustment is the introduction of the covariance component, which was assumed to be zero in the original Welch's *t*-test.

[144] Stock, 2011, p. 82

9. Empirical Results

It is now time to see how the methodology of the momentum strategies translates to the Danish stock market. In this section, the empirical results of the different momentum strategies will be presented. Section 9.1 focuses on the results for the equally weighted portfolio strategies, while section 9.2 looks at the market weighted portfolio strategies. Section 9.3 adjusts the results from the previous sections for transaction costs. In section 9.4, a selection of strategies will be investigated through sub-samples based on their stocks market beta and market capitalization, and an analysis of sub-periods will be carried out. Finally, section 9.5 presents some of the strategies' results in greater detail to give investors some perspective.

9.1 Results for Equally Weighted Portfolios

When one creates an investment strategy the most important question is often whether it produces a positive return. From table 9.1 it is evident that the winner portfolios for all the 16 distinct momentum strategies produce a positive return. Furthermore, all the of strategies' winner portfolios have significantly positive returns at the 99% significance level. Furthermore, they all have an average monthly return above 1% with the average being 1.66%, and an average standard deviation of 5.78%. However, the loser portfolios of all the momentum strategies do not manage to create significant positive returns. Although they all produce positive average monthly returns, none of these results are significantly positive. The loser portfolios also exhibit substantially higher standard deviations than the winner portfolios, with the average standard deviation being 7.69%.

Furthermore, the strategies with longer formation periods perform better than those with shorter formation periods. A quick comparison between the different winner strategies reveals that on average, the average monthly return for the strategies with a 3-month formation period is 1.35%, while the strategies with a 12-month formation period on average have an average monthly return of 1.89%. This is a noteworthy difference. However, these average returns and the fact that they are significantly different from zero doesn't tell us whether the strategies are good or not, more on this soon.

In addition to the winner and loser strategies, which are based on holding portfolios of either previous winners or previous losers, this analysis also considers zero-cost strategies. These strategies consist of long positions in previous winners and short positions in previous losers. Just like the winner strategies, the zero-cost strategies manage to produce average monthly returns that are significantly greater than zero. The returns on the zero-cost strategies reveal that on average the winner portfolios outperform the loser portfolios by 1,45% per month, ranging from 1.14% to 1.81% across the different strategies. Furthermore, the best performing zero-cost strategies are also the ones with the most volatile return. Thus, there seems to be a positive correlation between average monthly return and standard deviation. Overall, the results provide the first indications that the momentum strategies work, and that the '*momentum effect*' is real and observable on the Danish stock market.

To assess if the returns of the strategies are better (higher) than what an investor could have gotten by simply holding a standard index portfolio/fund, we compare the average monthly returns obtained in table 9.1 with those from our benchmark. In this analysis, the benchmark is the Danish OMXC index, which was described previously in the methodology section. To test if the momentum strategies based on winner portfolios and zero-cost portfolios produce abnormal returns compared to the benchmark, three different *t*-tests are applied. In short, each test has its own strengths and weaknesses that depend on the characteristics of the data being analyzed. In this study, it is assumed that the adjusted Welch *t*-test is the most fitting, given that the return on the different strategies and the return on the benchmark have unequal variances, but some degree of covariance. Nonetheless, the student's- and standard Welch *t*-test also provide information regarding the strategies relative performance, and are therefore also presented.

Table 9.1: Returns on winner, loser and zero-cost portfolios (Equally weighted)

The table shows the average monthly return for the winner, loser and zero-cost portfolios for all of the 16 distinct momentum strategies, while the numbers in parentheses are the standard deviations (decimal number). Furthermore, the table shows whether the results are significantly different from zero according to the student's *t*-test (H_0: $\bar{r} = 0$).

Formation (J)		Holding (K) 3		6		9		12	
3	Winner	1,39%	***	1,29%	***	1,31%	***	1,40%	***
		(0,061)		(0,056)		(0,054)		(0,054)	
	Loser	0,12%		0,15%		0,14%		0,23%	
		(0,077)		(0,071)		(0,068)		(0,065)	
	Zero-C	1,26%	***	1,14%	***	1,18%	***	1,16%	***
		(0,061)		(0,05)		(0,043)		(0,039)	
6	Winner	1,59%	***	1,67%	***	1,64%	***	1,56%	***
		(0,06)		(0,061)		(0,058)		(0,057)	
	Loser	0,13%		0,15%		0,15%		0,27%	
		(0,084)		(0,08)		(0,075)		(0,071)	
	Zero-C	1,46%	***	1,52%	***	1,49%	***	1,29%	***
		(0,071)		(0,067)		(0,058)		(0,052)	
9	Winner	1,86%	***	1,79%	***	1,74%	***	1,79%	***
		(0,057)		(0,057)		(0,057)		(0,057)	
	Loser	0,00%		0,08%		0,16%		0,46%	
		(0,086)		(0,081)		(0,077)		(0,073)	
	Zero-C	1,85%	***	1,71%	***	1,58%	***	1,33%	***
		(0,077)		(0,071)		(0,066)		(0,061)	
12	Winner	1,98%	***	1,83%	***	1,94%	***	1,81%	***
		(0,06)		(0,059)		(0,059)		(0,058)	
	Loser	0,17%		0,24%		0,46%		0,52%	
		(0,086)		(0,082)		(0,079)		(0,077)	
	Zero-C	1,81%	***	1,59%	***	1,49%	***	1,29%	***
		(0,078)		(0,073)		(0,07)		(0,066)	

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

The test results in table 9.2 reveal that there are momentum strategies that struggle to produce returns high enough to significantly outperform the benchmark. This is particularly the case for the strategies with a 3-month formation period. Although these strategies do have a higher average monthly return compared to those of our benchmark, they are not significantly different from the benchmark according to both the student's- and the Welch *t*-test. However, when we take into consideration the covariance between the observations and apply the adjusted Welch *t*-test, the picture changes. The strategies based on winner portfolios with a short formation period now manage to outperform the benchmark at the 90% significance level. In fact, the adjusted Welch *t*-test generally improves the significance of the results compared to the two other test statistics. Consequently, all winner strategies significantly outperform the benchmark at the 90% significance level. The winner strategies with a formation period of either 9 or 12 month produce returns that are above the benchmark and highly significant at the 99% level. Not surprisingly, it is also these strategies that show the most significant results in the student's- and Welch *t*-test.

Table 9.2: Excess return on winner and zero-cost portfolios

The table shows the average monthly excess return for the winner and zero-cost portfolios for all of the 16 distinct momentum strategies, while the numbers in parentheses are the standard deviations. Furthermore, the table includes indicators from 3 different tests, all testing whether the average monthly return on the portfolios are significantly larger than the average monthly return on the benchmark. Test 1 (T1): Student's *t*-test; Test 2 (T2): Welch's *t*-test, Test 3 (T3): Adjusted Welch's *t*-test.

Formation (J)		Holding (K)															
		3	(T1)	(T2)	(T3)	**6**	(T1)	(T2)	(T3)	**9**	(T1)	(T2)	(T3)	**12**	(T1)	(T2)	(T3)
3	Winner	0,53%			*	0,43%			*	0,37%			*	0,43%			**
		(0,061)				(0,056)				(0,054)				(0,054)			
	Zero-C	0,41%				0,28%				0,23%				0,20%			
		(0,061)				(0,05)				(0,043)				(0,039)			
6	Winner	0,79%	**	*	**	0,75%	**	*	**	0,66%	*		**	0,61%	*		**
		(0,06)				(0,061)				(0,058)				(0,057)			
	Zero-C	0,66%	*			0,60%				0,51%				0,33%			
		(0,071)				(0,067)				(0,058)				(0,052)			
9	Winner	1,01%	***	**	***	0,84%	**	*	***	0,76%	**	*	***	0,71%	*		***
		(0,057)				(0,057)				(0,057)				(0,057)			
	Zero-C	1,00%	**	*	*	0,76%				0,61%				0,24%			
		(0,077)				(0,071)				(0,066)				(0,061)			
12	Winner	1,10%	***	**	***	0,89%	**	*	***	0,84%	**	*	***	0,75%	**		***
		(0,06)				(0,059)				(0,059)				(0,058)			
	Zero-C	0,92%	*	*		0,64%				0,38%				0,22%			
		(0,078)				(0,073)				(0,07)				(0,066)			

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

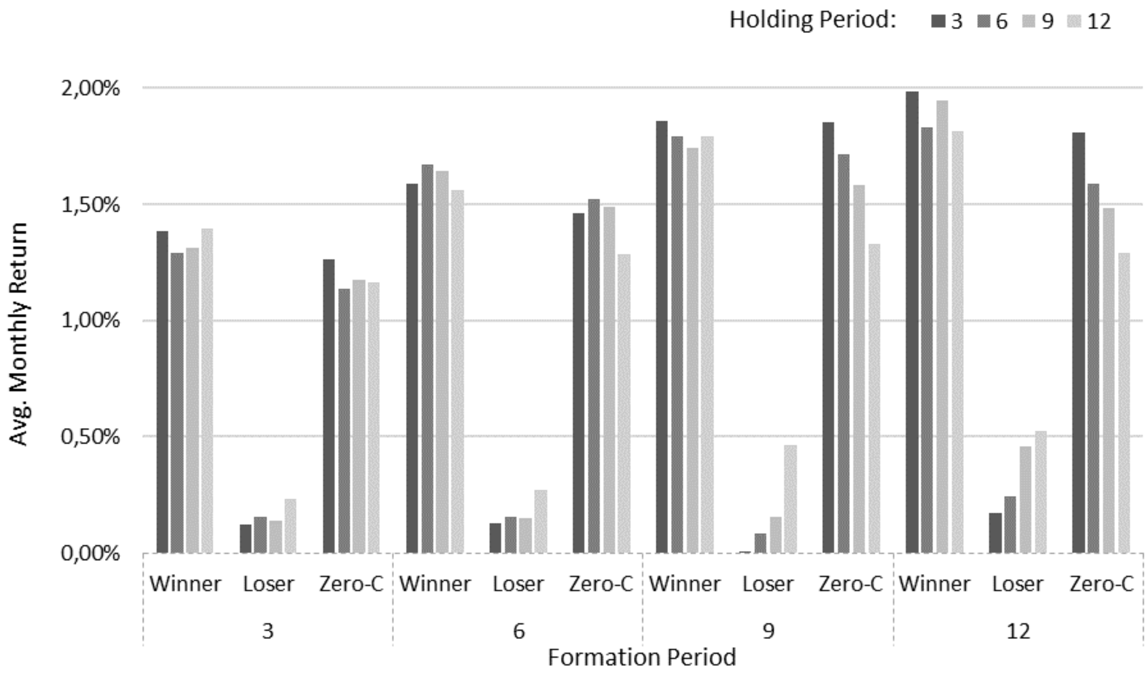
While all winner strategies are producing good results that are significantly positive and above the benchmark, they don't perform equally well. In this analysis, two strategies stand out slightly in comparison to the rest. The 9/3- and the 12/3-strategies manage to produce some of the highest average monthly returns while also creating the most significant results in all tests. The average monthly return of the 9/3 and the 12/3-strategies are respectively 1.86% and 1.98%, which is more than double the return on the benchmark in the same period. In section 9.5 these strategies among a few others will be analyzed in greater detail.

Focusing on the zero-cost strategies in table 9.2, all of them manage to create average monthly returns larger than those of the benchmark. On average, these 16 zero-cost strategies have an average monthly return of 1,45%, with an average standard deviation of 6.25%, and similar to the strategies based solely on previous winners, the strategies with a longer formation period also exhibit higher returns compared to those with shorter formation periods. Furthermore, the zero-cost strategies with a shorter holding period perform relatively better than those with a longer holding period, and this is particularly noticeable for the strategies with a longer formation period. But the similarities between the zero-cost- and winner strategies stop here. Because in contrast to the winner strategies, most of the zero-cost strategies are not able to produce returns that are statistically significantly different from the benchmark. For the adjusted Welch's *t*-test, only one zero-cost strategy is able beat the benchmark at a 90% significance level. The 9/3-zero-cost strategy generates an impressive average monthly return of 1.85%, more than double the return on the benchmark of 0.85%.

To illustrate the performance of the strategies, figure 9.1 presents the results from table 9.1 in a visual manner. Doing so highlights some of the key points, particularly the patterns emerging from the different formation- and holding periods.

Figure 9.1: Return over time on zero-cost portfolios (Index: 1 = Strategy start)

The figure shows the average monthly return on the winner, loser and zero-cost portfolios for all of the 16 distinct momentum strategies. The x-axis represents the formation period and portfolio type, while the color of the individual bars represents the holding period (see the legend).



9.2 Results for Market Capitalization Size Weighted Portfolios

As an alternative to the equally weighted portfolios, the scheme followed by most previous studies, this study now present the results using a weighting scheme based on the relative market capitalization of the individual stocks in the portfolios.

Just as the winner strategies using equally weighted portfolios in table 9.1, the winner strategies in table 9.3 all generate an average monthly return above zero at the 99% significance level, and thus on average provide the investor with a positive return. The opposite is true for the loser strategies, which are not able to generate returns that are significantly positive at any relevant significance level. Another characteristic shared by the equally weighted- and cap weighted scheme, is how the winner portfolios with a longer formation period perform better than those with a shorter formation period, which at this point gives us a strong indication that the strategies employing longer formation periods are favorable. However, there are also differences between the two weighting schemes.

Table 9.3: Returns on winner, loser and zero-cost portfolios (Cap weighted)

The table shows the average monthly return for the winner, loser and zero-cost portfolios for all of the 16 distinct momentum strategies, while the numbers in parentheses are the standard deviations (decimal number). Furthermore, the table shows whether the results are significantly different from zero according to the student's t-test ($H_0: \bar{r} = 0$).

Formation (J)		Holding (K) 3		6		9		12	
3	Winner	1,56%	***	1,42%	***	1,50%	***	1,49%	***
		(0,082)		(0,068)		(0,067)		(0,065)	
	Loser	-0,34%		-0,10%		-0,03%		0,14%	
		(0,095)		(0,089)		(0,084)		(0,078)	
	Zero-C	1,90%	***	1,53%	***	1,53%	***	1,35%	***
		(0,089)		(0,074)		(0,063)		(0,054)	
6	Winner	1,63%	***	1,87%	***	1,91%	***	1,74%	***
		(0,075)		(0,075)		(0,073)		(0,071)	
	Loser	-0,26%		-0,02%		0,10%		0,32%	
		(0,108)		(0,1)		(0,091)		(0,086)	
	Zero-C	1,89%	***	1,89%	***	1,82%	***	1,41%	***
		(0,1)		(0,092)		(0,081)		(0,068)	
9	Winner	1,84%	***	1,99%	***	2,03%	***	2,06%	***
		(0,075)		(0,071)		(0,07)		(0,068)	
	Loser	-0,08%		0,29%		0,35%		0,71%	
		(0,108)		(0,102)		(0,097)		(0,092)	
	Zero-C	1,91%	***	1,70%	***	1,68%	***	1,35%	***
		(0,11)		(0,098)		(0,09)		(0,079)	
12	Winner	2,02%	***	2,03%	***	2,28%	***	2,18%	***
		(0,071)		(0,068)		(0,068)		(0,067)	
	Loser	0,23%		0,37%		0,55%		0,77%	
		(0,109)		(0,107)		(0,106)		(0,097)	
	Zero-C	1,80%	***	1,66%	**	1,73%	**	1,41%	**
		(0,108)		(0,1)		(0,1)		(0,085)	

*Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

When we compare table 9.1 and 9.3, it becomes obvious that the strategies using market capitalization weights generate higher average monthly returns and has higher standard deviations. On average, the winner strategies in table 9.3 have an average monthly return of 1.89% and an average standard deviation of 7.09%. This means that on average, these strategies provide a monthly return that is 0.30%-point higher, but also more volatile, than the strategies using equal weights. The matter of volatility is highly relevant when we discuss the pros and cons on the different weighting schemes, and the topic will therefore be revisited in the end of this section.

On further inspection, table 9.3 presents a new pattern among the winner- and loser strategies, which is in strong contrast to the strategies using equally weighted portfolios. While the length of the holding period seemed to have a negative effect on the average monthly return in table 9.1, the opposite holds for the strategies employing a market-capitalization weighting scheme. The effect is biggest among the loser strategies, but is nonetheless also present among the winner strategies, especially for the strategies with a longer formation period.

The test results in table 9.4 reveal that many winner strategies generate average monthly returns significantly above those of the benchmark. In the adjusted Welch's *t*-test, all strategies generate returns significantly above the benchmark at the 95% level, while only four strategies fail the normal Welch's *t*-test. The test results in table 9.4 are generally a little better than those in table 9.2 for the equally weighted portfolios. Thus, based on table 9.3 and 9.4 one could easily jump to the conclusion that using market weights would be in the investor's best interest when building a portfolio. But as will be shown later, other factors are worth considering before selecting one weighting scheme over another.

But first, the focus turns to the zero-cost portfolios. It is evident that the zero-cost strategies using a market weight scheme also manage to generate quite impressive average monthly returns that are significantly positive, which comes at the cost of a high standard deviation. On average, the monthly return for all the zero-cost strategies is 1.66%, with an average standard deviation of 8.69%. Moreover, in contrast to the equally weighted zero-cost strategies in table 9.2, it is the zero-cost strategies with a shorter formation period that provide the highest average monthly returns in table 9.4, although the difference is subtle. However, not many of these strategies generate returns that outperform the benchmark at a statistically significant level. In fact, while many of the strategies have relatively high average monthly returns, only the 3/3-zero-cost strategy outperforms the benchmark at the 90% significance level when the adjusted Welch's *t*-test is applied.

Table 9.4: Excess return on winner and zero-cost portfolios (Market Capitalization weighted)

The table shows the average monthly excess return for the winner and zero-cost portfolios for all of the 16 distinct momentum strategies, while the numbers in parentheses are the standard deviations. Furthermore, the table includes indicators from 3 different tests, all testing whether the average monthly return on the portfolios are significantly larger than the average monthly return on the benchmark. Test 1 (T1): Student's *t*- test, Test 2 (T2): Welch's *t*-test, Test 3 (T3): Adjusted Welch's *t*-test.

		Holding (K)															
Formation (J)		**3**	(T1)	(T2)	(T3)	**6**	(T1)	(T2)	(T3)	**9**	(T1)	(T2)	(T3)	**12**	(T1)	(T2)	(T3)
3	Winner	0,70%			**	0,56%			**	0,55%			**	0,53%			**
		(0,082)				(0,068)				(0,067)				(0,065)			
	Zero-C	1,04%	**	*	*	0,66%				0,58%				0,39%			
		(0,089)				(0,074)				(0,063)				(0,054)			
6	Winner	0,83%	*		**	0,96%	**	*	***	0,93%	**	*	***	0,78%	*		***
		(0,075)				(0,075)				(0,073)				(0,071)			
	Zero-C	1,09%	*	*		0,97%	*			0,83%	*			0,46%			
		(0,1)				(0,092)				(0,081)				(0,068)			
9	Winner	0,99%	**	*	***	1,04%	**	*	***	1,05%	**	*	***	0,97%	**	*	***
		(0,075)				(0,071)				(0,07)				(0,068)			
	Zero-C	1,06%	*			0,75%				0,70%				0,26%			
		(0,11)				(0,098)				(0,09)				(0,079)			
12	Winner	1,14%	**	**	***	1,09%	**	**	***	1,17%	**	**	***	1,12%	**	**	***
		(0,071)				(0,068)				(0,068)				(0,067)			
	Zero-C	0,91%				0,72%				0,62%				0,34%			
		(0,108)				(0,1)				(0,1)				(0,085)			

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

Before we move on to the next section it is worth returning to the matter of volatility and diversification. Because while the strategies employing market-weighted portfolios provide higher returns than the strategies employing equally weighted portfolios, there are also noteworthy disadvantages to using such a weighting scheme. In general, the portfolio composition in the market-weighted strategies was such that in roughly 50% of the holding months, the individual portfolios were dominated by one single stock accounting for more than 50% of the weight in the portfolios. Moreover, in some months, the relative weight of one single stock exceeded 90%. This lack of diversification affects the strategies and makes them riskier, which is also reflected in the relatively high standard deviation in table 9.3 and table 9.4. This heavy reliance on single assets and lack of diversification is considered an unattractive characteristic in any investment strategy.

Besides from the substantial increase in volatility, the market-capitalization weighting scheme also adds what some might see as unnecessary transaction costs. The entire point of adding additional stocks to a portfolio is basically lost, if they don't have any noteworthy influence on the portfolio's expected return and risk. For all the strategies in this section, there are several months in which the portfolio composition is such that 5 or more stocks only have a portfolio weight of 1% or less; one example of this is the 12/9-strategy, where 35% of the monthly portfolios bought have 5 or more stocks with a weight of 1% or less. Consequently, buying stocks with insignificant weights, and thereby, insignificant impact on the portfolio itself, will only introduce a somewhat unnecessary transaction cost to the investor. Furthermore, these transaction costs are an even bigger issue for smaller investors, because many brokers require a minimum transaction fee for smaller investments. Thus, applying these strategies on a small scale will make the transaction costs relatively more expensive compared to larger investments, and make the strategies less profitable in the end.

Given these considerations about the market-capitalization weighting scheme, we believe that applying an equal weighting scheme to the momentum strategies is the better alternative, since this eliminates the issues presented above. Therefore, the rest of this analysis will focus on the strategies employing equal weights to the assets traded each month. Furthermore, using equally weighted portfolios for the rest of the analysis also makes our findings easier to compare to previous studies that predominantly employed an equal weighting scheme.

9.3 Results for Momentum Strategies Adjusted for Transaction Costs

So far the study has shown the first indications of a '*momentum effect*' and that it is possible to exploit related market dynamics and create profitable trading strategies. However, it should not necessarily be assumed that investors would be able to put this knowledge to use and profit of off it. An important aspect of any investment strategy is the transaction costs, which can have a significant effect on the return on any actively managed trading strategy. Therefore, this section adjusts the results from the winner and zero-cost strategies employing equal portfolio weights in section 9.1, and investigates whether these strategies still produce significant returns.

Table 9.5: Returns on winner, loser and zero-cost portfolios (adjusted for transaction costs)

The table shows the average monthly return for the winner portfolios for all of the 16 distinct momentum strategies adjusted for transaction costs, while the numbers in parentheses are the standard deviations. The table also includes indicators from 3 different tests all testing whether the average monthly return on the winner portfolios are significantly larger than the average monthly return on the benchmark for the same time periods. Test 1 (T1): Student's *t*-test, Test 2 (T2): Welch's *t*-test, Test 3 (T3): Adjusted Welch's *t*-test.

Formation (J)		Holding (K) 3		6		9		12	
3	Winner	1,21%	***	1,20%	***	1,25%	***	1,35%	***
		(0,061)		(0,056)		(0,058)		(0,054)	
	Zero-C	0,92%	**	0,96%	***	1,06%	***	1,08%	***
		(0,061)		(0,05)		(0,043)		(0,039)	
6	Winner	1,42%	***	1,58%	***	1,58%	***	1,51%	***
		(0,06)		(0,061)		(0,058)		(0,057)	
	Zero-C	1,12%	**	1,35%	***	1,37%	***	1,20%	***
		(0,071)		(0,067)		(0,059)		(0,052)	
9	Winner	1,69%	***	1,71%	***	1,68%	***	1,75%	***
		(0,056)		(0,057)		(0,057)		(0,057)	
	Zero-C	1,51%	***	1,54%	***	1,47%	***	1,24%	***
		(0,077)		(0,071)		(0,066)		(0,061)	
12	Winner	1,81%	***	1,74%	***	1,89%	***	1,77%	***
		(0,06)		(0,059)		(0,059)		(0,058)	
	Zero-C	1,47%	***	1,42%	***	1,37%	***	1,20%	***
		(0,078)		(0,073)		(0,07)		(0,066)	

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

The strategies and their returns in this section have all been adjusted to include the transaction costs induced in both the start and the end of each holding period, as outlined in the methodology section. The strategy returns are then compared to a 'buy and hold' strategy on the benchmark, just like in the previous sections, to see if the average monthly return is significantly bigger than that of the benchmark. It should be noted however, that the returns on the benchmark are not adjusted for transaction cost, simply because these are assumed to be insignificant, given that the transaction costs for a buy and hold strategy would only occur twice, once when the index portfolio is bought and then again when it is sold at the end of the analysis period. While this lack of adjustment is not in line with reality, it should not decrease the validity of the results in any significant way since only 2 out of 170+ observations are affected slightly.

As expected the introduction of transaction costs decrease the average monthly return on the momentum strategies substantially, as evident in 9.5. On average, the monthly return for all the winner strategies is 1.57%, which is a decrease compared to the 1.66% in section 9.1, while the standard deviation doesn't change much. The change in return is most significant in the strategies with a shorter holding period, which is at least partly explained by the increasing number of transactions that follow from using a strategy with shorter holding periods. But while the average monthly return decreases, the winner and zero-cost portfolios still manage to produce significantly positive results.

Furthermore, unlike in section 9.1, not all winner strategies significantly outperform the benchmark when transaction costs are accounted for, as evident in table 9.6. Three strategies with a 3-month formation period fail to significantly outperform the benchmark. The relatively less impressive outcomes are also reflected in the results from the student's- and Welch's *t*-tests when comparing with table 9.2. However, the adjusted Welch's *t*-test, shows that all winner strategies with a formation period of 6 months or longer produces an average monthly return that is significantly larger than the benchmark. Lastly, because of the transaction costs, the best performing strategy is no longer the 12/3, but the 12/9-strategy.

So far we have seen that a large part of the winner strategies proved to be profitable and outperformed the benchmark even after accounting for transaction costs, but the same cannot be said about the zero-cost strategies in table 9.6. None of the 16 distinct zero-cost strategies significantly outperform the benchmark. Especially the zero-cost strategies with a short formation period perform poorly when compared to a simple 'buy and hold' strategy holding the benchmark. On average, the monthly return of the 16 zero-cost strategies is 1.27% compared to 1.45% in section 9.1, while the average standard deviation stays close to the same. The 9/3-strategy is once again among the best performing zero-cost strategies, like in section 9.1, with an average monthly return of 1.51%, just about 0.4 %-point less than the best strategies based solely on winner portfolios. Since the zero-cost strategies do not significantly outperform a simple 'buy and hold' strategy, it makes them somewhat less desirable, given that an investor could get an average monthly return close to the zero-cost portfolios, but with much less transaction costs, both time- and moneywise. Nonetheless, the zero-cost strategies still pose as an interesting investment strategy. Although they fail to significantly outperform the benchmark, they still produce significant positive returns, while only requiring relatively little initial financing.

Table 9.6: Excess return on winner and zero-cost portfolios (adjusted for transaction costs)

The table shows the average monthly excess return for the winner and zero-cost portfolios for all of the 16 distinct momentum strategies, while the numbers in parentheses are the standard deviations. Furthermore, the table includes indicators from 3 different tests, all testing whether the average monthly return on the portfolios are significantly larger than the average monthly return on the benchmark. Test 1 (T1): Student's *t*-test, Test 2 (T2): Welch's *t*-test, Test 3 (T3): Adjusted Welch's *t*-test.

			Holding (K)															
			3	(T1)	(T2)	(T3)	**6**	(T1)	(T2)	(T3)	**9**	(T1)	(T2)	(T3)	**12**	(T1)	(T2)	(T3)
Formation (J)	**3**	Winner	0,35%				0,34%				0,31%				0,39%			*
			(0,061)				(0,056)				(0,058)				(0,054)			
		Zero-C	0,06%				0,10%				0,11%				0,11%			
			(0,061)				(0,05)				(0,043)				(0,039)			
	6	Winner	0,62%	*		**	0,67%	*		**	0,60%	*		**	0,56%	*		**
			(0,06)				(0,061)				(0,058)				(0,057)			
		Zero-C	0,32%				0,43%				0,39%				0,25%			
			(0,071)				(0,067)				(0,059)				(0,052)			
	9	Winner	0,83%	**	*	***	0,76%	**	*	***	0,70%	*		***	0,66%	*		**
			(0,056)				(0,057)				(0,057)				(0,057)			
		Zero-C	0,66%				0,59%				0,49%				0,16%			
			(0,077)				(0,071)				(0,066)				(0,061)			
	12	Winner	0,93%	**	*	***	0,80%	**	*	***	0,78%	**	*	***	0,70%	*		**
			(0,06)				(0,059)				(0,059)				(0,058)			
		Zero-C	0,59%				0,47%				0,26%				0,14%			
			(0,078)				(0,073)				(0,07)				(0,066)			

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

9.4 Results for Momentum Strategies based on Sub-samples

The previous sections demonstrated how the momentum strategies create both positive- and abnormal returns on a systematic basis on the Danish stock market. But at this point it is not known if the profitability of the strategies is confined to specific types of stocks. Therefore, the purpose of this section is to investigate whether the observed success of the strategies can be linked to certain characteristics in the stocks. As mentioned in the initial theory section, both the market beta and the size of a company have, throughout the financial literature, been related to risk and return, and thus, this section will revolve around these factors. As mentioned in the methodology section, we implement the momentum strategies on three size-based sub-samples (small, medium, and large), and three beta-based sub-samples (low, medium, and high). To keep this section short and focused we only conduct this sub-sample analysis on a selection of the best performing strategies from section 9.1 and section 9.3. These are the 6/6-, 9/3-, 9/6-, 12/3- and the 12/9-strategy. Lastly, the performance of these strategies will be analyzed further in three sub-periods, to see if the performance of the strategies is related to specific market conditions.

9.4.1 Market Beta

The market beta-based sub-sample analysis suggests that the profitability of the momentum strategies is limited to stocks with certain beta values. However, there are notable differences in the sub-sample. In table 9.7 the medium-beta stocks are performing the best. Here, the 5 different winner portfolios in the sub-sample produce on average a monthly return of 2.10%. The medium-beta sub-sample is followed by the high-beta sub-sample. Common for the medium- and high-beta sub-samples is how their strategies produce average monthly returns that are somewhat close to the initial results including all stocks in section 9.1. However, the same can't be said about the low-beta stocks, which does not share many similarities with previous findings. Here, there is a relatively small difference between the average monthly return on the winner portfolios and the loser portfolios, which reflects itself in the zero-cost portfolios that produce returns far below what have been seen in the analysis so far. The main reason for these irregularities is the loser portfolios, which are all performing astonishingly good, producing returns on the same level as the benchmark. Consequently, 4 out of 5 zero-cost portfolios in the low-beta segment fail to produce average monthly returns that are significantly positive. However, all other zero-cost and winner portfolios in the two other segments manage to produce significantly positive average monthly returns. Nonetheless these results indicate that the momentum strategies are confined to medium and large beta stocks, since only 1 out of 5 zero-cost portfolios in the small-beta segment show significant positive returns.

Table 9.7: Returns on beta-based portfolios (Equally weighted)

The table shows the average monthly return for the winner, loser and zero-cost portfolios for a selection of momentum strategies using a sub-sample of stocks based on beta value. The numbers in parentheses are the standard deviations. Furthermore, the table shows whether the results are significantly different from zero according to the student's t-test ($H_0: \bar{r} = 0$).

			Sub Sample - Beta									
Strategy			Low			Medium			High			All	
6/6	Winner	1,34%	(0,048)	***	2,03%	(0,062)	***	1,55%	(0,067)	***	1,67%	(0,061)
	Loser	1,06%	(0,057)	***	0,17%	(0,066)		-0,07%	(0,098)		0,15%	(0,08)
	Zero-cost	0,28%	(0,056)		1,86%	(0,056)	***	1,62%	(0,079)	***	1,52%	(0,067)
9/3	Winner	1,54%	(0,052)	***	2,21%	(0,068)	***	1,88%	(0,072)	***	1,86%	(0,057)
	Loser	1,17%	(0,061)	***	0,07%	(0,069)		0,11%	(0,113)		0,00%	(0,086)
	Zero-cost	0,37%	(0,066)		2,14%	(0,068)	***	1,77%	(0,101)	**	1,85%	(0,077)
9/6	Winner	1,46%	(0,049)	***	2,23%	(0,063)	***	1,67%	(0,071)	***	1,79%	(0,057)
	Loser	1,11%	(0,06)	***	0,11%	(0,068)		-0,18%	(0,101)		0,08%	(0,081)
	Zero-cost	0,35%	(0,064)		2,12%	(0,061)	***	1,85%	(0,089)	***	1,71%	(0,071)
12/3	Winner	1,72%	(0,054)	***	1,90%	(0,065)	***	2,16%	(0,073)	***	1,98%	(0,06)
	Loser	0,96%	(0,061)	***	-0,23%	(0,071)		0,27%	(0,112)		0,17%	(0,086)
	Zero-cost	0,76%	(0,069)	*	2,12%	(0,071)	***	1,89%	(0,108)	**	1,81%	(0,078)
12/9	Winner	1,52%	(0,049)	***	2,13%	(0,064)	***	1,86%	(0,072)	***	1,94%	(0,059)
	Loser	0,92%	(0,06)	***	0,23%	(0,075)		-0,18%	(0,094)		0,46%	(0,079)
	Zero-cost	0,59%	(0,063)		1,91%	(0,065)	***	2,04%	(0,087)	***	1,49%	(0,07)

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

9.4.2 Market Capitalization

In table 9.8 we see the results from the sub-sample analysis based upon size (market capitalization). This analysis show that the sub-sample with large stocks generally produce the highest average returns, however, even the loser portfolios create average monthly returns on the same level as the benchmark, and this strong performance is further underlined by the test results that indicate significantly positive returns on all portfolios in the large size segment. The 5 different winner portfolios in the large size segment produce on average a monthly return of an impressive 2.3%. The second best performing segment is the one consisting of small stocks, where the average monthly return on the different winner strategies is 1.57%. All winner portfolios in the sub-sample manage to produce significantly positive average monthly returns. The zero-cost portfolios also produce positive returns, and only 1 out of the 15 zero-cost portfolios in this sub-sample analysis is not significantly positive. Given the results in the table, there is no basis for rejecting the profitability of the momentum strategies on companies with a certain size. With that being said, the results do show some differences between the segments, but none that strongly indicate that momentum returns are confined to certain stock sizes.

Table 9.8: Returns on size-based portfolios (Equally weighted)

The table shows the average monthly return for the winner, loser and zero-cost portfolios for a selection of momentum strategies using a sub-sample of stocks based on their market capitalization (size). The numbers in parentheses are the standard deviations. Furthermore, the table shows whether the results are significantly different from zero according to the student's t-test ($H_0: \bar{r} = 0$).

		Sub Sample - Size										
		Small			Medium			Large			All	
Strategy												
6/6	Winner	1,29%	(0,062)	***	1,23%	(0,058)	***	2,25%	(0,067)	***	1,67%	(0,061)
	Loser	0,57%	(0,086)		0,33%	(0,088)		1,03%	(0,067)	**	0,15%	(0,08)
	Zero-cost	0,73%	(0,083)		0,91%	(0,071)	*	1,22%	(0,058)	***	1,52%	(0,067)
9/3	Winner	1,63%	(0,065)	***	1,54%	(0,061)	***	2,37%	(0,067)	***	1,86%	(0,057)
	Loser	0,52%	(0,1)		0,28%	(0,092)		0,81%	(0,07)	*	0,00%	(0,086)
	Zero-cost	1,11%	(0,099)	*	1,27%	(0,082)	**	1,56%	(0,068)	***	1,85%	(0,077)
9/6	Winner	1,46%	(0,059)	***	1,32%	(0,059)	***	2,39%	(0,068)	***	1,79%	(0,057)
	Loser	0,13%	(0,091)		0,46%	(0,088)		0,85%	(0,071)	*	0,08%	(0,081)
	Zero-cost	1,33%	(0,088)	**	0,86%	(0,076)	*	1,54%	(0,065)	***	1,71%	(0,071)
12/3	Winner	1,97%	(0,067)	***	1,58%	(0,062)	***	2,24%	(0,071)	***	1,98%	(0,06)
	Loser	0,52%	(0,103)		0,29%	(0,095)		0,89%	(0,074)	*	0,17%	(0,086)
	Zero-cost	1,45%	(0,102)	**	1,29%	(0,089)	**	1,35%	(0,071)	***	1,81%	(0,078)
12/9	Winner	1,49%	(0,062)	***	1,23%	(0,063)	***	2,25%	(0,068)	***	1,94%	(0,059)
	Loser	0,05%	(0,092)		0,41%	(0,087)		0,93%	(0,074)	*	0,46%	(0,079)
	Zero-cost	1,44%	(0,089)	**	0,82%	(0,075)	*	1,32%	(0,066)	***	1,49%	(0,07)

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

9.4.3 Sub-periods

So far the sub-analyses have illustrated how the profitability of the momentum strategies is not strictly confined to specific stock characteristics. But other non-firm-specific factors might also influence the profitability and eligibility of the momentum strategies. An important one is the general market conditions. Thus, to try and test the strength of the strategies under different market conditions, the last part of this section will split the total sample period into three distinct sub-periods, each one representation somewhat different market conditions. The three sub-periods are 1) 2001-2005, 2) 2006-2010 and 3) 2011-2016, where especially the second period is of interest because of the subprime crisis that unfolded during this period. For further details on these periods, please refer to the methodology section.

Table 9.9 provides some interesting information, since the momentum strategies seem to react distinctively different in each of the three sub-periods. In the first period from 2001 to 2005, both the winner and loser portfolios produce some remarkably high average monthly returns, which are both significantly positive, and well above those of the benchmark. In fact, the average monthly return on the benchmark is just around 1% during that period, while on average the return on the loser portfolios is 2.12% per month and 2.98% per month on the winner portfolios respectively. Consequently, these high returns on particularly the loser portfolios are also reflected in the low returns on the zero-cost portfolios, which all fail to produce significantly positive returns for the period. Still, the high returns on the loser portfolios are quite surprising, and it turns out that they are due to some extraordinary high returns in 2005. To give an example, the 6/6-loser portfolio generates an average monthly return of 5.8% in 2005 compared to just 0.07% in the previous 4 years.

The second period also shows that the momentum strategies are not without limitations. During this period, the winner portfolios create non-significant positive returns smaller than the benchmark, while the loser portfolios on average produce an average monthly return of -0.56%. However, the zero-cost portfolios produce an average monthly return of 0.84%, which is higher than the benchmark. It should be noted though that the returns on 4 out of 5 zero-cost portfolios during this period are not significantly positive, due to the high volatility at the time.

In the most recent sub-period from 2011 to 2016, the results for the winner and loser portfolios are more distinctive from each other. The winner portfolios generate on average a monthly return of 2.29%, while the loser portfolios generate -0.80%. Combined, this leads to an impressive 3.09% average monthly return across all the zero-cost portfolios. Both the winner and zero-cost portfolios in this last period generate returns that are significantly positive.

The analysis above showed that the momentum strategies didn't perform equally well under all market conditions. But a few points are worth making. In the first period the loser portfolios experienced some extraordinary returns in 2005, and had it not been for these the zero-cost portfolios would have generated significantly positive returns. Furthermore, in the second period only one zero-cost portfolio managed to produce significantly positive returns, which could indicate that the momentum strategies are not well suited for market conditions with rapidly changing dynamics or falling stock prices. However, from an investor's point of view, questions remain as to how recommendable the momentum strategies are, and if so, which ones to choose.

Table 9.9: Returns in sub-periods (Equally weighted)

The table shows the average monthly return for the winner, loser and zero-cost portfolios for a selection of momentum strategies during three sub-periods. The numbers in parentheses are the standard deviations. Furthermore, the table shows whether the results are significantly different from zero according to the student's *t*-test ($H_0: \bar{r} = 0$).

		Sub Sample - Time Period								
		2001 - 2005			**2006 - 20010**			**2011 - 2016**		
Strategy										
6/6	Winner	2,77%	(0,071)	***	0,42%	(0,059)		1,81%	(0,05)	***
	Loser	1,75%	(0,074)	**	-0,57%	(0,094)		-0,62%	(0,07)	
	Zero-cost	1,02%	(0,066)		0,99%	(0,07)		2,43%	(0,064)	**
9/3	Winner	2,72%	(0,056)	***	0,49%	(0,06)		2,29%	(0,052)	***
	Loser	1,96%	(0,078)	**	-0,93%	(0,1)		-0,86%	(0,077)	
	Zero-cost	0,76%	(0,069)		1,42%	(0,084)	*	3,15%	(0,075)	***
9/6	Winner	2,79%	(0,053)	***	0,29%	(0,064)		2,29%	(0,051)	***
	Loser	1,99%	(0,072)	**	-0,65%	(0,094)		-0,87%	(0,074)	
	Zero-cost	0,81%	(0,06)		0,94%	(0,079)		3,16%	(0,071)	***
12/3	Winner	3,25%	(0,052)	***	0,00%	(0,068)		2,64%	(0,054)	***
	Loser	2,28%	(0,074)	**	-0,48%	(0,099)		-0,97%	(0,079)	
	Zero-cost	0,97%	(0,063)		0,47%	(0,087)		3,61%	(0,077)	***
12/9	Winner	3,36%	(0,047)	***	0,24%	(0,071)		2,40%	(0,051)	***
	Loser	2,64%	(0,065)	***	-0,14%	(0,091)		-0,70%	(0,076)	
	Zero-cost	0,72%	(0,051)		0,39%	(0,076)		3,10%	(0,074)	***

* Significant at the 0.10 significance level.
** Significant at the 0.05 significance level.
*** Significant at the 0.01 significance level.

9.5 Practical Observations Regarding the Momentum Strategies

The purpose of this last section is to present some practical observations about the strategies performance. As such, the previous results, primarily concerning the average monthly returns, don't provide the full picture - at least not from the investor's point of view. Thus, this sub-section will differ from previous studies, and present some observations that are relevant for practitioners. Please note that because this section seeks to investigate the strategies from the investor's point of view, all tables and figures in this section are reporting numbers from equally weighted portfolios adjusted for transaction costs.

Table 9.10: Percentage of months with positive returns

The table shows the relative number of months in which the monthly return was positive on the winner and zero-cost portfolios for all 16 distinct strategies. The returns are based on an equal weighting scheme and have been adjusted to account for transaction costs.

Formation (J)		Holding (K) 3	6	9	12
3	Winner	54,8%	58,1%	61,6%	63,1%
	Zero-cost	58,4%	57,1%	61,6%	63,7%
6	Winner	59,8%	63,3%	63,7%	63,1%
	Zero-cost	59,3%	62,2%	62,6%	60,8%
9	Winner	62,3%	63,8%	64,8%	66,5%
	Zero-cost	62,3%	57,3%	62,6%	61,8%
12	Winner	66,0%	66,5%	68,8%	67,6%
	Zero-cost	57,4%	57,7%	58,5%	58,8%

So far we've seen lots of monthly average returns for different strategies; some were significantly positive and some weren't. In continuation of these results, table 9.10 shows the percentage of months in which returns were positive. During the analysis period the winner portfolios create positive returns on average in 63.4% of the months, while the fraction is 60.1% on the zero-cost portfolios. The 12/9-winner strategy creates positive returns in 68.8% of the months, which is the highest of any of the strategies. Among the winner strategies there is a clear tendency that those with a longer formation period experience relatively more months with positive returns, which acts to support previous indications that winner strategies with longer formation periods were preferable. However, the same pattern is not clear among the zero-cost portfolios. In general, it is difficult to deduce anything meaningful from the zero-cost strategies in the table, partly because there is less of a spread among the strategies. Thus, for now we will just conclude what was likely already expected, which is that there seems to be a positive correlation between the winner portfolios average monthly return and the number of months in which the strategies create a positive return. Further, this indicates that longer formation periods create better returns.

Table 9.11: Total return (Equally weighted and adjusted for transaction costs)

The table shows the total return for the winner and zero-cost portfolios for all 16 distinct strategies. The total returns are based on an equal weighting scheme, with partial monthly rebalancing and reinvestment of profits and losses. Furthermore, the returns have been adjusted to account for transaction costs.

			Holding (K)		
		3	**6**	**9**	**12**
Formation (J)	**3** Winner	645%	634%	665%	755%
	Zero-cost	319%	392%	495%	496%
	6 Winner	991%	1276%	1194%	955%
	Zero-cost	425%	714%	777%	542%
	9 Winner	1714%	1618%	1377%	1415%
	Zero-cost	888%	962%	824%	515%
	12 Winner	2008%	1591%	1879%	1373%
	Zero-cost	774%	697%	617%	430%

*Total return on benchmark from 2000-2016 was 387%

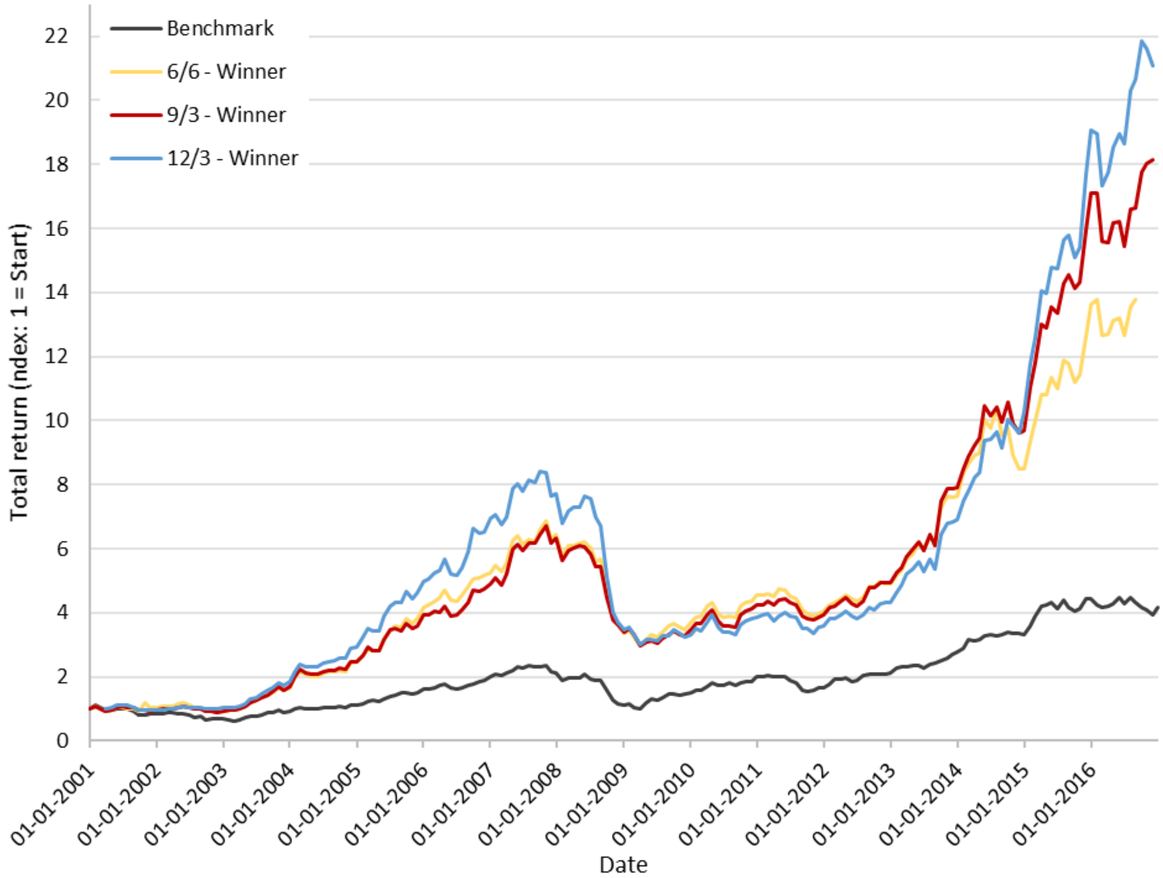
For most investors, the number of utmost importance is the return on their investment by the end of the investment period, but the average returns presented earlier doesn't offer any insight into this matter. In table 9.11 the total return accumulated over the 16-year period of analysis is shown. Not surprisingly, the strategies with the highest monthly average return are also among the strategies with the highest total return. And just like the results in previous sub-sections, the table shows a relatively large spread between the return on the different strategies, clearly indicating that some strategies outperform others. The 12/3-winner portfolio takes the top spot with a staggering total return of 2008% after transaction cost. In comparison the benchmark earns a total return of 387%. Impressively enough, all winner portfolios manage to earn a total return substantially larger than the benchmark. Most of the zero-cost portfolios also perform well compared to the benchmark. The 9/6-zero-cost portfolio earns a total return of 962%, which makes it the best zero-cost strategy. Almost every zero-cost strategy accumulates a total return higher than the benchmark; only the 3/3-zero-cost strategy earns less over the course of the analysis period.

By now it's more than evident that some of the strategies produce great results. However, it is still not clear how the strategies developed over time. Did the total return accumulate steadily, or did the high average monthly returns mainly occur due to extreme positive outliers? To answer these questions, we will look at the return as it accumulated in event time.

In figure 9.2 the total return on three selected strategies based on the winner portfolios is shown in event time together with the benchmark. The three strategies are selected because they have different formation period lengths, which previously proved to partly explain differences in returns, and because these strategies were top performers. The figure clearly illustrates the impressive performance of the strategies, especially in relation to the benchmark. Moreover, the strategies seem to be performing particularly well in upward trending markets, like in the mid 2000's and from 2012 and onwards. In these periods the strategies noticeably distance themselves from the benchmark. However, when the market drops, so does the return on the strategies. In the months of the subprime crisis the benchmark dropped by around 65%. Surprisingly though, 2 out of the 3 strategies only dropped by around 45%, indicating that the momentum strategies don't necessarily loose as much as the average market when things go down. With that said, the 12/3-strategy dropped by around 60%. Furthermore, all the selected winner strategies dropped to the same level during the subprime crisis, which is puzzling.

Figure 9.2: Return over time of winner portfolios (Index: 1 = Strategy start)

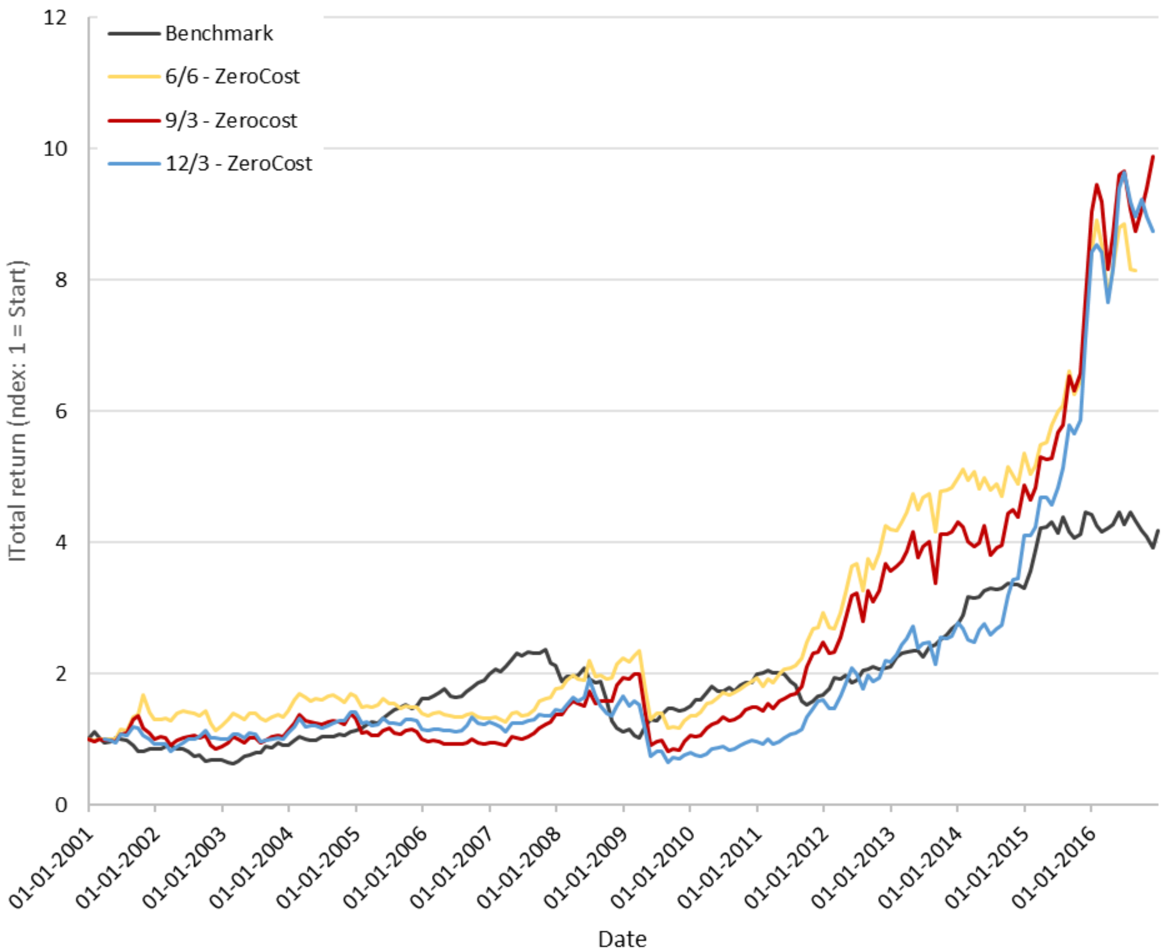
The figure shows the development in total return for the winner portfolios for 3 distinct strategies. The returns are based on an equal weighting scheme, with partial monthly rebalancing and reinvestment of profits and losses. Furthermore, the returns have been adjusted to account for transaction costs. The benchmark shows the return of a buy and hold strategy holding the Danish OMXC index.



The zero-cost portfolios depictured in figure 9.3 showed that, in the bull years leading up to the subprime crisis, the zero-cost strategies perform worse than the benchmark. This relatively bad performance is due to the loser portfolios creating impressively good returns from 2005 to 2006, decreasing the profitability of the zero-cost strategies. When the market drops, the return on the zero-cost portfolios doesn't follow along immediately. This tendency can be seen in the figure all the way up until march 2009; 7 months after the subprime crisis struck the stock market. At this point, the zero-cost strategies fall with 40%–60% the following months, which makes the total return on the 9/3 and 12/3-strategy turn negative (below index 1). However, as the market begins to recover, so does the zero-cost strategies, although each at a different pace. Throughout the period of analysis, the 6/6-strategy performs the best for a long stretch of time, but in the last year of the analysis, the two other strategies generate some impressive returns and even end up surpassing the 6/6-strategy's performance.

Figure 9.3: Return over time on zero-cost portfolios (Index: 1 = Strategy start)

The figure shows the development in total return for the zero-cost portfolios for 3 distinct strategies. The returns are based on an equal weighting scheme, with partial monthly rebalancing and reinvestment of profits and losses. Furthermore, the returns have been adjusted to account for transaction costs. The benchmark shows the return of a buy and hold strategy holding the Danish OMXC index



Consequently, the success of the momentum strategies cannot be attributed to steady and continuous positive return rates throughout the analysis period. The analysis shows that the strategies have periods with positive returns, some with negative returns, and some periods where the returns stagnate. The strategies' biggest and most obvious strength is that they manage to generate some impressively high returns when evaluated over a long-term horizon. Furthermore, the strategies seem to be performing just as well, and maybe even slightly better, compared to the general market when things go down.

10. Analysis of Empirical Results

The results have been presented and the most important findings highlighted. With this, it is now time to analyze the momentum strategies, and see if they deviate from previous studies, and furthermore assess if the results generated in this paper are only due to chance. But just as important, this analysis will look into possible explanations for the empirical results. First section, 10.1, considers the main findings related to the overall strategies presented in section 9.1. From here the paper will move on to section 10.2 in which we will take a closer look at the sub-samples to make some more detailed conclusions about the momentum strategies. Lastly, section 10.3 will present some of the possible explanations behind the results, which entails relating our results to the conventional theory presented in the beginning of this paper. Furthermore, the results will briefly be related to alternative explanations rooted in the relatively new theoretical field called '*Behavioral Finance'* before a more detailed analysis of behavioral models is presented in the next main section.

10.1 Analysis of the Main Momentum Strategies

In any analysis of momentum strategies, it is imperative to establish whether the momentum strategies are profitable or not. In previous studies by Jegadeesh and Titman (1993), Rouwenhorst (1998), Schiereck et al. (1999), and more, this question is answered by looking at the return on the winner- and loser portfolios, and more specifically, if the winner portfolios significantly outperform the loser portfolios. This has been done by creating zero-cost portfolios. However, the analysis concerning the profitability of these serves a far more important purpose than simply showing if the zero-cost strategies present a profitable investment opportunity. A significant positive average return on these zero-cost portfolios tells us that it is possible to pick high performing stocks on a systematic basis, based only on their prior returns. This is proof that a '*momentum effect*' exists, which consequently has significant implications for the market dynamics and the financial theories- and models seeking to explain these.

The results from the zero-cost strategies in this paper are all significantly positive, as evident in section 9.1, with the monthly average return across all 16 strategies being 1,45%, and the most successful one being the 9/3-strategy yielding an average monthly return of 1.85%.

Rouwenhorst's (1998) article was the last published article to confirm the profitability of momentum strategies on the Danish stock market, and so our results prove that the momentum strategies are still relevant almost 20 years after his analysis. The results in Rouwenhorst's article are smaller than what have been observed in this study. Back in the 1980's and 1990's the 6/6-zero-cost portfolio generated an average monthly return of 1.09%, whereas the 6/6-strategy in this paper generates an average monthly return of 1.52%. The paper by Chan et al. (2000) also investigated the Danish stock market, or rather the Danish SE general index[145]. But in contrast to Rouwenhorst's results and those of this paper, they were not able to confirm the profitability of momentum strategies on the Danish stock market for holding periods of 3 and 6 months. However, differences in methodology between this and the Chan et al. (2000) study make them difficult to compare directly. Thus, on the grounds of our own results and those of Rouwenhorst (2000), it can be concluded that the '*momentum effect*' exists on the Danish stock market and has done so for at least 35 years now.

Furthermore, the results strongly suggest that the stock market is not efficient as proposed by the Efficient Market Hypothesis in the beginning of the paper. As noted earlier, one of the main implications of the Efficient Market Hypothesis is that stock prices follow a random walk, and that any kind of technical analysis therefore cannot predict future prices. However, the success of the momentum strategies contradicts the EMH in its weak form as they show it is possible to earn abnormal profits through technical analysis that solely relies on past stock prices. One of the biggest surprises in the analysis is how close the results are to earlier studies conducted on different markets through time. The first example of this is the top performing winner portfolio in this paper's analysis; the 12/3-strategy with an average monthly return of 1.98%. In Jegadeesh & Titman's (1993) original article on the NYSE- and AMEX market, it is also the 12/3-winner strategy that proves to be the most successful among the 16 distinct strategies with an average monthly return of 1.92%. And again, in Rouwenhorst's (1998) article on 12 European stock markets, it is likewise the 12/3-strategy that generates the highest returns among all the strategies based solely on winner portfolios with an average monthly return of 2.19%. The zero-cost portfolios also produce some strikingly similar results, although not as remarkable as for the winner portfolios. The Jegadeesh & Titman (2001) article have the 12/3- and 9/6-strategy in their

[145] Chan et al., 2000, p. 158

top 2 over the most successful zero-cost strategies, while the same is the case in Rouwenhorst's (1998) article. However, as mentioned in the previous sub-section above, the 9/3-zero-cost strategy is performing the best in this paper, but is closely followed by the 12/3- and 9/6-strategy, which illustrates that there seems to be an almost universal pattern to which strategies that perform the best. But the results are not similar in all respects. Most noticeable is the 1.45% average monthly return across all zero-cost strategies in this paper, which is around 0.5%-point more than in the two papers mentioned above, indicating that the momentum effect is even more explicit in recent years, at least on the Danish market.

In the empirical results, it was evident that strategies with a longer formation period performed better than those with a short formation period, and as it turns out, this pattern is also present in previous comparable studies. In both Jegadeesh & Titman (1993) and Rouwenhorst (1998), the strategies with longer formation periods produce relatively higher average monthly returns. This is the case on both the winner and zero-cost portfolios. However, for the holding period the opposite is true: A shorter holding period produces the best results, at least on the zero-cost portfolios. For the winner portfolios, the pattern is not as clear-cut. This observation is also in line with the work of Jegadeesh & Titman (1993), Rouwenhorst (1998) and Schiereck et al. (1999), who all establish a negative correlation between the strategy returns and the length of the holding period. Thus, when we relate these patterns to the strategy results it is not that surprising that the 12/3-strategy comes out on top.

Furthermore, previous studies also concern the zero-cost strategies and the immediate source to their abnormal returns. Jegadeesh & Titman (1993) find that the buy side (winner portfolios rather than the sell side (loser portfolios) are the main source of profitability. Rouwenhorst (1998) find analogous results supporting this observation. In both articles the loser portfolios often produce average monthly returns that are positive but not significant, which thereby reduces the average return on the zero-cost portfolios compared to the winner strategies. The results in section 9.1, once again show that the results of this paper are very similar to the previous studies. The loser portfolios also produce non-significant positive average monthly returns in most cases, while all winner portfolios produce significant positive returns, which shows that the buy side are also the main source of profit in our momentum strategies.

10.2 Analyses of Sub-samples

The purpose of the sub-samples has already been explained on multiple occasions throughout this paper, but in short, the sub-samples are here to tell us if the momentum strategies are confined to stock characteristics or market conditions. In this paper, the three most frequently investigated factors throughout the literature are chosen for further analysis. These sub-sample analyses are concerned with two aspects: 1) Are the momentum strategies profitable across all sub-samples and segments, and 2) are there any segments that are more profitable than others. The answers to these questions were already more or less provided in the result section. Nonetheless it is still worth taking a look at their implications and at how they relate to previous studies.

The beta-based sub-sample represents the only real inconsistency in our analysis of the momentum strategies. As such, the medium beta segment displays some good results with an average monthly return of 2.03% across the 5 different zero-cost strategies, followed by the high beta segment and its monthly average return of 1.84%. In both cases the results are significantly positive. However, the low beta segment presents some less impressive results. The zero-cost strategies in this segment only generate an average monthly return of 0.47%, which is considerably less than all other zero-cost strategies investigated previously in this paper. Furthermore, only one out of five strategies tested in this segment provide a significantly positive return at the 90% significance level. As stated previously in section 9.3, the loser portfolios and their average return of 1.05% are to blame for the zero-cost portfolios weak results in this segment. Consequently, the results suggest that the profitability of the momentum strategies seems to be confined to the medium- and high beta stocks, at least in this study. In the article of Jegadeesh and Titman (1993), the zero-cost strategy in the low-beta segment also perform relatively weak, although the returns are significantly positive. In their analysis, it is also the loser portfolio that generates remarkably high returns, and thereby reduces the profitability of the zero-cost strategy. Furthermore, both studies indicate that the low beta segment and especially the loser portfolios within it, do not comply very well with the momentum strategies. However, one should be careful with concluding that the momentum strategies are strictly confined to medium- and high beta stocks, since the majority of the momentum literature does not find evidence that supports this claim. In the end, the results in this paper's low beta segment turn out to be quite unique, since this study is the first that fails to confirm the profitability of the momentum strategy across all beta-segments.

Almost all the zero-cost strategies in the size sub-sample produce significantly positive returns, proving that the momentum strategies are profitable regardless of the market capitalization (size) of a stock, just like many previous studies have already shown. In this paper the large cap segment is the most successful one, with an average monthly return of 1.4%. The previous studies by Jegadeesh and Titman (1993), Rouwenhorst (1998) and Schiereck et al. (1999) also show that the momentum strategies are significantly profitable regardless of the stock size. However, in contrast to this paper's results, the large cap segment in these studies produce the smallest average returns when it comes to the zero-cost strategies. Only the paper by Liu & Lee (2001) on the Japanese stock market find evidence of large cap stocks generate the highest return. However, their results are not significant and therefore don't provide compelling evidence. The fact that the momentum strategies are more successful on large cap stocks in this paper doesn't fit well with common expectations. In the words of Jegadeesh and Titman (1993): *"… the strategies are likely to generate higher returns when they are implemented within the small-firm subsample that consists of less actively traded stocks and to generate lower returns when they are implemented within the large-firm subsample*[146]." Furthermore, the large cap stocks are noticeably less volatile than the small cap stocks. Thus, traditional portfolio theory and the relationship between expected return and risk, also cannot explain why these results are observed. There could be many reasons as to why the results of this paper deviate from previous studies in this manner. One might simply be, that the momentum effect on the Danish stock market is more predominant on stocks that are traded broadly and often, thereby acting as a driver for the momentum effect.

Market dynamics change as markets go up and down, which naturally also affects the strategies trying to exploit market dynamics. Therefore, it is no big surprise that the momentum strategies also go through ups and downs in certain periods. In the sub-period analysis, the zero-cost strategies only manage to produce significant positive returns in the latest sub-period from 2011 and onwards. However, it should be said that had the significance level been lowered to 85%, then 4 out of 5 zero-cost strategies in the first sub-period from 2001-2005 would have

[146] Jegadeesh and Titman, 1993, p.76

returned significant positive returns. Furthermore, the lack of significant results in this sub-period was, as pointed out earlier in the results, due to some remarkably high average monthly returns on the loser portfolios in 2005. In the second period from 2006 – 2010 the zero-cost portfolios also fail to produce significant positive results in 4 out 5 cases, but this time around it is due to both the winner- and loser portfolios. The relatively weak performance in this period can most likely be linked to the subprime crisis and the changes in dynamics that occurred at the time. From the above it is clear that the zero-cost momentum strategies perform better under certain market conditions. This is also the conclusion in Jegadeesh and Titman's (1993) original article. They show the zero-cost strategies perform better in periods with stability and stock prices going up. Somewhat similar to the results of this paper, their 6/6-zero-cost strategy also fails to generate significant positive returns in the 1970's, which can likely be explained by the high market instability during that period. The results in Lee and Liu (2001) also show that the momentum strategies perform weaker in bear markets, but once again it should be noted that none of their results are significant.

In sum, the sub analyses showed some less compelling results. The momentum strategies implemented in the low beta segment was unable to create significant positive returns, and the performance of the strategies was inconsistent in some periods. However, this doesn't imply that the momentum effect is a fluke or that momentum strategies are without merit. What it shows is that the momentum effect should be perceived as persisting throughout longer periods and across most types of stocks, and ultimately as phenomenon that varies in strength.

10.3 Theoretical Considerations

Although the sub-sample analyses presented some inconsistencies, it should still be evident that the momentum strategies are significantly profitable in general, and that the results are widely supported by multiple studies employing a similar methodology on various markets. The profitability of the strategies arises from the momentum effect, but the source behind the momentum effect is uncertain and heavily debated to this date. Therefore, the following section will consider some of the possible explanations for the observed momentum effect, including both old and new theories.

10.3.1 Risk

The basic joint concept of risk and return are in many ways the foundation for all modern portfolio theory, whether it is a continuation of the concept or a critique, most modern literature refers to this concept in some way. In the initial theory section at the start of the paper, it was shown how the Modern Portfolio Theory by Markowitz, the CAPM, and Arbitrage Models all claim that differences in return across stocks can be explained by differences in risk factors. For some years, the market beta was in large seen as the only risk factor of importance, but with the development of Multi-Factor Models other risk factors were also introduced, like size. If the traditional notion that return and risk are related is universally true, then we should expect to see our winner portfolios consist of stock with relatively high market betas and/or with small market capitalizations.

To check if the market risk (market beta) can explain the momentum profits, a small sub-sample of strategies will be analyzed further. The strategies in question are the 6/6- and the 9/3-strategies. For the 6/6-strategy, the winner portfolio has a beta value of 0.80 and the loser portfolio a beta of 1.13. For the 9/3-strategy, the winner portfolio has a beta value of 0.76 and the loser portfolio a beta of 1.13. In both cases, it is evident that the loser portfolio has a higher market beta than the winner portfolio, which shows that the market risk is not a useful explanatory factor.

Previous studies, like those of Jegadeesh and Titman (1993), Rouwenhorst (1998) and Schiereck et al. (1999), also fail to find any evidence indicating that the momentum profits are due to differences in market risk on the winner- and loser portfolios. Jegadeesh and Titman (1993) investigates the 6/6-strategy too, and find that the winner portfolio has a smaller market beta compared to the loser portfolio. In a similar manner, Schiereck et al. (1999) find that the loser portfolio has a noticeably higher beta than the winner portfolio. Rouwenhorst (1998) takes a more overall approach and considers the return on the winner- and loser portfolios across all 16 strategies at the same time. He finds that the beta-value on the winner- and loser portfolios are very close to each other, which is reflected in the zero-cost portfolios' betas not being significantly different from zero. Even when Rouwenhorst (1998) allow the betas to vary with the market conditions to test if the momentum returns can be explained by market dependent betas, the results still point in the opposite direction of what should be expected. Thus, Rouwenhorst (1998) concludes that the market beta cannot explain the momentum effect. In total, these results are in stark contrast to what the traditional theory predicts. Especially to the CAPM that is made on the concept that a stock's market beta is the only important explanatory factor for expected returns. As mentioned above, traditional theory expects that the winner portfolios consist of high-beta stocks and loser portfolios of low-beta stocks. But since the opposite is true in this and previous studies, it can be concluded that the market beta cannot explain the momentum returns that our momentum strategies generate.

The next risk factor being investigated is the size (market capitalization) of the stocks. Once again we will analyze the same two strategies as before. The average market cap on the 6/6-winner portfolio is 111,170 m. DDK and 44,938 m. DDK on the loser portfolio, while on the 9/3-winner portfolio the average market cap is 129,466 m. DDK and 46,592 m. DDK on the loser portfolio. This shows us that the winner portfolios generally consist of bigger stocks compared to the loser portfolios. In fact, the winner portfolios are on average more than double the size of the loser portfolios. These results suggest that differences in size can't explain the momentum returns, at least not if we are to apply the traditional theory which states that smaller sized stocks are riskier than larger stocks, and as such, investors should be compensated by a higher expected return when holding small stocks.

Jegadeesh and Titman (1993) also investigates the 6/6-strategy and finds somewhat similar results to compare to the abovementioned. In their analysis, the winner portfolio is also more than twice the size of the loser portfolio. Moreover, they expand their analysis and include all the ranked decile portfolios in-between the winner and loser portfolio. Their results lead them to the conclusion that differences in size across the ranked portfolios cannot explain the momentum returns. Likewise, Rouwenhorst (1998) finds that the winner portfolios on average consist of stocks larger than those in the loser portfolios, thus further supporting the claim that size is not able to explain the momentum returns. In his article he goes on to conclude that: *"…a risk adjustment for market and size makes the continuation effect appear more at odds with the joint hypothesis of market efficiency and the two- factor model*[147]*."* Hence, in the search to find an explanation for the observed momentum effect, all signs so far point away from the traditional theory. Thus, this paper will move on and look at some alternative explanation.

[147] Rouwenhorst, 1998, p. 277

But before the alternative is presented, it is worth mentioning one other risk related factor that is also often investigated in momentum studies. The book-to-market value of a stock, along with beta and size, is one of the most commonly applied risk factors and is a fundamental part of Fama and French's Three Factor Model[148]. According to the traditional theory, value stocks (high book-to-market value) are expected in the winner portfolios, since these are considered riskier than growth stocks (low book-to-market value), which are expected in the loser portfolios. In our study, the book-to-market value has not been included due to a lack of data availability in the early years of the sample period, but luckily others have. Jegadeesh and Titman's follow up paper in 2001 considers additional explanations for the momentum returns such as differences in book-to-market value on winner and loser portfolios. And so, in continuation to their findings 8 years prior, they find that differences in book-to-market value also cannot explain the momentum return. Ultimately they conclude that the traditional theory cannot provide a rational explanation for the observed momentum returns. The results from Jegadeesh and Titman (2001) on the US market are backed by Dijk and Huibers' (2002) analysis on the European market. Although their approach differs from that of Jegadeesh and Titman (2001) their results are still insightful. Their analysis finds a negative relationship between monthly momentum returns and the book-to-market value of the portfolios, a result in stark opposition to what the traditional theory would have us expect.

Combined, these results clearly suggest that the momentum returns observed are not related to the models and market dynamics embedded in the traditional theory. This also generally seems to be one of the reoccurring conclusions in many momentum studies as evident above and in the literature review. Even some of the biggest names within the traditional finance theory are reaching similar conclusions. Fama and French, the creators of the Fama-French Three Factor Model, also fail to provide an economic and rational explanation for the momentum effect in their 1996 paper on pricing anomalies in their multifactor model. They go on to provide two alternative explanations: 1) The momentum effect is a result of data snooping, which in their view is the most likely, or 2) the momentum effect is a result of irrational asset pricing (irrational investors)[149].

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[148] Fama and French, 1996, p. 56
[149] Fama and French, 1996, p. 81

10.3.2 Data Snooping

The sheer amount of previous studies into momentum related strategies, and the many persuasive results coming from these, makes one question the accusations of data snooping. Nonetheless, Fama and French (1996) are not the only ones who have previously voiced their concern about the possibility that the momentum returns are merely due to data snooping. In a recent 2012 paper by Metghalchi et al., the main topic is the potential problem of data snooping in momentum related studies. Metghalchi et al. (2012) describe the phenomenon as follows; "*Data-snooping occurs when a given data set is used more than once for the purpose of inference and/or model selection. Reusing the same data set can imply the possibility that any satisfactory results may be simply due to pure luck rather than to any real merit of a particular model*"[150]. After referring to a range of previous studies that also point to the potential problem of data snooping, they go on to implement White's (2000) Reality Check test on their own momentum analysis on the European stock market. The Reality Check test is a test that quantifies the data snooping bias and makes the proper adjustments to account for it. Ultimately, their results show that a momentum strategy can outperform a simple buy-and-hold strategy even after accounting for data snooping biases. It should be noted though, that their momentum strategy is not directly comparable to the one presented in this paper, but even so, the results still provide valuable evidence in favor of the momentum effect, thus further validating many of the previous studies investigating momentum strategies.

Furthermore, in this paper that examines the Danish Stock market during the past 17 years, the potential problem of data snooping is hardly an actual issue. One reason being that this study focuses on a market which previously has only been a small part of a much bigger analysis into multiple markets regarding the validity of momentum strategies and the existence of the momentum effect. But most of all, this study uses data from a period that has hardly been investigated before in momentum studies. The literature review made it quite clear that most previous studies were published in the 1990's and the early start of this millennium, meaning that the data used was predominantly from the 1970's, 1980's and 1990's. Thus, the results presented in this analysis don't build upon data that has already been used before to infer similar conclusions. Consequently, data snooping is not seen as a valid concern in regard to this study. In

[150] Metghalchi et al., 2012, p. 1540

fact, this paper is providing additional evidence in favor of the momentum effect, and just like Metghalchi et al. (2012), it is further validating many of the previous studies, showing that those results were not just a fluke, but insightful and highly relevant to this date.

10.3.3 Behavioral Finance

The traditional financial theory did not provide any rational explanations for the observed momentum effect, and the suggestion that the results are merely due to data snooping seems a bit misplaced at this point considering the volume of distinct studies providing significant results continuously throughout the past 20 years. Consequently, the result of this paper represents an anomaly to the traditional theory.

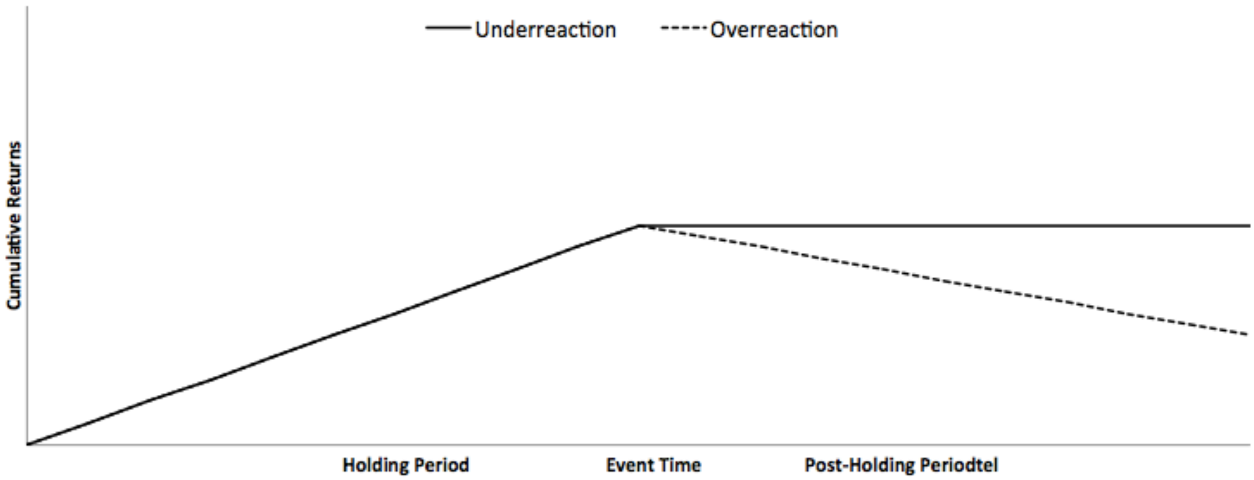
The momentum effect is just one of many anomalies that has been discovered since the introduction of the conventional financial theory. Common for these anomalies are that they contradict the Efficient Market Hypothesis and the traditional equilibrium pricing models, demonstrating that the market is not always efficient in its weak form. Some of these anomalies are short lived, while others are persistent. In response to the apparent shortcomings of the traditional theory, a new field within finance emerged in the 1980's called Behavioral Finance (Bodie, 2011). Behavioral finance attempts to explain some of the anomalies by relaxing the assumption that investors are fully rational, thereby also criticizing the conventional models and theories, implying that asset pricing is irrational in some aspects.

In the previous literature, Chan, Jegadeesh and Lakonishok (1996) suggested that markets respond gradually to new information. Thus, they tend to underreact to news and continue to be surprised in the same direction over the following period. They then assume that this effect will simply fade out resulting in zero post holding period returns[151]. This explains short-term price momentum but fails to account for long-term reversal. Jegadeesh and Titman (2001) rejected the models of underreaction as they failed to explain long-term reversal[152]. In general, long-term reversal has been a phenomenon proven multiple times throughout the literature, thus supporting the rejection of the underreaction models. In figure 10.1 below, the concept of under- and overreaction are illustrated graphically. The figure shows how both theories explain the holding period momentum and how underreaction fails to address the subsequent reversal.

[151] Chan, Jegadeesh and Lakonishok, 1996, pp.1709-1710
[152] Jegadeesh and Titman, 2001, pp. 718-719

Figure 10.1: Under- and Overreaction

The figure shows how underreaction explains holding period price momentum and then expects the post-holding period returns to be 0. Further, the figure shows how overreaction explains holding period price momentum and the subsequent post-holding price reversal.



Source: Own creation

In the next section the intuition behind behavioral finance will be presented and alternative explanations for the momentum effect will be explored.

11. Behavioral Finance

The field of behavioral finance is a relatively young one compared to the conventional field of financial theory. As such, many questions are still unanswered, indicating that the research agenda within the field is still closer to the beginning than to the end. Nonetheless, behavioral finance presents a wide range of interesting theories, each one attempting to explain how and why the behavior of investors might diverge from the '*homo economicus'* assumed in the conventional theories. As such, behavioral finance provides alternative explanations as to why market anomalies, like price momentum, exist. The purpose of this section is not to give a comprehensive walkthrough of the literature, but rather to introduce the theoretical field and the intuition behind it, and then move on to two alternative behavioral theories that might hold the explanation to the momentum effect observed in this and previous studies.

11.1 Introduction

In general behavioral finance can be split into two broad topics: Investor psychology and limits to arbitrage[153].

11.1.1 Limits to Arbitrage

In the Efficient Market Hypothesis, the price of a stock equals its fundamental value, meaning that '*prices are right'* and that there are no arbitrage opportunities, meaning that there is '*no free lunch*'. However, behavioral finance argues that investors who aren't fully rational can bring about deviations in stock prices and move these away from their fundamental value. The conventional theory suggests that in such cases rational traders will quickly flock to the attractive investment (arbitrage) opportunity created by irrational investors, and thereby immediately revert prices back to their fundamental value. This suggestion rests on two assumptions: 1) Whenever there is a mispricing, an attractive investment opportunity exists, and 2) rational investors will immediately jump to the attractive opportunity and revert the mispricing. Behavioral finance is not arguing against the second point, but rather that a mispricing might not necessarily be equal to an attractive investment opportunity. Instead they claim that even when securities are highly

[153] Barberis and Thaler, 2002, p. 2

mispriced, it can be both risky and costly to try and exploit the mispricing. What conventional theory sees as obvious arbitrage opportunities might not be opportunities for riskless profits in the eyes of behavioral economists. This is important because supporters of the conventional theory point to the inability of active investment managers to create continuous abnormal returns as evidence of an efficient market. But just because there is apparently '*no* free lunch' for investors, it does not imply that '*prices are right'* - the two are not equivalent. Thus, a market can be inefficient even though there is '*no free lunch*'[154]. This is what is referred to as '*limits to arbitrage*', and it allows for prices to persistently deviate from their fundamental value.

The reason as to why limits to arbitrage exist is partly due to risk. Fundamental risk can occur from bad news combined with a lack of perfect substitute hedges. Noise trader risk transpires due to the actions of irrational traders[155]. Naturally, this risk factor is not included in conventional literature. The irrational traders can cause the price of an already mispriced stock to deviate even further from its fundamental value for no rational reason. Ultimately, this can potentially force the arbitrageurs (rational traders) trying to exploit the mispricing to liquidate their position early at a high loss. This is especially true for money managers and investors trading at the mercy of other investors and creditors. As John M. Keynes once said; "… *markets can remain irrational longer than you can remain solvent*"[156]. Even without the pressure from outside stakeholders, the risk is still an issue for investors with a short-term investment horizon. Thus, even if it is assumed that fundamental risk can be removed, the presence of noise trader risk will limit the aggressiveness of arbitrageurs[157].

Another reason as to why limits to arbitrage exist is implementation costs. The implementation costs of arbitrage strategies are related to commissions, bid-ask spreads, constraints, and the process of finding mispriced stocks that present an arbitrage opportunity. Together, these costs and the risks above will make any potential arbitrageurs more reluctant when they consider what the conventional theory considers arbitrage opportunities, which consequently supports an inefficient market[158].

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[154] Barberis and Thaler, 2002, p. 4
[155] Ibid, p. 5
[156] Bodie et al., 2011, p. 415
[157] De Long et al., 1990a, p. 735
[158] Barberis and Thaler, 2002, pp. 6-8

The best-known example of inefficient market dynamics is probably the twin shares of Royal Dutch and Shell, who merged in 1907 on a 60:40 basis while remaining separate entities. Thus, if '*prices are right*' the market value of Royal Dutch should be 1.5x bigger than that of Shell. However, historical data shows that this is not always the case. In fact, the data shows a quite persistent mispricing, causing the Royal Dutch share to be both under- and overvalued at times, clearly indicating that prices are not always right. Hedge funds have attempted to exploit this obvious mispricing throughout the years by buying the undervalued share and shorting the other one, but none ever profited from this strategy in any significant way. The lack of success can be attributed to the drivers behind limits to arbitrage discussed above - the risk introduced by noise traders, the arbitrageurs risk averseness and short-term investment horizons[159].

11.1.2 Investor Psychology

The above discussion on limits to arbitrage is an important one, since it explains why mispricing is not always corrected immediately, and thereby also helps setting up the premise for behavioral finance. But it doesn't explain why some investors invest in an irrational manner and how this cause mispriced securities. To answer these questions the theory turns to experimental studies within the field of cognitive psychology, and apply the findings to behavioral models capable of explaining why prices deviate from their fundamental value, and hence, why anomalies exist on the financial market in the first place. The psychological aspect is concerned with the cognitive systematic biases among investors that course mispricing to occur repeatedly in the financial markets[160].

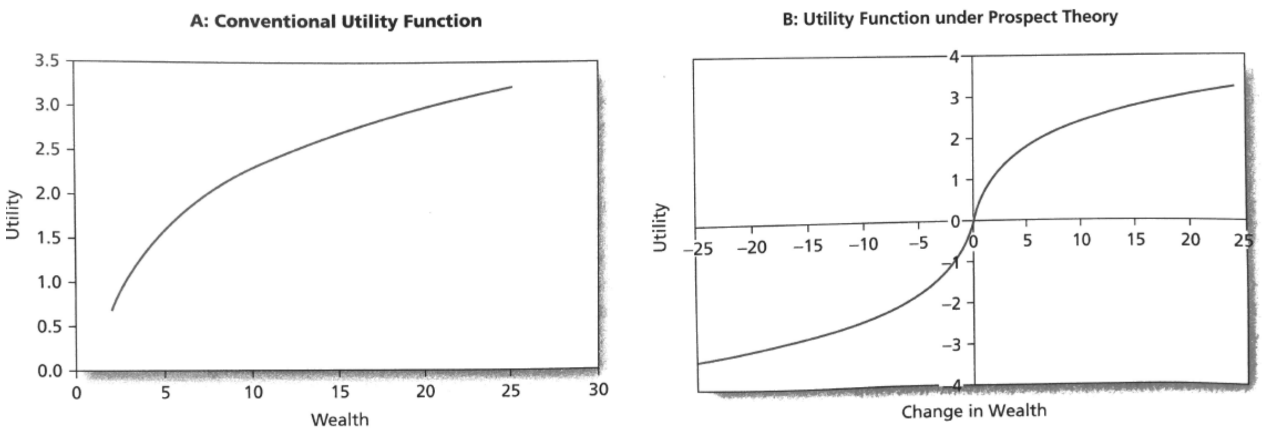
One of the main pillars in behavioral finance is its rejection of the conventional theories' assumption regarding investors' risk preferences. More specifically, behavioral finance argues that the Expected Utility Framework, which serves as a building block in many conventional theories, does not fit well with experimental studies on the topic. According to the Expected Utility Framework the utility function of an investor is defined in terms of the level of wealth and is concave, meaning that an increase in wealth leads to a higher utility but at a diminishing rate, thereby implying that investors are risk averse[161]. One of the alternative theories that has gained

[159] Barberis and Thaler, 2002, p. 9
[160] Bodie et al., 2011, pp. 410 - 414.
[161] Barberis and Thaler, 2002, p. 15

the most attention is Prospect Theory created by Kahneman and Tversky (1979), primarily because it has proven to be very successful in explaining observations from experimental studies[162]. Prospect theory suggests that the utility function of an investor is defined, not in terms of the level of wealth, but in terms of the changes in wealth from the current level. Furthermore, when the change in wealth becomes negative the utility function turns convex, rather than concave, which induces a risk seeking behavior among investors when they suffer losses. Thus, the risk preference of an investor doesn't change over time due to cumulative wealth, but rather depends on recent changes in wealth. Consequently, the investor in Prospect theory exhibits loss aversion rather than risk aversion according to Kahneman and Tversky (1979)[163]. The differences between the two theories are illustrated in figure 11.1[164]. Prospect theory is an example of behavioral models help us understand how a concept like bounded rationality, where individuals try to make the best decision while limited on their own cognitive limitations of their minds, can lead to mispricing in the financial market due to decisions that are seemingly irrational.

Figure 11.1: Expected Utility Framework vs. Prospect Theory

Panel A: A conventional utility function in accordance with the Expected Utility Framework. Panel B: A utility function according to Prospect Theory. Note the differences in curvature and how A depends on the level of wealth and how B depends on the change in wealth. Furthermore, the convex part in B is supposed to be steeper than the concave part.



Source: Bodie et al., 2011, p. 414

Throughout the years, many aspects of the human psychology have been analyzed and included into the field of behavioral finance. Which leads us to one of the main criticisms of behavioral finance, which is the sheer amount of theories within the field. Perhaps the biggest and

[162] Barberis and Thaler, 2002, p. 16
[163] Ibid, p. 16
[164] Bodie et al., 2011, p. 414

most outspoken opponent of behavioral finance is Eugene Fama. Fama (1998) argues that many theories proposed by behavioral finance are only tailored to explain very specific data samples, but fail to account for the overall market as it appears over longer periods of time. Furthermore, he argues that many theories within behavioral finance contradict each other, which he exemplifies by pointing to two different theories trying to explain the same phenomenon, but with contradicting theories of under- and overreaction. In the end, he practically ridicules behavioral finance and states: "*… it is safe to predict that we will soon see a menu of behavioral models that can be mixed and matched to explain specific anomalies*"[165]. This paper finds the critique is too harsh. Because while it is true that some theories don't stand the test of time and that sometimes there seems to be a lack of consensus on '*what is left and right'* within the field of behavioral finance, it is nonetheless still a step in the right direction towards developing a better understanding of how investors act and interact on the financial markets.

As indicated, there are multiple behavioral theories, and many of these have also been linked to the momentum effect. The most cited are models related to underreaction and overreaction among investors. However, as evident from the last section, the models of underreaction failed to explain the subsequent price reversal that has been documented by multiple previous studies. Therefore, the next two sections will take a closer look at two selected theories from within behavioral finance revolving around the concept of overreaction, and investigates how the momentum effect observed in the empirical section and previous studies can be explained by these.

11.2 Positive Feedback Trading

Positive feedback trading is defined as buying stocks when prices move up and selling them when prices move down[166]. If positive feedback trading is a widespread and systematic way of trading among investors, then it is easy to see how this could help explain the momentum returns that were observed in the empirical section as well as in previous studies. This kind of trading represents one of many forms of noise trading. The immediate motives for such trades are not rooted in stock fundamentals, but rather technical analysis and/or cognitive biases among

[165] Fama, 1998, p. 291
[166] Koutmos, 2014, p. 156

investors. The momentum strategies and positive feedback trading might look the same, but there are differences. For one, the momentum strategies are highly systematic in their implementation and execution, while the opposite might as well be true for positive feedback trading. Second, positive feedback trading might involve overreactive and ad hoc transactions based on the investor's own judgement and biases, whereas the momentum strategies set forth a very strict set of guidelines that somewhat prevent the investor's ability to make any personal decisions concerning the portfolio composition.

There are multiple reasons as to why an investor might engage in positive feedback trading when faced with uncertainty. These include representativeness heuristics, anchoring and extrapolative expectations. The representativeness heuristic is a concept developed by Kahneman and Tversky (1974) and refers to people's tendency to make decisions based on stereotypes. When faced with uncertainty, people assess the probability of an object or scenario by look for representative stereotypes, and end up neglecting the relevant basic information available[167]. Anchoring is another concept introduced by Kahneman and Tversky (1974). This heuristic bias refers to people's tendency to form expectation based on some initial value/information that they then adjust away from, but from which they fail to make adequate adjustments, and consequently end up putting too much weight on the initial value/information[168]. It is easy to see why some noise traders might trade on upward-/downward going price trends, if they form their return expectations based on recent returns due to either representativeness heuristics and-/or anchoring.

The concept of extrapolative expectations is somewhat related to those above and refers to investors who believe that high (low) past stock returns predict high (low) future returns[169]. Andreassen and Kraus (1988), an unpublished study referred to by De Long et al. (1990b), did an experiment with people who had training in economics to see how they would react and trade given different price patterns. Their results show that in periods exhibiting a price trend and with high period-to-period variability the subject start to extrapolate price changes, rather than price levels, and consequently engage in positive feedback trading. In periods with low

[167] Kahneman and Tversky, 1974, p. 1124
[168] Ibid, pp. 1128-1129
[169] De Long et al., 1990b, pp. 381-382

variability the examined subjects traded in a rational manner[170]. Furthermore, De Long et al. (1990b) cites Shiller's (1988) investor survey conducted in the wake of the 1987 market crash. It shows how most sellers mentions falling prices as the reason for selling. This indicates that they expected further price drops due to recent price drops[171]. Both cases illustrate how investors sometimes find themselves chasing a trend, either due to anchoring or extrapolative expectations. Consequently, the investors engage in noise trading, rather than trading based on fundamentals.

11.2.1 The Positive Feedback Model

Previously it was mentioned how critiques of behavioral finance generally argued that rational traders would quickly identify the mispricing caused by noise traders and take advantage of the arbitrage opportunity, thereby stabilizing the market and assuring that prices stick to their fundamental value. But it turns out even rational traders might have an incentive to drive prices away from their fundamental value, at least in the short term. This is illustrated in the positive feedback trading model published by De Long et al. (1990b). In this model the rational traders trade on news, but also anticipate that positive feedback traders will trade in the same direction when they realize the upward (downward) going trend. Therefore, rational traders turn into rational speculators and drive prices up (down), even though the news might be uncertain. In the next period, the noise traders will buy (sell) in response to the returns created by the rational speculators and thereby push prices further above (below) the fundamental level. Thus, even though some part of the price change is rational, another part of it is due to the trades made in anticipation of the noise traders and the trades made by the noise traders in response to those previous trades[172].

The positive feedback trading model by De Long et al. (1990b) consists of four periods (t = 0 – 3), two assets (cash and stock), and three different types of traders: Positive feedback traders (noise traders), informed rational traders (speculators), and passive investors who's demand for stocks in all periods only depends on the current prices relative to the fundamental value. The purpose of including passive investors is mainly to make sure the prices don't run wild. Cash is in perfectly elastic supply and pays no net return, while stocks are in zero

[170] De Long et al., 1990b, p. 382
[171] Ibid, p. 382
[172] Ibid, p. 380

net supply. In period 3, stocks are liquidated and pay a risky dividend of $\Phi + \theta$. Here Φ has a mean of zero and can take on 3 values (-ϕ, 0, $+\phi$)[173]. Furthermore, the true value of Φ is released in period 2. That said, a noise signal is released in period 1, which only the rational investors will react upon. Lastly, θ is normally distributed and with a mean of zero, and no information about this value is released before period 3[174].

In their paper, De long et al. (1990b) consider the effect of a (possible) positive signal in period 1 related to dividends, which implies that $\varphi = +\phi$ with a 50% probability and that $\varphi = 0$ with a 50% probability. Given the market clearing condition and the demand of the rational investors in period 1, caused by the noise signal and the anticipation of positive feedback traders in period 2, they derive the price of the stock in period 1[175 176]:

$$p_1 = \frac{\phi}{2} \cdot \frac{a}{a - \beta} \qquad (30)$$

Where $a = \frac{1}{2}\gamma \cdot \sigma_\theta^2$ in which γ is the risk aversion coefficient, and where β is the positive feedback coefficient. Both a and β are also parameters that respectively determine the slopes on the demand curves of the passive investors and the positive feedback traders. A positive β reflects Andreassen and Kraus's results from previously, indicating that positive feedback trades take place in response to recent price changes. Furthermore, for the model to have a stable equilibrium it is assumed that $a > \beta$, and that $\beta > \frac{a}{2}$ for illustrative purposes[177 178]. The price derived in period 1 is above the fundamental value of $\frac{\phi}{2}$ when $\beta > \frac{a}{2}$, and illustrates how rational speculators in this scenario push the price above its fundamental level based only on a noisy positive signal. However even when the last assumption is ignored, a positive noise signal will still induce rational speculators to bet on Φ being high in period 2, due to the anticipated positive feedback trader demand that is independent of the news regarding ϕ in period 2. Thus, rational speculators drive up prices in period 1 in anticipation of future positive feedback trader demand. In period 2, the positive feedback traders respond to the price movement generated by rational speculators in period 1 and buy the stock, which makes the price drift up further, thus creating momentum. At

[173] De Long et al., 1990b, p. 384
[174] Ibid, pp. 384-387
[175] Ibid, p.389
[176] For a detailed step-by-step derivation of the formula: De Long et al., 1990b, pp. 384–392.
[177] De Long et al., 1990b, p. 386
[178] Ibid, p. 388

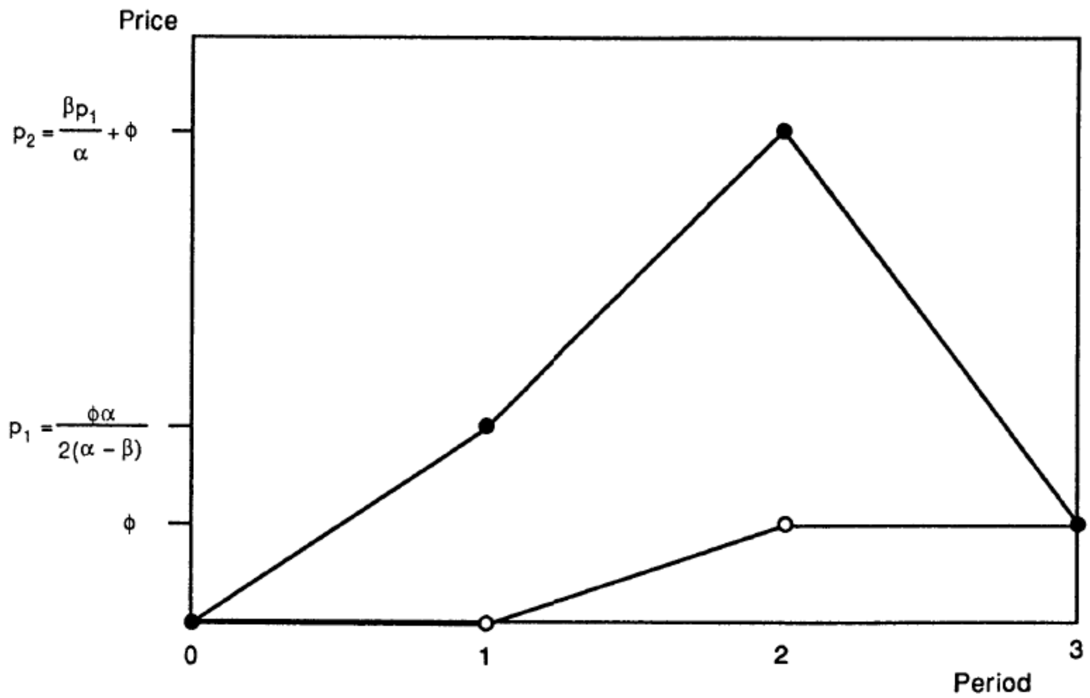
the time news are released regarding the true value of ϕ, which is $\phi = +\Phi$. The rational speculators will realize that the stock is overvalued at this point, and will bet on a reversal back to the fundamental value in period 3. Therefore, rational speculators will unload their positions and sell short as the demand from positive feedback traders keep the price above the fundamental level. The equilibrium price in period 2 is given below[179]:

$$p_2 = \frac{a}{\beta} \cdot p_1 + \Phi \qquad (31)$$

In the last period there is no trading, only investors paying each other according to the positions they hold. Furthermore, because the value of the dividend, and thus the fundamental value, is known at this point, the rational investors will push the price down to its fundamental value equal to $\phi = +\Phi$. In figure 11.2[180] it can be seen how this scenario plays out when $\beta > \frac{a}{2}$, and how it would have unfolded without any rational speculators.

Figure 11.2: The Positive Feedback Model (with a noisy signal)

The (•) line illustrates the price development with informed rational speculators, and the (○) line illustrates the price development without any informed rational speculators. Note how both lines converge to the fundamental value of $\varphi = +\Phi$ in period 3.



Source: De Long et al., 1990b, p. 390

[179] De Long et al., 1990b, p. 390
[180] Ibid, p. 390

The model is seemingly consistent with the short-term momentum returns present in the empirical section and furthermore seems capable of explaining long-term reversals. As such, positive feedback trading is likely to be one of the explanations for the momentum effect in the financial markets. But what is particularly interesting about the model is that the model illustrates how investors who are considered rational can turn into rational speculators and purposely course mispricing in the short-term. Consequently, these rational speculators trigger/excite positive feedback traders, who go on to push prices further away their fundamental value, thereby creating what resembles the momentum effect. It was previously argued that mispricing might prevail due to limits to arbitrage, which could prevent arbitrageurs from stabilizing the market. However, this model presents another possible explanation as to why mispricing in the stock market continues to exist. The rational investors, who are believed to keep the market efficient in the conventional theory, might very well be those who destabilize the market in the first place. In the paper by De Long et al. (1990b) investment banks and brokers are mentioned as likely rational speculators. As they are familiar with the customer order flow, they also likely have the best information about future demand – information that they can exploit by acting as front-runners, and hence use to destabilize the prices[181].

11.2.2 Empirical Evidence

Considering the model above, one might be inclined to believe that only small uninformed investors would engage in positive feedback trading, but according to Nofsinger & Sias (1999) that is not the case. In their paper they investigate herding and positive feedback trading among institutional investors trading on the NYSE. They analyze the correlation between returns and the %-change in institutional ownership on the NYSE from 1977–1996, by forming 10 ranked portfolios each month based on their change in institutional ownership over the past 12 month (t = 0 to 11)[182]. Their results show a very strong positive correlation between the %-change in institutional ownership and returns, demonstrating herding behavior[183] among institutional investors. But even more relevant, they show that the portfolio with the largest increase in institutional ownership is also the one with the highest return in the 12 months prior (t = -1 to -12), which could very well

[181] De Long et al., 1990b, p. 394
[182] Nofsinger and Sias, 1999, pp. 2267 and 2270
[183] Herding is a group of investors trading in the same direction over time. (Nofsinger & Sias, 1999, p. 2263)

mean that institutional investors also participate in positive feedback trading[184]. Furthermore, if institutional investors engage in positive feedback trading, then it seems highly likely that this is also the case among private investors. Finally, Nofsinger & Sias (1999) investigate the relation between the %-change in institutional ownership and momentum, by sorting winner and loser portfolios (based on returns from t = -1 to -6) into portfolios based on the %-change in institutional ownership over 12 month (t = 0 to 11). The results show a strong correlation between subsequent changes in institutional ownership and subsequent returns. More specifically, both the winner and loser portfolio show that the decile with the largest increase in subsequent ownership is also the one with the highest subsequent returns, while the opposite holds for the decile with the largest decrease in ownership[185]. Consequently, these results suggest that positive feedback trading and the degree of change in institutional ownership is related to the momentum effect. It should be noted however, that Nofsinger and Sias (1999) mention that the causality is ambiguous. As such, it is impossible to know the '*direction*' of the relationship between subsequent returns and subsequent changes in ownership.

So far it seems like positive feedback trading provide a solid explanation for the price momentum observed in the empirical results previously. However, the model is not able to provide a direct explanation as to why the momentum effect is not present in some markets like the Japanese.

However, the experimental study conducted by Masuda et al. (2001) could provide some valuable insights. In the experiment, American and Japanese respondents are showed animated scenes, to which they are asked a series of questions[186]. The results find that the Japanese respondents are significantly better at seeing the '*whole picture*', and as such are better at reporting the broader context, whereas the Americans seem to focus on the focal objects[187]. These findings indicate that Americans are more likely to focus on a more narrow set of information, whereas the Japanese are more likely to consider the all information present. This narrow focus could consequently mean that Americans are also more likely to apply heuristics when trying to make sense of the limited amount of information they absorb.

[184] Nofsinger and Sias, 1999, p. 2269
[185] Nofsinger and Sias, 1999, p. 2275
[186] Masuda et al., 2001, pp. 924-925
[187] Ibid, pp. 932 - 934

This proposed relationship is nothing more than a hypothesis based upon a single experiment not directly related, and therefore obviously need more conclusive evidence; nonetheless it could be an interesting topic for further research. Should the relationship above turn out to be true, then this would also have a noticeable effect in the positive feedback trading model. Let's assume that Japanese traders are less likely to use heuristics when trading because they take all available information into consideration. Then this would mean that the parameter β, which indicates the responsiveness of positive feedback traders' demand to past price changes, would be smaller on the Japanese market. Consequently, the demand from positive feedback traders would be smaller and rational speculators would be less inclined to try and push prices in the first place. Eventually, the dynamics creating price momentum would be non-exciting.

11.3 Confidence Models

In 1998 Daniel, Hirshleifer and Subrahmanyam (1998) wrote an article on investor psychology and stock market overreactions. They base their article on the anomalies related to the Efficient Market Hypothesis of short-term momentum and long-term reversals. That is, the positive short-term autocorrelation and negative autocorrelation of short-term returns separated by long lags, which does not comply with the assumption that all stocks are rationally priced[188]. They suggest a theory based on investor confidence and variations in confidence arising from biased self-attribution. The component of investor confidence relies on previous work by DeBondt and Thaler (1995) who state: "*Perhaps the most robust finding in the psychology of judgement is that people are overconfident*"[189]. The second component related to biased self-attribution, they argue, is based on a large amount of evidence from psychological experiments and surveys showing that individuals overestimate their own abilities[190]. This assumption is in accordance with the attribution theory by Bem (1965), which states: "*Individuals too strongly attribute events that confirm the validity of their actions to high ability, and events that disconfirm the action to external noise or sabotage*"[191]. In the theory of Daniel et al. (1998), the overconfidence of investors implies that they see themselves as more able to value stocks than they really are. This

[188] Daniel et al., 1998, pp. 1839-1840
[189] Ibid, p. 1844
[190] Ibid, p. 1841
[191] Ibid, p. 1842

in turn leads to them underestimating the forecast-error variance[192]. Regarding the biased self-attribution, the attribution theory of Bem (1965) is applied to the situation at hand and thus leads to investors whose confidence grows when public information confirms their own information but whose confidence does not decrease equally when it does not.

11.3.1 A Static Confidence Model

Daniel et al. (1998) start by introducing a simple model assuming constant confidence and all investors are assumed overconfident. That is, if the investor receives a private signal, it's precision will be overestimated. There are two groups of investors: The informed investors who receive the private signal and who are risk-neutral and the uninformed investors who do not receive the signal and who are risk-averse. The simple model assuming static confidence has 4 phases: At $t = 0$ all investors have identical beliefs and trades for optimal risk-transfer purposes. Then, at $t = 1$, informed traders receive a private signal and trades with the uninformed traders. At $t = 2$ a public signal enters the market and further trading is conducted. Finally, at $t = 3$, conclusive public information arrives. The risky security has a terminal value equal to θ and the terminal value is assumed normally distributed with a mean of $\bar{\theta}$ and a variance equal to σ_θ^2. The private signal received at $t = 1$ by the informed traders are equal to $s_1 = \theta + \epsilon$ where $\epsilon \sim \mathbb{N}(0, \sigma_\epsilon^2)$. The uninformed investors correctly assess the error term's variance while it is underestimated by the informed traders as $\sigma_C^2 < \sigma_\epsilon^2$. This assessment difference is assumed public knowledge for all investors. Further, the rationale of overconfident investors is, that they have a personal attachment to their own signals. The public signal arriving at $t = 2$ is equal to $s_2 = \theta + \eta$ where $\eta \sim \mathbb{N}(0, \sigma_\eta^2)$. For the public signal, all traders correctly assess the error-term's variance and the error term is independent of both θ and ϵ. Due to the initial risk-assessment of each group of investors, the informed, and by definition overconfident, investors will drive prices away from their fundamental values. Based on the above, at each point in time prices will be equal to[193]:

$$P_1 = E_C[\theta | \theta + \epsilon] \qquad (32)$$

$$P_2 = E_C[\theta | \theta + \epsilon, \theta + \eta] \qquad (33)$$

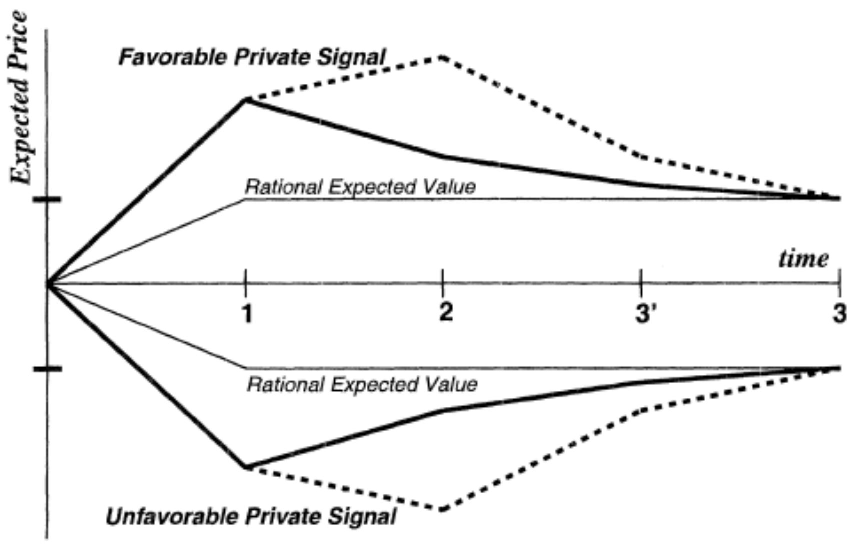
$$P_3 = \theta \qquad (34)$$

[192] Daniel et al., 1998, p. 1844
[193] Ibid, pp. 1845-1846

Where E_C indicates that the prices at $t = 1$ and $t = 2$ are given as the expectations of the informed investors confident beliefs. The above price-movements indicate that the influence of the informed investors at $t = 1$ will cause an overreaction whether the initial private signal is positive or negative. When the public signal arrives at $t = 2$, the deviation of the price at $t = 1$ is partially corrected on average. This happens as the public signal partly reveals the overreaction, thus driving the price closer towards the fully rational level. Finally, at $t = 3$, the price will be adjusted fully back to the fundamental level, as conclusive public information is readily available to all investors. The mentioned price-movements are summed up in figure 11.3 below, where the solid line represents the model outlined above[194].

Figure 11.3: The Confidence Models

This figure shows price as a function of time for the dynamic confidence model with a dashed line and for the static confidence model with a solid line.



Source: Daniel et al., 1998, p. 1847

In figure 11.3, the phase from time 0 to time 1 is called the overreaction phase while the subsequent phase is referred to as the correction phase. The correction phase taking place from $t = 1$ an onwards implies a negative correlation between the overreaction and the correction phase, $cov(P_3 - P_1, P_1 - P_0) < 0$. Further, as the correction phase is partially implemented at $t = 2$ and fully implemented at $t = 3$, a positive correlation exists throughout the correction phase, $cov(P_3 - P_2, P_2 - P_1) > 0$. As such, the price changes caused by private signals are reversed in the long run, and price changes caused by public signals tend to be positively

[194] Daniel et al., 1998, p. 1847

correlated with subsequent price changes[195]. The model described above seems to comply with the theory of long-term reversals but not with short-term momentum. At first, it might seem as if the overreaction indicates short-run momentum, but the momentum effect requires a subsequent period where the overreaction continues, thereby indicating momentum. Therefore, the static-confidence model does not imply short-term momentum. However, this model has relied upon static confidence levels, thus not taking biased self-attribution into account. Therefore, the model will be adjusted to allow for this component. The next section will describe a model with dynamic confidence able to explain both the short-term momentum effect and the long-run reversal effect.

11.3.2 A Dynamic Confidence Model

The static model relied on investors being overconfident from the beginning. However, if the informed investor is not overconfident from the start, trading at $t = 1$ will simply be based on the private signal received. As the public signal arrives at $t = 2$, this will either confirm or contradict the private signal. Given the attribution theory of Bem (1965), investor confidence will grow if the public signal is confirming the private signal but decrease by a smaller magnitude or not at all if it is contradictory. Thus, on average, the investor confidence will grow when the public signal arrives, thereby intensifying overreaction. This prolonged overreaction causes short-term positive autocorrelation, while public signals received later will eventually drive the prices back towards the fully fundamental levels[196]. This process is shown in figure 7 above as the dashed line. As such, the overreaction phase is prolonged and intensified from $t = 1$ through $t = 2$ before it is gradually reversed in the long run. The unobservable stock value is given as $\tilde{\theta} \sim \mathbb{N}\,(0, \sigma_\theta^2)$ and the variance term remains public knowledge. As for the static confidence model, a private signal is emitted as $t = 1$ equal to $\tilde{s_1} = \tilde{\theta} + \tilde{\epsilon}$ where $\tilde{\epsilon} \sim \mathbb{N}\,(0, \sigma_\epsilon^2)$. At $t = 2$ through $t = T$, public signals arrive equal to $\tilde{\phi} = \tilde{\theta} + \tilde{\eta_t}$ where the error-term is an independent and identically distributed random variable and where $\tilde{\eta_t} \sim \mathbb{N}\,(0, \sigma_\eta^2)$. The variance of the public signal error-term is public knowledge as well. The average of all public signals emitted from $t = 2$ through $t = T$ equals[197]:

$$\Phi_t = \frac{1}{t-1}\sum_{\tau=2}^{t} \tilde{\phi} = \theta + \frac{1}{t-1}\sum_{\tau=2}^{t} \tilde{\eta_t} \qquad (35)$$

[195] Daniel et al., 1998, p. 1847
[196] Ibid, p. 1856
[197] Ibid, p. 1859

Where $\widetilde{\Phi_t} \sim \mathbb{N}\,(\theta, \frac{\sigma_\eta^2}{t-1})$. The informed investors have rational expectations regarding the stock's value except for the investor's perception of his or her private signal precision. Therefore, the error-term variance of the private signal is incorrectly assessed by the informed investor and is assessed using the following rule[198]:

$$if \begin{cases} sign(s_1 - \Phi_{t-1}) = sign(\phi_t - \Phi_{t-1})\ and\ |s_1 - \Phi_{t-1}| < 2\sigma_{\Phi,t} \\ then\ \ v_{C,t} = (1+\bar{k})v_{C,t-1} \qquad otherwise\ \ v_{C,t} = (1-\underline{k})v_{C,t-1} \end{cases} \qquad (36)$$

Further, a restriction is applied stating $\bar{k} > \underline{k} > 0$, and the ratio $\frac{1+\bar{k}}{1+\underline{k}}$ is an index of the investor's self-attribution bias. The restriction is applied to reflect the self-attribution bias. As the informed investor is assumed risk-neutral, and therefore able to affect prices, the stock price at *t* is equal to the expectation of the terminal value given the signals received at time *t*[199]:

$$P_t = E_C[\tilde{\theta}|s_1, \phi_2, \dots, \phi_t] = E_C[\tilde{\theta}|s_1, \Phi_t] \qquad (37)$$

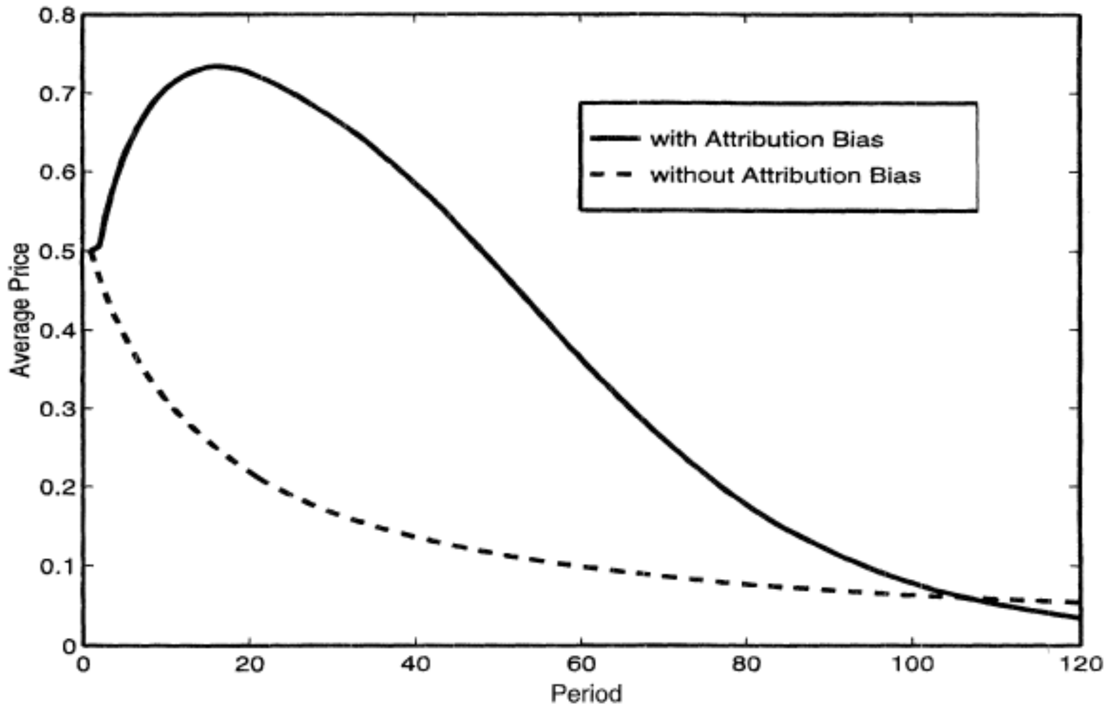
Daniel et al. uses a Monte Carlo simulation approach, giving the variables various estimates, running 50.000 simulations. They include the average price path obtained when the private signal value is equal to 1, and the value of θ is set equal to zero – in other words, a scenario in which the private signal is strictly indicating a buy. As shown in figure 11.4 below[200], the price initially jumps from the assumed value of 0 to 0.5, where the investor's self-attribution bias drives the overreaction phase upward and away from the true value. As previously stated, this is due to the excessive weight placed on the private signal received. In subsequent periods, as the public signals become more and more precise, the correction phase drives the stock price towards the initial value of 0.

From the simulation described above, yet another feature stands out. The theory of price momentum would suggest a positive level of autocorrelation for low lag-periods, while the reversal theory would suggest a negative level of autocorrelation once the lag-length is sufficiently high. The average price change autocorrelations are derived and presented by Daniel et al. (1998) with the level of autocorrelation depicted as a function of the lag-length in figure 11.5 below[201]:

[198] Daniel et al., 1998, p. 1860
[199] Ibid, p. 1860
[200] Ibid, p. 1861
[201] Ibid, p. 1862

Figure 11.4: The Dynamic Confidence Model with and without Self-attribution Bias

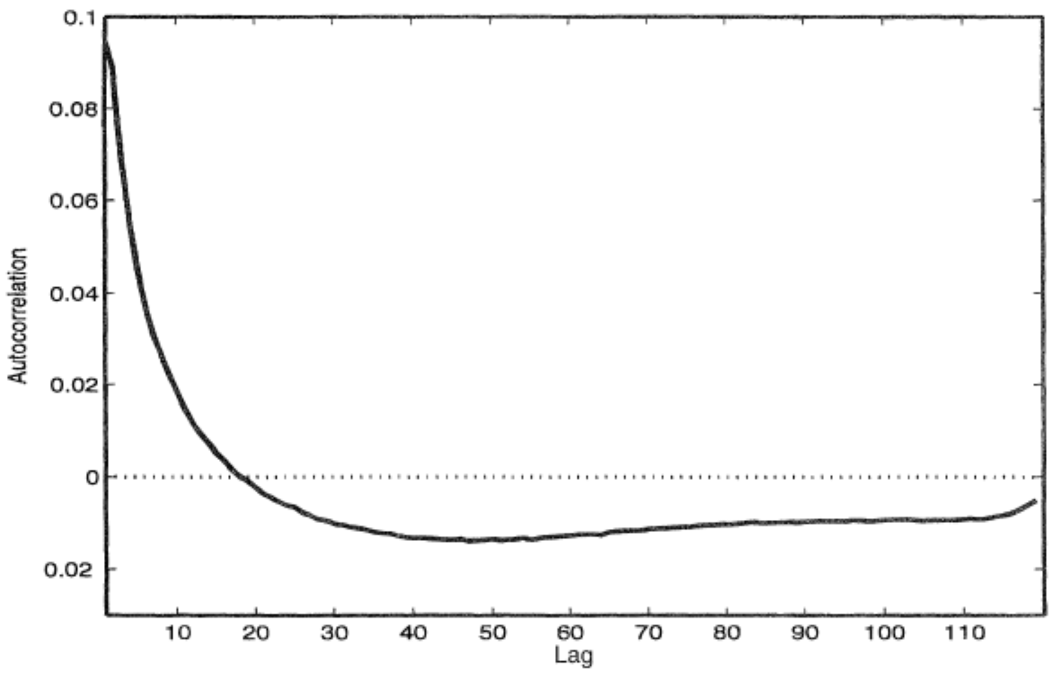
This figure shows the average price path calculated using a Monte Carlo simulation, following a private information shock, $s_1 = 1$. The price path is shown for the dynamic confidence model with (solid line) and without (dashed line) self-attribution bias.



Source: Daniel et al., 1998, p. 1861

Figure 11.5: Average Price Change Autocorrelations

This figure presents the unconditional average autocorrelations (at lags between 1 period and 119 periods), calculated using the Monte Carlo simulation.



Source: Daniel et al., 1998, p. 1862

As shown, the expected pattern is indeed visible. That is, the theory of Daniel et al. (1998) based on dynamic confidence and self-attribution bias seems able to predict and explain short-term momentum and long-term reversal. Therefore, as an explanatory model, it seems to hold for the majority of the results produced in the literature and in this paper as well. But exceptions do exist. As previously mentioned, the price momentum effect has not been shown to exist in some Eastern countries such as Japan. It seems striking that various studies seem to confirm Japan as an exception to the otherwise overwhelming set of evidence towards price momentum. With this in mind, the model laid out above does not appear able to fully explain this anomaly. Thus, the models of confidence have not offered anything that the positive feedback trading model has not. The level of explanatory seems to be similar and the same shortcomings are faced. However, further examination of the assumptions proclaimed in the dynamic confidence model might indeed prove valuable.

11.3.3 The Self-attribution Bias in USA and Japan

As shown in figure 8 above depicting the dynamic confidence model, the overreaction phase is only present in a scenario with the self-attribution bias. In the scenario without, the hump indicating the overreaction phase is eliminated and therefore the assumption of self-attribution bias seems to be critical to the result of the model as it is confirming both short-term momentum and long-term reversal. This assumption, as previously mentioned, was based on a large amount of evidence from psychological experiments and surveys proving this tendency. The attribution theory set out by Bem (1965) also confirms this tendency. However, when looking at the "*large amount of evidence*" cited by Daniel et al. (1998), it turns out the evidence exclusively examines the Western world – US and UK college students are the clear favourite subject to test upon[202]. This said, as the favourable test subjects are students within the Western world, this do not exclude them from being of Eastern origin. The subjects might however be affected by the Western culture. If the self-attribution bias is only occurring in the Western world, then this could explain why Japan does not experience short-term price momentum. This conundrum of self-attribution bias in the US and UK has been assessed by Kitayama, Markus, Matsumoto and Norasakkunkit (1997). Combining the empirical results of Kitayama et al. (1997) with the dynamic

[202] See Johnson, Feigenbaum and Weiby (1964); Beckman (1970); Schopler and Layton (1972); Beckman (1973); Miller and Ross (1975); Langer and Roth (1975); Bradley (1978); Zuckerman (1979); and Taylor and Brown (1988).

confidence model of Daniel et al. (1998) might be able to increase the explanatory power of this model to further explain the lack of short-term momentum in certain countries such as Japan.

The phenomenon of positive self-attribution in the Western world is defined as self-enhancement by Kitayama et al. (1997). However, this phenomenon does not seem to be occurring in non-Western, and especially Asian groups[203]. Markus and Kitayama (1991) argue that people from different cultures have very different construals of the self, of others and of the interdependence of the two. Further, these construals can influence and even determine the nature of individual experience including cognition, emotion and motivation. Regarding Asian groups, they argue that in these cultures there seem to exist "*distinct conceptions of individuality, which insist on the fundamental relatedness of individuals to each other*"[204]. Thus, the Asian culture has a focus towards attending to others, to fitting in and to harmonious interdependence with others. In contrast, they argue that American culture does not value such a connectedness among individuals. In this part of the world the "*individual seek to maintain their independence from others by attending the self and by discovering and expressing their unique inner attributes*"[205]. In addition, Heine & Lehman (1995) show that Japanese people seem to be more inclined to accept their own failures than their successes[206]. This contrast in cultural construals is the foundation used by Kitayama et al. (1997). They define the increased sensitivity towards negative self-relevant information of the Japanese inhabitants as self-criticism. That is because the Japanese culture rewards this type of behavior. Information of where one has failed to meet the standards of excellence can be used to improve and thereby affirm one's belonging in the society. The ability to use the information in this manner is, in Japan, something that is encouraged and embedded in the culture. Kitayama et al. (1997) proceeds to expand on the construals introduced by Markus and Kitayama (1991). They state that the Western cultures are "*organised according to meanings and practices that promote the independence and autonomy of the self*"[207]. This then leads to people having a tendency towards positive characteristics of the self. The Asian cultures are constructed very differently compared to Western cultures, and does not encourage the separation of each individual but instead promotes "*the fundamental connectedness among*

[203] Kitayama et al., 1997, p. 1246
[204] Markus and Kitayama, 1991, p. 224
[205] Markus and Kitayama, 1991, p. 224
[206] Heine and Lehman, 1995, p. 605
[207] Kitayama et al., 1997, p. 1247

individuals within a significant relationship" [208]. Therefore, being separate from the social context is not a priority in these cultures. Instead, it is all about affirming one's belongingness to the social unit. The above descriptions of cultural differences sums up to the final part of the authors' theoretical framework. They argue that the acquisition and maintenance of psychological processes such as a self-enhancing and a self-critical tendency, is the result of a collective process where social acts and situations are socially defined, constructed, held in place and experienced in each culture[209].

11.3.3 Empirical Evidence

Kitayama et al. (1997) found a way of testing their theoretical framework. In order to test it, a more formal definition of self-enhancement and self-criticism was needed and Kitayama et al. provided one. They define self-enhancement as a propensity to assign a greater estimate of influence to success situations than to failure situations. In turn, self-criticism is defined as a propensity to assign a greater estimate of influence to failure situations than to success situations[210]. The used test subjects were Japanese individuals living in Japan, American individuals living in the US and Japanese individuals living in the US. Each group was to supply a vast amount of situations, which had either increased or decreased their self-esteem, and describe how their confidence was affected. This way, the authors collected situations, which would affect confidence levels in each of the sample countries. Next, they removed the emotional context of the situations obtained. For instance, a situation affecting confidence would thus go from: "*My self-esteem increased when I got a haircut*" to "*I got a haircut*". In the end, they were left with a list of emotionally objective situations, which had a tendency to affect the self-esteem in each country. The idea was, that the situations collected from Japanese individuals in Japan would be more prone to self-criticism and the opposite for the American situations. The test-subjects were then given a questionnaire consisting of various situations originating from each of the countries. They were then to evaluate whether the given situation would affect their confidence level and if so, whether the effect would be positive or negative[211].

[208] Kitayama et al., 1997, p. 1247
[209] Ibid, p. 1248
[210] Ibid, p. 1252
[211] Kitayama et al., 1997, pp. 1249-1250

The results were quite conclusive. Japanese individuals in Japan were more inclined to have their self-esteem affected more by situations originally provided by Japanese test-subjects than those from US test subjects. The same pattern holds for the American test subjects as they were more often influenced by situations originating in the US. Further, no matter which situations they were presented (American or Japanese origin), the Japanese test subjects would more often find original failure-situations relevant to their self-esteem than success-situations, while American respondents would more often find original success-situations relevant to their self-esteem. For the Japanese respondents in the US, the effect was similar to those living in Japan, but not as excessive. The results obtained and described can be seen in table 11.1 below[212].

Table 11.1: Situations Relevant to Self-esteem

The Proportion of Success and Failure Situations Perceived by Japanese and American Individuals as Relevant to Their Self-Esteem

	Japanese respondent in Japan				Japanese respondent in U.S.				American respondent in U.S.			
	Japanese situation		U.S. situation		Japanese situation		U.S. situation		Japanese situation		U.S. situation	
Situation valence	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Success	.78	.19	.69	.25	.74	.20	.69	.23	.84	.19	.88	.13
Failure	.84	.15	.79	.19	.77	.16	.73	.18	.76	.17	.82	.15

Source: Kitayama et al., 1997, p. 1251

Having established a clear pattern regarding which situations the respondents found relevant to their self-esteem, the study turned its focus towards the level of influence. As seen in table 11.2 below[213], the Japanese respondents show a clear tendency towards self-criticism. That being said, the effect is more explicit when responding to Japanese situations rather than American situations. Looking at the American respondents, there is a tendency towards self-enhancement, and again, the tendency is strongest when responding to situations originating in the US. Interestingly, for the Japanese individuals living in the US, a tendency towards self-enhancement shows when responding to American situations while the opposite holds for Japanese situations.

[212] Kitayama et al., 1997, p. 1251
[213] Ibid, p. 1252

Table 11.2: Self-esteem changes

The Extremity of Self-Esteem Change Reported by Japanese and American Individuals in Success and Failure Situations That Differed in Their Cultural Origin

	Japanese respondents in Japan				Japanese respondents in U.S.				Americans in U.S.			
	Japanese situation		U.S. situation		Japanese situation		U.S. situation		Japanese situation		U.S. situation	
Situation valence	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Success	1.92	1.01	2.10	0.61	2.12	1.08	2.44	0.49	2.19	1.09	2.67	0.52
Failure	2.42	0.51	2.24	0.75	2.47	0.52	2.31	0.82	2.00	0.62	2.15	0.89

Source: Kitayama et al., 1997, p. 1252

Kitayama et al. (1997) believes the two-faced tendency of the Japanese individuals in the US indicates that once one gets acculturated into a foreign culture, one may develop alternate ways of self-making and alternate between these depending on the immediate cultural context[214]. The conclusion from the above is, that American respondents find success-situations more relevant to their confidence level than failure situations and further found success-situations to improve self-esteem more than failure situations decreased their self-esteem. Thus, they showed a strong tendency of self-enhancement. In contrast, Japanese respondents found failure-situations more relevant to their confidence level than success situations. It was further shown that their self-esteem decreased more in failure-situations than it increased in success situations. Thus, a clear tendency of self-criticism was found for the Japanese respondents.

Whether the situations originated from Japan or the US had an effect as well. Respondents found their respective tendency of either self-enhancement or self-criticism enforced in situations originating in their home country. Not only does the results confirm the theoretical framework of self-enhancement and self-criticism, but suggests further that the social situations in Japan is biased towards self-criticism while the social situations in the US is biased towards self-enhancement. The final part of the results showed that the Japanese living in the US showed a lower degree of self-criticism. As stated previously, this indicates some level of acculturation while living in the US.

[214] Kitayama et al., 1997, p. 1253

11.3.4 Volatility Resulting from Overconfidence

Odean (1998) published an article on overconfidence in the financial markets and made an interesting observation of volatility levels resulting from overconfidence. His model, like the one by Daniel et al. (1998), is based on over-confident investors receiving private signals. The article argues, that when the investors are over-confident, they will overvalue their own private signal. Thus, the aggregate signal will be overvalued, and consequently overweighed errors in the aggregate signal will then increase the volatility of prices[215]. The section above argued that the Japanese culture had a tendency towards self-criticism rather that self-enhancement, and if this holds, the model by Odean (1998) implies that volatilities should be lower in Japan than in the Western markets. In fact, for countries experiencing short-term price momentum, the volatility levels should be higher than in countries where this phenomenon does not occur. Unfortunately, much of the literature on price momentum does not include statistics for volatility measurement. However, the study of price momentum in Japan by Liu and Lee (2001) does, and this paper on the Danish stock market has included the volatility measurement for the strategies as well. Thus, the amount of data being used for this comparison is rather small and any conclusions could potentially be due to chance. That being said, the results confirm the theory. Liu and Lee (2001) do not report the standard deviations for their overall momentum strategies but does so for their size-neutral portfolios where all portfolios have a standard deviation between 2% and 3%[216]. Looking at the comparable size-neutral subsample of this paper on the Danish stock market, the standard deviations range from 5.7% to 10.3%. These results are in accordance with the theory of Odean (1998). However, as stated above, the amount of available data is very limited and the two studies look at different time-periods as well. The cultural construals suggested by Markus and Kitayama (1991) would suggest that the differing time-periods would have a minimum impact, as the cultures are formed through centuries, and 15 years would not change that significantly.

11.3.5 Revisiting the Dynamic-confidence Model

The introduction of the dynamic-confidence model resolved many explanatory issues regarding short-term price momentum and long-term reversal. However, it seemed to be flawed as it failed

[215] Odean, 1998, p. 1900
[216] Liu and Lee, 2001, p. 330

to provide an explanation for markets such as Japan, where price momentum did not occur. However, revisiting one of the fundamental assumptions behind the model, the one of a self-attribution bias among investors, turned out to provide new insights. In a setting where no self-attribution bias exists, the overreaction to private signals does not occur as shown in figure 8 above. Therefore, the dynamic confidence model is also capable of explaining the lack of price momentum in countries that don't have a tendency towards self-attribution bias, or self-enhancement. The psychological studies on American- and Japanese respondents showed that the Japanese respondents did not show any signs of self-enhancement while confirming that American respondents did. Among Japanese respondents it showed a tendency towards self-criticism which, combined with the dynamic-confidence model, is in accordance with the results obtained by Liu and Lee (2001). Thus, the dynamic-confidence model combined with the self-attribution bias study by Kitayama et al. (1997) seems able to explain the momentum effect and which markets it exists in.

11.4 Summing up

The theory of positive feedback trading by De Long et al. (1990b) and the confidence models provided by Daniel et al. (1998) provide seemingly solid theories, as both are able to explain the phenomenon of short-term price momentum and long-term price reversal. However, both models in their original form failed to explain why price momentum has only been found in some markets. In the positive feedback trading section, an alternative hypothesis about differences in information processing and the consequent need for heuristics was presented to explain the absence of price momentum in Japan due to no positive feedback traders. However, the inferred causality between the evidence and hypothesis was a bit of long stretch. Fortunately, a further look at the self-attribution bias assumption of the confidence models proved more insightful. As such, if the self-attribution bias does not exist, the model would not predict short-term momentum but simply an instant reversal similar to the results shown by Liu and Lee's (2001) study on the Japanese stock market. As research conducted by Kitayama et al. (1997) presented evidence confirming a lack of self-attribution bias in Japan, the dynamic confidence model does indeed seem to hold explanatory power as to how and where price momentum occurs.

12. Discussion

In the past decades, the conventional financial theory has been a target for lots of criticism. The momentum effect presented in the literature review and the empirical results clearly indicate an anomaly that has persisted for decades, and which therefore cannot be discounted as the work of data snooping. This has implications for the market dynamics assumed to be in place in conventional theories, and consequently for the validity and applicability of these theories. The strongest argument against the conventional theory in this paper is the significantly positive returns created by the zero-cost portfolios. These returns cannot be explained by common risk factors and contradict a weak-form efficient market. However, many previous studies did find long-term price reversal when the time horizon was extended beyond the first 12 months, thereby indicating that markets could very well be efficient in the long term. Thus, when evaluating the applicability of the conventional theories, it might be appropriate to only view them as long-term theories. Nonetheless, they fail to explain the price development in the short term, and as such, there is a need for new theories and theories that can shed light on exactly how and why markets react as they do in both the short and in the long term.

In an attempt at filling this knowledge gap of the momentum effect this paper turns to behavioral finance. Multiple behavioral theories suggesting that investors underreact to news have been linked to the anomaly, but these typically don't manage to fully explain all available data, as they fail to explain long-term price reversals documented in previous studies. This leads to one of the main criticisms of behavioral finance; academic's tendency within the field to force their models onto a specific set of observations, leading to multiple theories that only explain part of a phenomenon, and theories that even contradict each other. The momentum effect is a prime example of this.

Given the apparent failure of behavioral theories related to underreaction, this paper focuses on two theories of overreacting among investors. The positive feedback model and the overconfidence models. In contrast to the underreaction theories, these two theories provide solid explanations, as they capture both short-term momentum and long-term reversal. Nevertheless, they fail to capture the whole picture, in that they don't provide explanations as to why some markets dont experience price momentum. However, instead of accepting that these theories seemingly only provide an explanation for the Western markets, this paper puts their assumptions under thorough scrutiny. Consequently, the dynamic confidence model provides the most compelling theory once differences in investors' self-attribution bias in the Western and Eastern countries are accounted for, showing that a documented lack of self-enhancement among Japanese is likely the reason to why the momentum effect is not existing on the Japanese market.

Further, evidence in favor of the dynamic confidence model can be found in the results of the sub-samples. In the sub-period ranging from 2006-2010 the momentum effect was noticeably absent. The same was the case in Jegadeesh and Titman's (1993) sub-periods covering the 1970's. While this could be seen as a sign contradicting the momentum effect, it further supports the dynamic confidence model, and the dynamics that drive the momentum effect since the dynamic confidence model relies on positive signals to induce overconfidence into investors. However, in periods with severe price drops, like in the periods above, the positive signals are few and likely overshadowed by negative signals. In turn, investors are less likely to engage in what can be described as overconfident behavior, simply because there are not enough positive signals to trigger this type of irrational behavior. Thus, there is no basis for price momentum in such bear markets where pessimism is thriving. This goes to show that behavioral models can provide far more nuanced explanations than the conventional theories. However, reaching this point requires a thorough analysis of the underlying assumptions, and how these might differ in other markets and in diverse conditions, something that seems to be missing in many studies within the field of behavioral finance.

Further research could provide additional and up-to-date insights. First, as this paper initially delimited itself from exploring the possibility of subsequent price reversal, the naturally next step would be to extend the current analysis and check for long-term price reversal in the OMXC. Next, more current inquiries into markets in countries of both Western- and Eastern culture could help validate the proposed causal relationship between self-attribution bias and price momentum. In relation to this, new experimental evidence on differences in self-enhancement and self-criticism between Western- and Eastern cultures could also help to further validate the suggested hypothesis, that high degrees of self-enhancement lead to high degrees of price momentum.

12. Conclusion

This paper investigates the degree to which price momentum is applicable to the Danish stock market by applying the momentum strategy framework by Jegadeesh and Titman (1993) to the OMXC index in the period from 2000-2017. The results show that the zero-cost strategies are significantly positive, indicating that previous winners outperform previous losers in the short-term, thereby confirming the momentum effect on the Danish stock market. The momentum strategies are also compared to a buy-and-hold strategy holding the OMXC index, which shows that many winner strategies and a few zero-cost strategies are able to significantly outperform the benchmark. Furthermore, there is a clear pattern among the 16 strategies analysed, showing that strategies with a long formation period outperform those with a short formation period. Adjusting for transaction costs does not change the overall conclusions

The paper then analyses the sturdiness of the momentum effect through sub-samples. These sub-analyses show that the momentum effect is not observable in the sub-period from 2006 to 2010, and likewise, that the effect is missing for stocks with small market betas. Although some of these sub-samples illustrate inconsistencies in the momentum effect, the overall results are strikingly similar to many previous findings. Consequently, the overall results, showing that price momentum exists on the Danish market, cannot be rejected.

Having confirmed the existence of price momentum on the Danish market, the paper goes on to explore possible explanations for this phenomenon. The conventional financial theory does not offer any useful explanation to the anomaly, as the risk factors analysed do not explain the difference in return on winner and loser strategies. Therefore, alternative explanations stemming from the field of behavioral finance are introduced. Both the positive feedback trading model and the dynamic confidence model are seemingly able to explain the phenomenon and subsequent price reversal reported in previous studies. However, both models are unable to explain why certain markets, like the Japanese, have not experienced any price momentum.

In the end, establishing a link between the cultural context of the self-attribution bias and the dynamic confidence model provides the most substantial and valid explanation. Thus, it would seem that the momentum effect can be linked to investors' level of overconfidence, which in turn depends on the cultural context and the general market conditions.

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14. Appendices

14.1 Appendix A

Excluded companies

A.P. Møller - Mærsk A A/S

Admiral Capital A/S

Asgaard Group A/S

Blue Vision A/S

Carlsberg A A/S

Copenhagen Capital A/S

CPHNW

Fast Ejendom Danmark A/S

Gyldendal A A/S

Højgaard Holding A A/S

LL-A

Newcap Holding A/S

Nordicom A/S

Prime Office A/S

Rockwool International A A/S

Scandinavian Private Equity

Small Cap Danmark A/S

Strategic Investments A/S

TK Development A/S

Victoria Properties A/S

14.2 Appendix B

Included companies

A.P. Møller – Mærsk B A/S

ALK-Abelló B A/S

Alm Brand A/S

Ambu A/S

Andersen & Martini B A/S

Arkil Holding B A/S

Atlantic Petroleum P/F

Bang & Olufsen Holding A/S

BankNordik P/F

Bavarian Nordic A/S

BioPorto A/S

Brd Klee B A/S

Brdr A & O Johansen prf

Brdr. Hartmann A/S

Brøndby IF Fodbold A/S

Carlsberg B A/S

cBrain A/S

ChemoMetec A/S

Chr Hansen Holding A/S

Coloplast B A/S

Columbus A/S

D/S Norden

Danske Andelskassers Bank A/S

Danske Bank A/S

Dantax A/S

Dfds A/S

Djursland Bank A/S

DLH A/S

DSV A/S

Egetræpper B A/S

Erria A/S

Euroinvestor.com A/S

EXP-B

F.E. Bording B A/S

FirstFarms A/S

FLSmidth & Co A/S

Flügger B A/S

Fynske Bank A/S

G4S PLC

Gabriel Holding A/S

Genmab A/S

German High Street Prospects

Glunz & Jensen Holding A/S

GN Store Nord A/S

Greentech Energy Systems A/S

Grønlandsbanken A/S

Gyldendal B A/S

H+H International A/S

Harboes Bryggeri B A/S

Hvidbjerg Bank A/S

Højgaard Holding B A/S

IC Group A/S

InterMail B A/S

ISS A/S

Jeudan A/S

Jutlander Bank A/S

Jyske Bank A/S

Kreditbanken A/S

Københavns Lufthavne A/S

LL-B

Lollands Bank A/S

Lundbeck A/S

Luxor B A/S

Lån og Spar Bank A/S

Matas A/S

Migatronic B A/S

MOLS

Monberg & Thorsen B A/S

Møns Bank A/S

NeuroSearch A/S

NKT Holding A/S

Nnit A/S

Nordea Bank A/S

Nordfyns Bank A/S

Nordic Shipholding A/S

Nordjyske Bank A/S

North Media A/S

Novo Nordisk B A/S

Novozymes B A/S

NTR Holding B A/S

Onxeo SA

Pandora A/S

Parken Sport & Entertainment

Per Aarsleff Holding A/S B

Rias B A/S

Ringkjøbing Landbobank A/S

Roblon B A/S

Rockwool International B A/S

Rovsing A/S

Royal Unibrew A/S

RTX A/S

Salling Bank A/S

Sanistål A/S

Santa Fe Group A/S

SAS AB

Scandinavian Brake Systems A/S

Scandinavian Tobacco Group A/S

Schouw & Co A/S

Silkeborg IF Invest A/S

SimCorp A/S

Skako A/S

Skjern Bank A/S

Solar B A/S

SP Group A/S

Spar Nord Bank A/S

Sydbank A/S

TDC A/S

Tivoli A/S

Topdanmark A/S

Torm PLC A

Totalbanken A/S

Tryg A/S

United International Enterprises

Veloxis Pharmaceuticals A/S

Vestas Wind Systems A/S

Vestjysk Bank A/S

William Demant Holding A/S

Zealand Pharma A/S

Össur hf

Østjydsk Bank A/S

Aalborg Boldspilklub A/S

Aarhus Elite B A/S

14.3 Appendix C

This section contains a guide to how the empirical results are computed using excel. The overall $J = 12$ document includes all formulas and will be used for the walkthrough.

1. Data

The first sheet, "*Prices*", contains the adjusted monthly closing prices mentioned in the methodology section. These have been collected from Bloomberg. The same goes for the third sheet named "*Market Cap*", which contains the market capitalizations for each OMXC stock. The second sheet, "*Returns*", is the monthly stock returns computed by applying the adjusted closing prices from the "*Prices*" sheet to formula (18) from the methodology section.

2. Ranking Stocks

The sheet "*Strategy*" contains the $K = 12$ strategy, in this case the 12/12-strategy. The stocks of the OMXC are listed in the columns and the 12-month formation periods can be seen on the left. Note that the excluded stocks mentioned in the methodology have been removed. Below, '*Screenshot 1*' shows the layout and the formula used to compute the formation period returns.

Screenshot 1

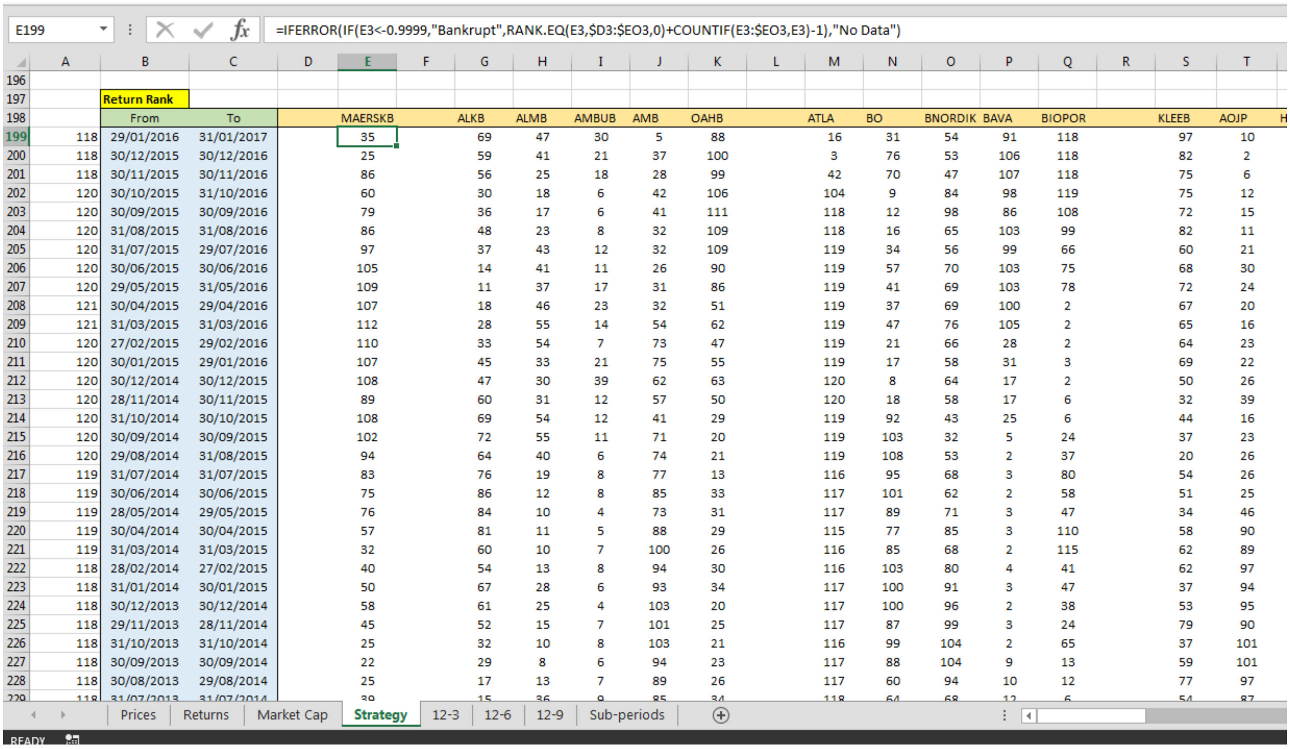
E3 =IFERROR((Prices!C2-Prices!C14)/Prices!C14,"-")

	A	B	C	E	G	H	I	J	K	M	N	O	P	Q	S	T
1		Formation Returns														
2		From	To	MAERSKB	ALKB	ALMB	AMBUB	AMB	OAHB	ATLA	BO	BNORDIK	BAVA	BIOPOR	KLEEB	AOJP
3	0	29/01/2016	31/01/2017	35%	8%	25%	39%	113%	-4%	67%	39%	22%	-6%	-52%	-8%	86%
4	1	30/12/2015	30/12/2016	30%	6%	19%	36%	21%	-15%	89%	-3%	8%	-30%	-56%	-7%	92%
5	2	30/11/2015	30/11/2016	-11%	5%	23%	32%	22%	-20%	14%	-2%	9%	-29%	-62%	-4%	68%
6	3	30/10/2015	31/10/2016	8%	25%	41%	92%	19%	-24%	-22%	68%	-6%	-15%	-53%	0%	48%
7	4	30/09/2015	30/09/2016	-2%	23%	40%	98%	21%	-30%	-45%	48%	-16%	-5%	-28%	3%	44%
8	5	31/08/2015	31/08/2016	-9%	14%	34%	62%	27%	-27%	-47%	44%	3%	-19%	-17%	-5%	54%
9	6	31/07/2015	29/07/2016	-19%	15%	10%	53%	19%	-32%	-73%	16%	1%	-21%	-5%	-3%	29%
10	7	30/06/2015	30/06/2016	-26%	51%	11%	59%	25%	-16%	-71%	2%	-5%	-25%	-10%	-4%	20%
11	8	29/05/2015	31/05/2016	-32%	53%	15%	38%	22%	-14%	-72%	10%	-3%	-24%	-10%	-4%	28%
12	9	30/04/2015	29/04/2016	-28%	34%	11%	28%	21%	7%	-74%	17%	-3%	-21%	156%	-2%	32%
13	10	31/03/2015	31/03/2016	-41%	30%	7%	45%	10%	4%	-73%	11%	-5%	-31%	179%	0%	42%
14	11	27/02/2015	29/02/2016	-33%	29%	11%	73%	0%	17%	-87%	45%	5%	34%	134%	7%	44%
15	12	30/01/2015	29/01/2016	-25%	27%	36%	53%	7%	20%	-83%	59%	18%	41%	194%	11%	52%
16	13	30/12/2014	30/12/2015	-18%	35%	50%	41%	25%	24%	-85%	129%	24%	81%	185%	33%	57%
17	14	28/11/2014	30/11/2015	-2%	22%	47%	91%	25%	30%	-83%	73%	24%	80%	128%	47%	43%
18	15	31/10/2014	30/10/2015	-18%	11%	20%	76%	28%	45%	-76%	-3%	27%	48%	103%	27%	57%
19	16	30/09/2014	30/09/2015	-17%	8%	15%	71%	8%	50%	-72%	-19%	37%	133%	45%	33%	45%
20	17	29/08/2014	31/08/2015	-9%	8%	29%	103%	2%	50%	-72%	-28%	16%	169%	33%	50%	41%
21	18	31/07/2014	31/07/2015	1%	4%	55%	85%	4%	66%	-59%	-8%	9%	180%	3%	16%	43%
22	19	30/06/2014	30/06/2015	2%	-7%	53%	77%	-5%	28%	-59%	-15%	9%	151%	11%	16%	33%
23	20	28/05/2014	29/05/2015	4%	-4%	72%	128%	5%	31%	-59%	-7%	6%	170%	23%	27%	23%
24	21	30/04/2014	30/04/2015	17%	7%	69%	97%	1%	35%	-56%	8%	2%	175%	-25%	17%	0%
25	22	31/03/2014	31/03/2015	30%	15%	72%	84%	-15%	40%	-59%	1%	12%	262%	-53%	14%	-6%
26	23	28/02/2014	27/02/2015	19%	11%	48%	69%	-12%	29%	-63%	-22%	-1%	109%	18%	9%	-14%
27	24	31/01/2014	30/01/2015	11%	5%	32%	78%	-14%	28%	-66%	-19%	-13%	112%	14%	27%	-14%
28	25	30/12/2013	30/12/2014	7%	7%	36%	103%	-23%	41%	-67%	-21%	-17%	122%	21%	9%	-16%
29	26	29/11/2013	28/11/2014	14%	11%	44%	66%	-18%	35%	-57%	-10%	-17%	113%	37%	1%	-11%
30	27	31/10/2013	31/10/2014	33%	29%	51%	70%	-21%	35%	-50%	-13%	-21%	175%	7%	26%	-15%
31	28	30/09/2013	30/09/2014	42%	37%	72%	91%	-5%	41%	-52%	1%	-12%	72%	56%	17%	-7%
32	29	30/08/2013	29/08/2014	51%	61%	70%	111%	9%	49%	-42%	25%	3%	75%	71%	14%	1%
33	30	31/07/2013	31/07/2014	51%	75%	52%	100%	12%	55%	-43%	28%	25%	91%	158%	35%	12%
34	31	28/06/2013	30/06/2014	68%	94%	61%	116%	19%	58%	-49%	31%	20%	110%	170%	38%	16%

Prices | Returns | Market Cap | Strategy | 12-3 | 12-6 | 12-9 | Sub-periods

As shown, the excel formula in cell E3 is using formula (18) from the methodology section to find the 12-month returns. Next up is the ranking of the stocks during the formation period. Below, *Screenshot 2* shows the layout and the formula used. As for the formation period stock returns, stocks are listed in the columns and the formation periods are listed to the left.

Screenshot 2



Row	A	From	To	MAERSKB	ALKB	ALMB	AMBUB	AMB	OAHB	ATLA	BO	BNORDIK	BAVA	BIOPOR	KLEEB	AOJP
199	118	29/01/2016	31/01/2017	35	69	47	30	5	88	16	31	54	91	118	97	10
200	118	30/12/2015	30/12/2016	25	59	41	21	37	100	3	76	53	106	118	82	2
201	118	30/11/2015	30/11/2016	86	56	25	18	28	99	42	70	47	107	118	75	6
202	120	30/10/2015	31/10/2016	60	30	18	6	42	106	104	9	84	98	119	75	12
203	120	30/09/2015	30/09/2016	79	36	17	6	41	111	118	12	98	86	108	72	15
204	120	31/08/2015	31/08/2016	86	48	23	8	32	109	118	16	65	103	99	82	11
205	120	31/07/2015	29/07/2016	97	37	43	12	32	109	119	34	56	99	66	60	21
206	120	30/06/2015	30/06/2016	105	14	41	11	26	90	119	57	70	103	75	68	30
207	120	29/05/2015	31/05/2016	109	11	37	17	31	86	119	41	69	103	78	72	24
208	121	30/04/2015	29/04/2016	107	18	46	23	32	51	119	37	69	100	2	67	20
209	121	31/03/2015	31/03/2016	112	28	55	14	54	62	119	47	76	105	2	65	16
210	120	27/02/2015	29/02/2016	110	33	54	7	73	47	119	21	66	28	2	64	23
211	120	30/01/2015	29/01/2016	107	45	33	21	75	55	119	17	58	31	3	69	22
212	120	30/12/2014	30/12/2015	108	47	30	39	62	63	120	8	64	17	2	50	26
213	120	28/11/2014	30/11/2015	89	60	31	12	57	50	120	18	58	17	6	32	39
214	120	31/10/2014	30/10/2015	108	69	54	12	41	29	119	92	43	25	6	44	16
215	120	30/09/2014	30/09/2015	102	72	55	11	71	20	119	103	32	5	24	37	23
216	120	29/08/2014	31/08/2015	94	64	40	6	74	21	119	108	53	2	37	20	26
217	119	31/07/2014	31/07/2015	83	76	19	8	77	13	116	95	68	3	80	54	26
218	119	30/06/2014	30/06/2015	75	86	12	8	85	33	117	101	62	2	58	51	25
219	119	28/05/2014	29/05/2015	76	84	10	4	73	31	117	89	71	3	47	34	46
220	119	30/04/2014	30/04/2015	57	81	11	5	88	29	115	77	85	3	110	58	90
221	119	31/03/2014	31/03/2015	32	60	10	7	100	26	116	85	68	2	115	62	89
222	118	28/02/2014	27/02/2015	40	54	13	8	94	30	116	103	80	4	41	62	97
223	118	31/01/2014	30/01/2015	50	67	28	6	93	34	117	100	91	3	47	37	94
224	118	30/12/2013	30/12/2014	58	61	25	4	103	20	117	100	96	2	38	53	95
225	118	29/11/2013	28/11/2014	45	52	15	7	101	25	117	87	99	3	24	79	90
226	118	31/10/2013	31/10/2014	25	32	10	8	103	21	116	99	104	2	65	37	101
227	118	30/09/2013	30/09/2014	22	29	8	6	94	23	117	88	104	9	13	59	101
228	118	30/08/2013	29/08/2014	25	17	13	7	89	26	117	60	94	10	12	77	97

The formula used in cell E1999 uses the output "*Bankrupt*" if the return is listed as -100%. If not, it ranks the given stock return among all stock returns for the given formation period. Further, if a stock return is identical to another return in a column to the right, 1 is deducted from the rank. If two stocks have identical returns they would, e.g., both be ranked "6". The next stock in the ranking would then be ranked 8. To avoid this issue, the first stock will get 1 deducted, thus being ranked "7". The next stock of the identical pair will have no identical match in a column to the right, and will thus get ranked "6". The same goes if 3 or more stocks have identical returns.

3. Identifying Winner and Loser Portfolios

The winner portfolios are located below the rankings in the sheet. The loser portfolios are located to the right of the winner portfolios and are based on an identical approach. Therefore, only the winner portfolio setup will be explained in detail. As seen in *Screenshot 3* below, the formation periods are once again on the left. Now, the winners are listed for each formation period using a look-up formula referencing the ranks of 1 to 10 seen in cell D398-M398. The formula in cell D399 can be seen in the screenshot below.

Screenshot 3

D399 =HLOOKUP(D$398,$D211:EO392,$A399,FALSE)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
394																
395	**Equally Wheighted portfolio**															
396		**Winner / Loser Portfolios**														
397		**Formation Periods**		Winners												
398		From	To	1	2	3	4	5	6	7	8	9	10	M1	M2	M3
399	182	30/01/2015	29/01/2016	CHEMM	MOLS	BIOPOR	HH	DFDS	CBRAIN	PNDORA	GEN	HOEJB	SIM	-10.21%	0.61%	2.44%
400	181	30/12/2014	30/12/2015	CHEMM	BIOPOR	MOLS	GEN	HH	SIM	DFDS	BO	VWS	SKAKO	-2.21%	-7.22%	4.65%
401	180	28/11/2014	30/11/2015	CHEMM	GEN	DFDS	SIM	PAALB	BIOPOR	ZEAL	SKAKO	MOLS	VWS	8.06%	-0.41%	-7.99%
402	179	31/10/2014	30/10/2015	CHEMM	GEN	PAALB	ZEAL	DFDS	BIOPOR	MOLS	VWS	SIM	HOEJB	15.73%	8.42%	0.53%
403	178	30/09/2014	30/09/2015	CHEMM	GEN	PAALB	DFDS	BAVA	MOLS	ZEAL	SIM	HOEJB	RTX	1.77%	14.41%	7.64%
404	177	29/08/2014	31/08/2015	CHEMM	BAVA	GEN	PAALB	DFDS	AMBUB	SIM	MOLS	ZEAL	PNDORA	-2.36%	2.08%	14.71%
405	176	31/07/2014	31/07/2015	CHEMM	GEN	BAVA	PAALB	DFDS	ZEAL	PNDORA	AMBUB	CBRAIN	SYDB	0.99%	-4.31%	1.82%
406	175	30/06/2014	30/06/2015	CHEMM	BAVA	GEN	PAALB	DFDS	CBRAIN	SYDB	AMBUB	PNDORA	OSSR	5.31%	1.62%	-6.30%
407	174	28/05/2014	29/05/2015	CHEMM	GEN	BAVA	AMBUB	OSSR	SYDB	DFDS	PAALB	CBRAIN	ALMB	0.13%	4.83%	1.01%
408	173	30/04/2014	30/04/2015	CHEMM	CBRAIN	BAVA	GEN	AMBUB	PAALB	PNDORA	SYDB	DFDS	RTX	5.90%	0.74%	7.76%
409	172	31/03/2014	31/03/2015	CHEMM	BAVA	CBRAIN	RTX	GEN	PAALB	AMBUB	OSSR	PNDORA	ALMB	0.16%	6.42%	-1.61%
410	171	28/02/2014	27/02/2015	CHEMM	CBRAIN	RTX	BAVA	GEN	OSSR	PAALB	AMBUB	PNDORA	TRYG	13.59%	-1.50%	5.58%
411	170	31/01/2014	30/01/2015	CBRAIN	CHEMM	BAVA	GEN	OSSR	AMBUB	MOLS	RTX	IMAILB	PAALB	6.06%	12.97%	0.20%
412	169	30/12/2013	30/12/2014	CBRAIN	BAVA	RTX	AMBUB	IMAILB	CHEMM	PNDORA	OSSR	GEN	VELO	17.18%	7.27%	8.75%
413	168	29/11/2013	28/11/2014	CBRAIN	RTX	BAVA	PNDORA	OSSR	CHEMM	AMBUB	VELO	LLB	PAALB	7.92%	15.34%	6.81%
414	167	31/10/2013	31/10/2014	CBRAIN	BAVA	VELO	RTX	CHEMM	PNDORA	OSSR	AMBUB	AAB	ALMB	-3.83%	5.58%	11.82%
415	166	30/09/2013	30/09/2014	CBRAIN	VELO	RTX	PNDORA	SBS	AMBUB	COLUM	ALMB	BAVA	OSSR	3.45%	-1.55%	6.86%
416	165	30/08/2013	29/08/2014	VELO	CBRAIN	RTX	VWS	SBS	PNDORA	AMBUB	OSSR	COLUM	BAVA	10.85%	0.57%	-1.43%
417	164	31/07/2013	31/07/2014	AAB	VELO	RTX	CBRAIN	COLUM	BIOPOR	VWS	SBS	AMBUB	HOEJB	-9.08%	8.15%	-9.00%
418	163	28/06/2013	30/06/2014	RTX	VWS	CBRAIN	COLUM	BIOPOR	VELO	SBS	HOEJB	PNDORA	AMBUB	-0.18%	-2.52%	10.03%
419	162	31/05/2013	28/05/2014	VWS	RTX	CBRAIN	COLUM	SBS	NORDIC	VELO	ERRI	ALKB	HOEJB	0.23%	-0.20%	-3.48%
420	161	30/04/2013	30/04/2014	VWS	RTX	NORDIC	SBS	ERRI	HOEJB	AAB	COLUM	PNDORA	VELO	11.77%	-0.38%	8.18%
421	160	27/03/2013	31/03/2014	VWS	RTX	NORDIC	SBS	HOEJB	ERRI	VELO	PNDORA	SPG	SPNO	1.62%	11.84%	1.35%
422	159	28/02/2013	28/02/2014	VWS	ERRI	RTX	PNDORA	HOEJB	GEN	VELO	SBS	NORDIC	SPG	8.46%	0.89%	12.64%
423	158	31/01/2013	31/01/2014	VWS	ERRI	RTX	NORDIC	PNDORA	HOEJB	GEN	VELO	SKJE	BAVA	2.34%	3.89%	3.26%
424	157	28/12/2012	30/12/2013	VWS	GEN	ERRI	RTX	PNDORA	HOEJB	COLUM	PAALB	SAS	VELO	10.52%	3.64%	3.88%
425	156	30/11/2012	29/11/2013	VWS	GEN	ERRI	COLUM	SAS	HOEJB	PNDORA	LOLB	HH	PAALB	-0.33%	5.96%	6.49%
426	155	31/10/2012	31/10/2013	VWS	GEN	PNDORA	SAS	ERRI	HOEJB	COLUM	BNORDIK	EI	RTX	-0.29%	0.34%	9.71%
427	154	28/09/2012	30/09/2013	VWS	ERRI	GEN	SAS	PNDORA	BNORDIK	HOEJB	COLUM	PAALB	RTX	8.19%	0.95%	3.28%

Prices | Returns | Market Cap | **Strategy** | 12-3 | 12-6 | 12-9 | Sub-periods

The formula searches for the stock with a rank of "*1*" in the ranking-area, starting from the relevant formation period and all the way down, where the stocks are again listed. Thus, the top line in the referred ranking-area is always the corresponding formation period. When the formula identifies the ranking "*1*" is goes all the way down in the referred area and the stock is the output.

4. Calculating Monthly Portfolio Returns

Scrolling to the right of the stocks in the given portfolio, 3 different sets of calculations can be seen. These are referred to as "*M1-M10*", "*R1-R10*" and "*Split1-Split10*".

The "*Split1-Split10*" segment is the excel version of formula (21) from the methodology section. Thus, they compute the accumulated returns for the 10-stock winner portfolios for each holding month. To do this they use "*R1-R10*", which are simply 'look-up'-values to help look up the relevant monthly stock returns in the return spreadsheet.

Finally, "*M1-M10*" applies formula (24) from the methodology section, thus computing the monthly portfolio returns.

5. Monthly Strategy Returns

Having created the monthly portfolio returns, the next step is to compute the monthly strategy returns. Below, in *Screenshot 4*, is shown the columns to the right of the previous calculations. The column below the cell named "*Total*" is calculating the monthly strategy returns.

Screenshot 4

			N	170	
			Average	1.81%	
			SD	5.85%	
			Average	1.64%	0.00%
Split11	Split12		Total	1485.95%	
-15.31%	-10.68%		-7.63%	15.86	
-3.24%	-3.80%		1.26%	17.17	
10.89%	-0.59%		10.34%	16.95	
16.17%	14.71%		16.60%	15.37	
20.63%	22.30%		3.58%	13.18	
28.72%	24.85%		-6.00%	12.72	
23.28%	29.27%		-0.13%	13.53	
39.33%	33.14%		8.23%	13.55	
29.21%	37.89%		-3.21%	12.52	
37.47%	40.47%		5.72%	12.94	
38.01%	37.97%		-0.51%	12.24	
58.93%	48.11%		9.08%	12.30	
71.86%	80.92%		5.93%	11.27	
76.01%	107.21%		9.87%	10.64	
67.42%	87.31%		4.37%	9.69	
38.94%	47.28%		1.82%	9.28	
40.79%	32.78%		-5.91%	9.12	
55.82%	53.12%		2.19%	9.69	

These monthly returns are an average of the corresponding portfolio returns. However, the portfolios are at different points in their cycle. *Screenshot 5* below shows the formula used to calculate the first monthly strategy return of -7.63% in *Screenshot 4*.

Screenshot 5

SUM =AVERAGE(N399,O400,P401,Q402,R403,S404,T405,U406,V407,W408,X409,Y410)

AVERAGE(number1, [number2], [number3], [number4], **[number5]**, [number6], [number7], [number8], [number9], [number10], [number11], [number12], [number13], ...)

	A	B	C																	T	U	V	W	X	Y
394																									
395	**Equally Wheighted portfolio**																								
396		**Winner / Loser Portfolios**																							
397		**Formation Periods**		Winners																					
398		From	To	1	2	3	4	5	6	7	8	9	10	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
399	182	30/01/2015	29/01/2016	CHEMM	MOLS	BIOPOR	HH	DFDS	CBRAIN	PNDORA	GEN	HOEJB	SIM	-10.21%	0.61%	2.44%	6.16%	-5.86%	2.75%	-3.25%	3.64%	-2.53%	-13.97%	6.00%	5.47%
400	181	30/12/2014	30/12/2015	CHEMM	BIOPOR	MOLS	GEN	HH	SIM	DFDS	BO	VWS	SKAKO	-2.21%	-7.22%	4.65%	4.04%	3.48%	-3.80%	3.41%	1.26%	1.85%	1.97%	-9.54%	-0.58%
401	180	28/11/2014	30/11/2015	CHEMM	GEN	DFDS	SIM	PAALB	BIOPOR	ZEAL	SKAKO	MOLS	VWS	8.06%	-0.41%	-7.99%	4.41%	3.69%	1.36%	-2.10%	1.97%	-0.43%	1.22%	1.45%	-10.35%
402	179	31/10/2014	30/10/2015	CHEMM	GEN	PAALB	ZEAL	DFDS	BIOPOR	MOLS	VWS	SIM	HOEJB	15.73%	8.42%	0.53%	-8.08%	1.59%	1.75%	1.55%	-3.37%	2.09%	-3.37%	0.12%	-1.26%
403	178	30/09/2014	30/09/2015	CHEMM	GEN	PAALB	DFDS	BAVA	MOLS	ZEAL	SIM	HOEJB	RTX	1.77%	14.41%	7.64%	-0.98%	-7.44%	-0.08%	2.46%	6.67%	-1.15%	3.48%	-5.99%	1.39%
404	177	29/08/2014	31/08/2015	CHEMM	BAVA	GEN	PAALB	DFDS	AMBUB	SIM	MOLS	ZEAL	PNDORA	-2.36%	2.08%	14.71%	8.72%	-0.50%	-7.07%	0.71%	1.79%	10.70%	-2.95%	1.70%	-3.00%
405	176	31/07/2014	31/07/2015	CHEMM	GEN	BAVA	PAALB	DFDS	ZEAL	PNDORA	AMBUB	CBRAIN	SYDB	0.99%	-4.31%	1.82%	19.45%	9.24%	0.78%	-7.95%	-0.85%	1.94%	7.65%	-4.87%	4.86%
406	175	30/06/2014	30/06/2015	CHEMM	BAVA	GEN	PAALB	DFDS	CBRAIN	SYDB	AMBUB	PNDORA	OSSR	5.31%	1.62%	-6.30%	2.09%	19.39%	10.82%	2.11%	-7.12%	-1.10%	1.89%	7.63%	-4.44%
407	174	28/05/2014	29/05/2015	CHEMM	GEN	BAVA	AMBUB	OSSR	SYDB	DFDS	PAALB	CBRAIN	ALMB	0.13%	4.83%	1.01%	-6.68%	2.01%	20.92%	10.75%	1.36%	-7.37%	-0.48%	2.31%	6.72%
408	173	30/04/2014	30/04/2015	CHEMM	CBRAIN	BAVA	GEN	AMBUB	PAALB	PNDORA	SYDB	DFDS	RTX	5.90%	0.74%	7.76%	1.81%	-5.74%	1.94%	19.68%	8.65%	2.29%	-6.87%	-1.31%	2.18%
409	172	31/03/2014	31/03/2015	CHEMM	BAVA	CBRAIN	RTX	GEN	PAALB	AMBUB	OSSR	PNDORA	ALMB	0.16%	6.42%	-1.61%	8.23%	-0.95%	-6.89%	4.02%	17.91%	11.49%	4.11%	-7.40%	-0.03%
410	171	28/02/2014	27/02/2015	CHEMM	CBRAIN	RTX	BAVA	GEN	OSSR	PAALB	AMBUB	PNDORA	TRYG	13.59%	-1.50%	5.58%	-1.14%	7.74%	-0.65%	-6.79%	3.31%	17.16%	9.62%	2.81%	-6.81%
411	170	31/01/2014	30/01/2015	CBRAIN	CHEMM	BAVA	GEN	OSSR	AMBUB	MOLS	RTX	IMAILB	PAALB	6.06%	12.97%	0.20%	4.96%	-2.91%	11.35%	0.37%	-6.00%	3.36%	14.58%	12.92%	5.27%
412	169	30/12/2013	30/12/2014	CBRAIN	BAVA	RTX	AMBUB	IMAILB	CHEMM	PNDORA	OSSR	GEN	VELO	17.18%	7.27%	8.75%	-0.04%	6.94%	-5.33%	12.32%	-1.18%	-6.56%	8.14%	13.43%	17.73%
413	168	29/11/2013	28/11/2014	CBRAIN	RTX	BAVA	PNDORA	OSSR	CHEMM	AMBUB	VELO	LLB	PAALB	7.92%	15.34%	6.81%	10.34%	-0.94%	6.94%	-1.55%	10.29%	0.62%	-7.36%	6.44%	11.88%
414	167	31/10/2013	31/10/2014	CBRAIN	BAVA	VELO	RTX	CHEMM	PNDORA	OSSR	AMBUB	AAB	ALMB	-3.83%	5.58%	11.82%	9.19%	9.65%	-1.43%	6.79%	-4.24%	10.67%	-1.10%	-7.34%	6.00%

The formula represents the average of the first monthly return of the portfolio established most recently, the second monthly return of the second most recent portfolio and so on. Again, these monthly returns are based on formula (24) from the methodology section. The column next to the monthly strategy returns represents the investment return based on a starting investment amount of 1 unit. Thus, in the above, 1 unit is turned into 15.86 units using the 12/12-strategy throughout the sample period.

6. Strategy Statistics

The abovementioned investment return translates into a 1486% total return for the strategy. In *screenshot 4*, the summary statistics are shown above the total investment return. As such, two averages, the standard deviation and the amount of monthly returns for the strategy, N, is reported. N is found using the COUNT function in excel, the standard deviation is found using the STDEV.S function and the first average, the one equaling 1.81% in *Screenshot 4*, is found using the AVERAGE function. All of these functions are applied to the column of monthly strategy returns. The second average represents the CAGR, which has not been included in the paper.

7. Market Weighted Portfolios

In the bottom of the sheet "*Strategy*", the approach already outlined is replicated for the market cap weighted portfolios with slight adjustments. Instead of listing the winner stocks, it lists the percentage the market capitalization of the respective stock represents of the total portfolio capitalization. From here is uses an almost identical approach to the abovementioned. The only adjustment is, than when implementing formula (21) in the "*Split1-Split10*" columns, instead of using the AVERAGE function, the weights are multiplied to each stocks compounded return.

8. Remaining Sheets

The remaining sheets, representing the remaining *J*/*K*-strategies when *J=12*, are identical to the approach just described. They do not include formation period stock returns and the ranking section as this is identical for all $J = 12$ strategies. The final sheet, "*Sub-periods*" is simply calculating the total return, average, standard deviation and N for the sub-periods described in the methodology section, using the strategies listed for further investigation in the empirical results section.

9. Remaining documents

This approach is identical to the one used for the documents containing the $J = 3$, J$= 6$ and $J = 9$ strategies. However, due to the size of the documents, formulas may have been overwritten with hardcoded values in these. Thus, if formulas wants to be examined, the $J = 12$ document should be used. In addition, similar documents containing the $J = 3$ to $J = 12$ strategies have been expanded to account for transactions costs. The methodology applied for this step has been described in the methodology section.

Further sub-analyses for the strategies chosen in the empirical section have been created in separate documents. As such, market capitalization sub-sample documents and beta sub-sample documents represents the size-neutral and the beta-neutral sub-samples. These sub-sample documents only contain slight alterations to the setup described above for the 12/12-strategy. Instead of ranking formation period stock returns first, they rank size and betas respectively. The only further adjustment is, that the winner and loser portfolios only consist of 5 stocks each, as explained in the methodology section.

Finally, the document named "*Results*" contain all the monthly average returns, standard deviations etc. from the documents listed above and further contains the *t*-tests mentioned in the methodology section. Specifically, formulas (27), (28) and (29) are used for calculating the *t*-statistics in this document.

10. List of Excel documents used for the elaboration of this paper
The naming of the documents is considered explanatory.

“J=3 Overall Strategies.xlsx”

“J=6 Overall Strategies.xlsx”

“J=9 Overall Strategies.xlsx”

“J=12 Overall Strategies.xlsx” ***(Used for the walkthrough above)***

“J=3 Overall Strategies with Transaction Costs.xlsx”

“J=6 Overall Strategies with Transaction Costs.xlsx”

“J=9 Overall Strategies with Transaction Costs.xlsx”

“J=12 Overall Strategies with Transaction Costs.xlsx”

“J=12 Sub-sample where Beta = Small.xlsx”

“J=12 Sub-sample where Beta = Medium.xlsx”

“J=12 Sub-sample where Beta = Large.xlsx”

“J=9 Sub-sample where Beta = Small.xlsx”

“J=9 Sub-sample where Beta = Medium.xlsx”

“J=9 Sub-sample where Beta = Large.xlsx”

“J=6 Sub-sample where Beta = Small.xlsx”

“J=6 Sub-sample where Beta = Medium.xlsx”

“J=6 Sub-sample where Beta = Large.xlsx”

“J=12 Sub-sample where Size = Small.xlsx”

“J=12 Sub-sample where Size = Medium.xlsx”

“J=12 Sub-sample where Size = Large.xlsx”

“J=9 Sub-sample where Size = Small.xlsx”

“J=9 Sub-sample where Size = Medium.xlsx”

“J=9 Sub-sample where Size = Large.xlsx”

“J=6 Sub-sample where Size = Small.xlsx”

“J=6 Sub-sample where Size = Medium.xlsx”

“J=6 Sub-sample where Size = Large.xlsx”

“Results.xlsx”