Master Thesis

The Momentum Effect on Stock Markets

- a Literature Review and an Empirical Study -

M.Sc. Finance and Accounting (Cand.merc.FIR)
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Abstract

In contrast to the traditional finance theory, stating that predictability of future stock prices and identification of continuously profitable trading strategies are impossible, an extensive body of finance literature in the 1980’s documents that stock prices are, at least somewhat, predictable based on past returns. In 1993, Jegadeesh and Titman publish the first article on medium term momentum in stock prices, documenting that, over 3 to 12 months horizons, past winners continue to outperform past losers by around 1% per month. A significant number of subsequent studies document that the momentum effect is a worldwide phenomenon, which is robust across both different types of stocks and time periods.

Apart from clarifying what has already been documented on momentum strategies, the thesis tests whether the momentum effect has existed on the Danish stock market over the period from 1996 through 2009, and finds substantial evidence that it has. The momentum returns from a total of 16 examined strategies all turn out to be significantly positive with average monthly returns ranging from 0.61% to 1.55%. Consistent with previously conducted studies, strategies with long formation periods and short holding periods turn out to be the most successful. The momentum returns continue to be positive even after accounting for transaction costs, and also the momentum effect appears relatively robust across different types of stocks and sub-periods.

From a presentation of possible explanations of the momentum effect, it is found that none of the three risk measures from the Three-Factor Model (i.e. beta, size, and book-to-market values) are able to account for the observed return pattern. Also explanations related to data snooping and flawed methodology seem unfounded due to the many studies documenting the momentum effect. The models from behavioural finance, using psychological biases and interaction between different investor types, thus appear to provide the best explanations for the momentum phenomenon. The behavioural models are, however, many and no single model is found to be superior. One possibility could be that all the models individually contribute to explaining the momentum effect, but that different models turn out to be superior in different markets or different types of stocks. This hypothesis, however, remains to be tested.
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1. Introductory Chapter

1.2. Introduction

One of the most interesting and fiercely debated areas in finance has probably been whether, or to what extent, the capital market is efficient, and thus whether or not future stock prices are predictable. The proponents of the traditional finance theory strongly believe the market to be efficient when it comes to the pricing of financial assets. This view is especially recognised after Fama, in 1970, publishes his article about the Efficient Market Hypothesis. According to this hypothesis, the prices of financial assets immediately incorporate all relevant information in a way so that neither technical nor fundamental analysis can be used to identify stocks that will earn abnormal returns.

In the mid 1980’s an extensive body of finance literature, however, documents that future stock prices are, at least somewhat, predictable based on past returns. For example, De Bondt and Thaler (1985, 1987) discover that long term past losers tend to outperform long term past winners over a period of 3 to 5 years; meaning that the market tends to mean revert. Also Jegadeesh (1990) and Lehmann (1990) find a tendency for mean reversion over very short horizons of only 1 to 4 weeks.

In 1993, Jegadeesh and Titman add a new angle to the above literature by documenting that, over an intermediate horizon of 3 to 12 months, past winners, on average, continue to outperform past losers. In other words, they document the existence of momentum in stock prices, meaning that stocks with strong past performance continue to do well, while stocks with poor past performance continue to do poorly. Following the article by Jegadeesh and Titman (1993), numerous researchers have documented the momentum effect across different markets and time periods. However, it still seems difficult to explain why it occurs. In fact, the observed momentum in stock prices is referred to as one of the most puzzling anomalies in finance.

Motivated by the above, this thesis is written to study what has already been documented concerning momentum strategies in various markets, to test whether the momentum effect has existed on the Danish stock market, and to identify possible explanations for the observed phenomenon.

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1 Jegadeesh and Titman (1993) p. 65
2 Jegadeesh and Titman (1993) p. 66
3 Jegadeesh and Titman (1993) p. 65
4 Grinblatt and Han (2002) p. 1
1.3. Problem Statements

In short, the purpose of the thesis is to:

1. Clarify what has already been documented on momentum strategies.
2. Test whether the momentum effect has existed on the Danish stock market in more recent times.
3. Present and evaluate possible explanations for the momentum phenomenon.

1.4. Scope

Several types of momentum have been documented in the literature; including industry momentum, earnings momentum, and price momentum. In short, *industry momentum* is the phenomenon, whereby industries with strong past performance continue to outperform industries with poor past performance. *Earnings momentum* concentrates on return drifts following good or bad earnings announcements, meaning that positive announcement stocks will outperform negative announcement stocks in the post-announcement period. And last, *price momentum* refers to the phenomenon where stocks with high past returns continue to outperform stocks with low past returns. To limit the scope of the thesis, it has been determined to focus on price momentum only. Thus, throughout the thesis the term momentum refers to price momentum unless otherwise is stated.

In terms of markets, no geographical limitations are made concerning the literature review. The empirical study, however, is conducted on the Danish stock market only.

Finally, although the momentum strategies can be implemented by both private and institutional investors, the strategies in the empirical part are conducted in the way that seems most convenient and feasible to the private investor.
1.5. Thesis Outline

In answering the above problem statements, the thesis goes through the following chapters:

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**Pricing of Financial Assets - Traditional versus Behavioural Finance:** This chapter is intended to provide the reader with a background as to how financial assets are priced according to traditional and behavioural finance theory. As will become clear, the pricing of financial assets is an important determinant in whether or not trading rules such as the momentum strategy can be consistently profitable.

**Trading Strategies Based on Technical Analysis:** A short one-page chapter, which briefly introduces trading strategies based on technical analysis.

**Literature Review of Price Momentum Strategies:** The literature review has the purpose of clarifying what has already been observed and documented in the area of price momentum strategies. The chapter is divided into studies of the American market, studies of other international markets, and a worldwide study.

**An Empirical Study of the Danish Stock Market:** In continuation of the literature review, the empirical part of the thesis investigates whether the momentum effect has existed on the Danish stock market in more recent times. Various robustness tests and sub-period analyses are, furthermore, conducted.

**Momentum Explanations:** The last chapter goes through different possible explanations for the observed momentum in stock prices. The chapter is divided into risk-based explanations, data snooping and flawed methodology, and explanations based on behavioural finance.

**Conclusion:** The conclusion sums up on the entire thesis, thereby answering the initial problem statements.
1.6. Criticism of Sources

The perhaps most important thing to state here is that the majority of the literature, upon which the thesis is based, is written by people who believe to have documented the momentum effect on various markets, as well as by people who generally question the validity of the traditional finance theory. Although it might well be that the traditional finance theory is faulty or insufficient in its way of explaining the financial market, it should at least be noticed that an equally large amount of studies could have been found in favour of the traditional finance theory if the purpose of the thesis had been to explore, say, the Efficient Market Hypothesis and the Random Walk Model. Thus, when reading the thesis one should bear in mind, who are the authors of the various articles.

In terms of the empirical analysis, one downside to be highlighted is that historical data has only been available for stocks currently listed on the market (i.e. going entities). This could introduce some survivorship bias in the data; however, whether the results would have turned out differently if the so-called dead stocks had been included is impossible to say. Finally, one should be aware of the length of the individual sample periods in the empirical study. Due to data unavailability, some tests are based on considerably shorter sample periods than others, which could lower the validity of these results.

As stated in the introduction, one of the most fiercely debated areas in finance has probably been whether or not future stock prices are predictable. In fact, empirical tests of whether stock prices move randomly or follow some predictable patterns move back over 100 years.\(^5\) The reason for the enormous interest in the subject is, obviously, that predictability of stock prices would enable investors to earn abnormal returns based on certain trading rules; among these the momentum strategy.

Whether future stock prices could be, at least somewhat, predictable is largely dependent on what is believed to influence and determine these prices. As this chapter will show, proponents of traditional and behavioural finance theory have very different views on this particular matter. In the following, the two contradicting views are gone through separately to give the reader a clear understanding of the differences and the implications of the two.

2.1. Traditional Finance Theory

In its attempts to model financial markets, traditional finance theory usually starts from a long list of appealing assumptions about investor behaviour and the conditions under which investors can trade in the market. In particular, many models require investors to be risk-averse expected utility maximisers and unbiased Bayesian forecasters and decision-makers; i.e. agents who make rational choices based on rational expectations obtained by using statistical tools appropriately and correctly when processing data.\(^6\)

In addition to the above, an essential prerequisite for most of the traditional models is an effective arbitrage mechanism, which continuously preserves the law of one price. In short, the law of one price states that two assets with identical attributes, as well as the same asset trading in two different markets, should sell for the same price. If not, a profitable opportunity arises to sell the expensive asset and buy the cheap. This opportunity will soon be exploited by well-informed and rational investors, making the security prices return to their long-term equilibrium.\(^7\) Miller and Modigliani (1958, 1961) have indeed emphasised the critical role played by arbitrage in determining security prices.\(^8\)

The following shortly presents some of the most widely used equilibrium asset pricing models from the traditional finance theory as well as the Efficient Market Hypothesis.

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\(^5\) Bird and Whitaker (2003) p. 223
\(^6\) Shefrin (2000) p. 4
\(^7\) Sornette (2003) pp. 136-137
\(^8\) Sornette (2003) p. 137
2.1.1. Equilibrium Asset Pricing Models

2.1.1.1. The Capital Asset Pricing Model

The perhaps most well-known model for asset pricing is the Capital Asset Pricing Model (CAPM) developed independently by Sharpe (1964), Lintner (1965), and Mossin (1966).\(^9\)

The model has its roots in the portfolio optimisation theory first presented in an article by Markowitz in 1952. In short, this portfolio theory states that all investors, due to the assumption that investors are rational mean-variance utility maximisers with homogeneous views regarding expected return and risk of all stocks in the market, will invest in a combination of a riskless security and the same well-diversified and efficient portfolio of risky stocks, i.e. the market portfolio\(^10\). In terms of asset pricing, Sharpe, Lintner, and Mossin suggest that, if all investors hold a well-diversified portfolio, thereby eliminating all specific risk, and if all investors are rational mean-variance utility maximisers, thereby requiring higher expected returns for bearing higher undiversifiable risk, there must be a linearly increasing relationship between the expected return of any given stock and its systematic risk, beta.\(^11\)

The linear relationship is given by the following equation\(^12\):

\[
E(r_i) = r_f + \beta_i (E(r_m) - r_f)
\]

where: \(E(r_i)\) = the expected return of stock \(i\); \(r_f\) = the risk free rate; \(E(r_m)\) = the expected return of the market portfolio; \(\beta_i\) = the sensitivity of stock \(i\)’s return to the return of the market portfolio.\(^13\)

Graphically, the CAPM can be illustrated as the Security Market Line (SML):

\(^9\) Haugen (2001) p. 201
\(^10\) The market portfolio is a portfolio in which the fraction invested in any asset is equal to the market value of that asset divided by the market value of all risky assets; Brown et al. (2007) p. 296. Graphically, the market portfolio is placed at the tangency point of the Capital Market Line and the Efficient Frontier.
\(^11\) Brown et al. (2007) p. 298
\(^12\) The assumptions behind the CAPM can be found in Appendix 1.
\(^13\) Beta can also be described as stock \(i\)’s co-variation with the market; \(\beta_i = \text{cov}(r_i, r_m)/\sigma_m^2\)
According to the CAPM, all assets, and portfolios of assets, in the economy must lie somewhere along this straight line. If any securities were to lie above or below the line, these would be considered either over- or undervalued and the arbitrage mechanism in the economy would set in until the securities had converged to the line.\(^\text{14}\) It follows that securities, according to the CAPM, always carry their correct fundamental value, and that differences in expected stock returns are only due to differences in stock betas.

### 2.1.1.2. Arbitrage Pricing Theory and the Three-Factor Model

Although the CAPM has been widely accepted by proponents of the traditional finance theory\(^\text{15}\), the many strict assumptions\(^\text{16}\) underlying the CAPM have led some researchers to look for new and different approaches to explain the pricing of financial assets. In 1976, Ross proposes the Arbitrage Pricing Theory (APT), which, as indicated by its name, has the law of one price as its main assumption.\(^\text{17}\)

The APT suggests that the expected return of any given stock is related to one or more indices, or factors, and that there exists a linear relationship between a stock’s expected return and its sensitivity to these indices. The mathematical equation for the APT looks as follows:\(^\text{18}\):

\[
E(r_i) = a_i + b_{i1}I_{i1} + b_{i2}I_{i2} + b_{i3}I_{i3} + ... + b_{ij}I_{ij}
\]

where: \(E(r_i)\) = the expected return of stock \(i\); \(a_i\) = the expected return of stock \(i\) if all indices have a value of zero; \(I_{ij}\) = the value of the \(j\)th index that impacts the return of stock \(i\); \(b_{ij}\) = the sensitivity of stock \(i\)’s return to the \(j\)th index.

In the APT, the value of the indices is thought to be identical for all securities, whereas the sensitivity to each of the indices is unique to the individual security. Thus, given the assumed arbitrage mechanism, two stocks with the same index, or factor, sensitivity must also have the same expected return. Similarly to CAPM’s Security Market Line in return-beta space, the APT can be graphically illustrated by a \(J\)-dimensional hyper plane in return-beta space. Securities, or portfolios, that plot above or below this plane will almost immediately converge to the plane due to arbitrageurs’ trading activity.\(^\text{19}\)

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\(^{14}\) Brown et al. (2007) p. 289

\(^{15}\) A number of traditional finance theorists have concluded that, even though the standard CAPM is based on many unrealistic assumptions, the model overall does a relatively good job in explaining actual returns and thus the behaviour of the financial market; Brown et al. (2007) p. 356.

\(^{16}\) The assumptions behind the CAPM can be found in Appendix 1.

\(^{17}\) Brown et al. (2007) p. 362

\(^{18}\) Brown et al. (2007) p. 363

\(^{19}\) Brown et al. (2007) p. 365
In terms of assumptions, the APT is clearly the CAPM superior. The major problem with the APT is, however, that neither the relevant indices, nor the size or the sign of these indices, are defined by the theory, making it less useful in practice.\(^{20}\)

In the absence of clearly defined indices, or factors, several researchers have attempted to hypothesise sets of possible indices. Among these researchers are Sharpe (1982), Chen, Roll, and Ross (1986), and Fama and French (1993).

Especially the model developed by Fama and French (1993) has come to be widely known. From investigating stocks on the NYSE, AMEX, and NASDAQ in the period from 1963 to 1990, Fama and French find that the expected return on a stock is best explained by the excess return of the market over the risk-free rate, a size factor (SMB), and a book-to-market equity factor (HML).\(^{21}\)

What they develop is a three-factor model with the following equation:

\[
E(r_i) = r_f + \beta_i(E(r_m) - r_f) + s_iE(SMB) + h_iE(HML)
\]

where: \(E(r_i)\) = the expected return of stock \(i\); \(r_f\) = the risk free rate; \(E(r_m)\) = the expected return of the market portfolio; \(E(SMB)\) = the expected difference in the return of a portfolio of small stocks and a portfolio of large stocks (small minus big); \(E(HML)\) = the expected difference in the return of a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks (high minus low); \(\beta_i\), \(s_i\), and \(h_i\) = the sensitivity of stock \(i\)’s return to the return of the market portfolio, the size factor and the book-to-market factor, respectively.

Fama and French argue that not only beta (as assumed in the CAPM) but also size\(^{22}\) and book-to-market values should be considered proxies for risk; with small cap stocks and stocks with high book-to-market values (i.e. value stocks) being more risky than large cap stocks and stock with low book-to-market values (i.e. growth stocks)\(^{23}\). Apart from that, the idea behind the Three-Factor Model is essentially the same as the one behind the CAPM. Thus, any security in the financial market is thought to be priced according to its amount of systematic risk, and arbitrage mechanism is assumed to prevent long term price deviation from the fundamental value of securities.

\(^{20}\) Brown et al. (2007) p. 373
\(^{21}\) Fama and French (1993) p. 38
\(^{22}\) Where size is measured in terms of market capitalisation.
\(^{23}\) Small stocks are considered riskier than large stocks in that the probability of small companies going bankrupt is greater. Stocks with high book-to-market values (i.e. value stocks) are considered riskier than stocks with low book-to-market values (i.e. growth stocks) as the low market value signalises poor expectations from the market.
2.1.2. The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) first appears in the 1960’s and is, amongst others, developed by Fama. In contrast to the above equilibrium models, the EMH is not a pricing tool, but merely a hypothesis stating that security prices at any point in time reflect fundamental values.\(^{24}\)

The most important characteristics of a pricing efficient market are as follows\(^{25}\):

- Security prices respond quickly and accurately to new information.
- Changes in expected returns are related only to changes in the level of the risk-free rate and in risk premiums. Consequently, at any given time, there is a linear relationship between expected return and risk.
- It is impossible to discriminate between profitable and unprofitable investments in the future. Thus, it is impossible to identify consistently profitable trading strategies.
- Differences in the investment performance of investors are entirely due to chance.

Fama argues that the market will exhibit pricing efficiency due to the many well-informed and rational investors constantly analysing, and trading in, the market. A fully pricing efficient market, however, requires the cost of obtaining information and trading securities to be zero. Realising that these are positive in the real world, Fama (1970) suggests three degrees of market efficiency: weak form efficiency, semi-strong form efficiency, and strong form efficiency. In short, a market that is weak form efficient refers to a market in which all historical information is incorporated in stock prices, in case of a semi-strong form efficient market all publicly available information, including all historical information, is incorporated\(^{26}\), and finally in a strong form efficient market both publicly available and insider information is incorporated. It follows that studying past price movements, i.e. conducting technical analysis, and investing based upon such observations will not enable investors to earn abnormal returns under any degree of market efficiency as historical information is always assumed to be incorporated in current stock prices. In a semi-strong form efficient market neither technical nor fundamental analysis can lead to abnormal returns, and in case of a strong form efficient market, no investor, not even insiders with specific knowledge about a company, will be able to earn continuous abnormal returns in the market.

\(^{24}\) Barberis and Thaler (2003) p. 1054
\(^{25}\) Haugen (2001) p. 580
\(^{26}\) Apart from historical information, public information includes information such as annual reports, news, economic data etc.
As opposed to some of the equilibrium pricing models, the EMH does not assume all investors to be rational; rather it assumes the market to be rational.\textsuperscript{27} The reason for this is that the irrational actions made by investors are thought to be random, and as a consequence the actions will, on average, cancel out each other in a way so that the net effect on the market is zero. If not, also the EMH assumes deviations to be instantaneously corrected by arbitrageurs. Hence, what the EMH predicts is that security prices reflect fundamental values and that they exhibit no systematic deviations from their efficient means.\textsuperscript{28}

\subsection*{2.1.3. Implications of Traditional Finance Theory}

A common belief in the traditional finance theory, no matter which of the equilibrium pricing models are chosen, is that financial assets are priced solely based on some fundamental risk factors, and that deviations from these equilibrium prices, whatever the reason might be, will soon be corrected by well-informed and rational arbitrageurs. Also, the EMH states that securities always trade at their fundamental values, as prices are assumed to respond quickly and accurately to new information. Both the equilibrium models and the EMH imply that it is just about impossible to find over- or undervalued securities, and that it is by all means impossible to identify particular trading strategies that generate consistently abnormal returns.\textsuperscript{29} In other words, security prices are believed to follow a random walk\textsuperscript{30}, making it impossible to predict the direction of the price change between today and tomorrow, or between any two other times.\textsuperscript{31}

It follows from the above that momentum strategies, which are based purely on the study of past stock prices, i.e. technical analysis, can only be profitable in case the traditional finance theory is insufficient, or directly incorrect, in explaining how the financial market functions. The following section looks at a more recently developed area of finance theory, come to be known as behavioural finance.

\begin{itemize}
\item \textsuperscript{27} Ritter (2003) p. 2
\item \textsuperscript{28} Shefrin (2000) p. 87
\item \textsuperscript{29} Barberis and Thaler (2003) p. 1054
\item \textsuperscript{30} The random walk model assumes that successive returns are independent and identically distributed over time; Brown et al. (2007) p. 403.
\item \textsuperscript{31} Sornette (2003) p. 39
\end{itemize}
2.2. Behavioural Finance

Although the traditional finance theory has enabled the development of a vast amount of financial models, these models tend to be based on strict, and in many cases unrealistic, assumptions. In addition to the many doubtful assumptions, scholars, in the 1980’s, begin to discover a host of empirical results inconsistent with the view that security prices are determined in accordance with the equilibrium models and the Efficient Market Hypothesis. Among these empirical findings are the medium term momentum effect, the long term reversal effect, the size effect, and the January effect. Proponents of the traditional finance theory regard the findings as anomalous and thus call them anomalies. The persistence of the so-called anomalies observed in the financial market, as well as the appearance of new anomalies, however, make scholars begin to wonder whether the traditional theory is in fact fully capable of explaining the market and thereby the pricing of financial assets.

In response to the shortcomings of the traditional finance theory in explaining the financial market, a field now known as behavioural finance emerges throughout the 1980’s. The field of behavioural finance rests on two pillars, being investor psychology and limits to arbitrage.

2.2.1. Investor Psychology

One of the main characteristics of behavioural finance is that it incorporates ideas from psychology and social sciences into the financial theory in order to account for the fact that the market reflects the thoughts, emotions, and actions of real people as opposed to the idealised economic investors, who underlie most of the traditional models. Thus, contrary to what is assumed in the traditional finance, theories from behavioural finance are built on the belief that investors do not always act rational and that this irrationality can make the market itself behave in an irrational manner.

In particular, the irrationality is thought to stem from psychological biases, which affect the way people form expectations and make decisions. Some of the psychological biases most often referred to are representativeness and availability heuristics, anchoring, conservatism, framing, overconfidence, selective exposure, and cognitive dissonance theory. These biases

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33 Shefrin (2000) pp. 8-9
34 Shefrin (2000) p. 81
36 Sornette (2003) p. 91
37 Definitions of some of the most often used psychological biases and decision-making errors in behavioural finance can be found in Appendix 2.
all lead to cognitive errors, which are errors resulting from the way people think. According to behavioural finance, errors might also be caused by investor risk preferences that differ from those under the traditional expected utility theory. The most recognised model for investor risk preferences in behavioural finance is the prospect theory, stating that investors, instead of being risk-averse in all situations, seem to be risk-averse over gains, but risk-seeking in relation to losses. Contrary to the traditional concave expected utility function, this leads to an s-shaped value function that is concave in the region of gains, but convex in the region of losses.\(^{38}\):

![S-Shaped Value Function](image)

Finally, bounded rationality theory suggests that deviations from rational choices may arise due to investors’ inability to correctly interpret the vast amount of information available.\(^{39}\)

By focusing only on what makes investors act in an irrational manner, one might question how great an impact these actions have on the market as a whole. After all, it was argued under the Efficient Market Hypothesis that in case the irrational actions are random they will cancel out each other, whereby the net effect on the market will be zero. For the actions to be random, investors are required to form expectations and make decisions independently of each other. However, if the behaviour of investors is dependent on the action of other investors, or if investors suffer from the same biases and have the same irrational risk preferences, the irrational behaviour could have a significant influence on the overall market behaviour. To explain the interaction between investors, behavioural finance operates with the concept of herd, or crowd, behaviour, which suggests that people, instead of following their own private signals, are prone to imitate the behaviour of others. The herding behaviour is

\(^{38}\) Kahneman and Tversky (1979) p. 279
\(^{39}\) Sornette (2003) p. 138
documented by several studies.\textsuperscript{40} Especially, it has been found that herding is strong when information is limited and when complexity is high\textsuperscript{41}, which is in accordance with the psychological concept of social comparison stating that people have a tendency to use the behaviour of others as a source of information about subjects they find difficult to understand.\textsuperscript{42} Thus, in a market where investors, consciously or unconsciously, imitate each other, the irrational behaviour resulting from the above-mentioned cognitive errors and irrational risk preferences can potentially lead to substantial mispricing of financial assets.

While behavioural finance contradicts the traditional finance theory in stating that investors often act in an irrational manner, for one reason or another, and that this irrationality has the potential to make prices deviate from their fundamental values, the most striking claim of behavioural finance is that prices are able to deviate for longer periods of time, leading to market inefficiency.\textsuperscript{43} The persisting mispricing is, according to behavioural finance, possible due to limits to arbitrage.

\textit{2.2.2. Limits to Arbitrage}

As might be recalled, price deviation is not a completely unfamiliar term in the traditional finance theory. However, proponents of traditional finance argue that there are, at any given time, enough well-informed arbitrageurs to seize all unexploited profit opportunities existing in the market.\textsuperscript{44} Thus, according to the traditional finance theory, deviations from fundamental values might occur, but will be extremely short-lived and insignificant for the market as a whole.

The idea that mispricing can exist only temporary is countered by proponents of behavioural finance, who claim that deviations can exist over extended periods of time due to limits to arbitrage. To understand this, it is essential to remember that one of the central assumptions concerning arbitrage in the traditional finance theory is that arbitrage trading is risk-free.\textsuperscript{45}

Being risk-free, naturally informed and rational investors will exploit all profit opportunities observed in the market. However, in an article from 1990, De Long, Shleifer, Summers and Waldmann argue that arbitrage opportunities may not always be risk-free, and that the risk associated with arbitrage trading is what prevents correcting arbitrage from taking place.

\begin{flushright}
\textsuperscript{40} Chan et al. (2000) p. 153 \\
\textsuperscript{41} Sornette (2003) p. 95 \\
\textsuperscript{42} Tvede (2007) p. 130 \\
\textsuperscript{43} Shefrin (2000) p. 38 \\
\textsuperscript{44} Shefrin (2000) p. 80 \\
\textsuperscript{45} Montier (2002) p. 29
\end{flushright}
More precisely, De Long et al. introduce a new risk term known as noise trader risk, where noise traders themselves are uninformed investors who trade based on noise which they, wrongly, interpret as valid information.\textsuperscript{46} Noise trader risk, then, is the risk that mispricing, created by noise traders, may worsen in the short run.\textsuperscript{47} For example, if noise traders have been bullish on a stock, making its price rise beyond its fundamental value, informed investors should, according to traditional finance, short-sell the stock, in the expectation that the stock will soon return to its fundamental value. Noise trader risk, however, is the risk, that the noise traders will become even more bullish about the stock looking forward. Therefore, given that the rational investors are risk-averse and have short investment horizons, they will be reluctant to exploit the deviation in the market and persisting mispricing over extended time periods might occur.\textsuperscript{48} Thus, according to behavioural finance, investor irrationality causes mispricing, whereas limits to arbitrage allow the mispricing to persist.

\subsection*{2.2.3. Implications of Behavioural Finance}

In contrast to the traditional finance theory, behavioural finance points at investor behaviour as being one of the main things determining asset prices. It, furthermore, states that investor behaviour might not always be rational due to psychological biases and non-rational risk preferences, and that this irrational behaviour in some situations can influence the overall behaviour of the market. Last, but not least, mispricing, broad about by uninformed and irrational investors, is believed to be potentially long-lived due to noise trader risk preventing correcting arbitrage from taking place.

For the purpose of this thesis, the most essential implication of behavioural finance is the fact that irrationality and limits to arbitrage can lead to market inefficiency, whereby assets do not necessarily carry their fundamental value or follow a random walk, as believed in the traditional finance theory. Instead, assets might turn out to be priced based on some predictable investment patterns followed by investors in the market. In other words, the implication of behavioural finance could be that asset prices are, at least somewhat, predictable, thereby enabling the identification of profitable trading strategies such as the momentum strategy.

\begin{itemize}
  \item De Long et al. (1990b) p. 706
  \item De Long et al. (1990b) p. 705
  \item De Long et al. (1990b) p. 705
\end{itemize}
3. Trading Strategies Based on Technical Analysis

As previously stated, various phenomena, which are inconsistent with the traditional finance theory, have been observed in the financial market. Among these phenomena are the momentum effect and the mean reversion effect. In short, momentum refers to positive autocorrelation in stock prices, whereby prices are found to drift either up or down. In contrast, mean reversion refers to the phenomenon whereby stock prices exhibit negative autocorrelation, and thus, after some time of deviation, revert and move back to their fundamental values. While both of the phenomena clearly contradict the Efficient Market Hypothesis and the Random Walk Model by indicating that it is possible to predict the direction of future stock prices and thereby identify profitable trading strategies, they also seem to contradict each other. In the case of momentum, relative strength strategies, being strategies that buy past winners and short-sell past losers, would turn out profitable. However, in the case of mean reversion, contrarian strategies, being strategies that buy past losers and short-sell past winners, would be to prefer.

The academic literature seems to have focused mainly on contrarian strategies throughout the 1980’s. For example, De Bondt and Thaler (1985) show that contrarian strategies that buy stocks that have performed poorly over the previous 3 to 5 years and sell stocks that have performed well over the same period achieve abnormal returns over holding periods of 3 to 5 years.\(^{49}\) In addition, Jegadeesh (1990) and Lehman (1990) document that contrarian strategies which select stocks based on their returns in the previous 1 to 4 weeks generate abnormal returns, due to short term reversals in the market.\(^{50}\)

Despite the fact that contrarian strategies for a long time receive the most attention in the academic literature, it turns out that a number of practitioners continue to use relative strength as one of their stock selection criteria. For example, Grinblatt and Titman (1989, 1991) find that the majority of the mutual funds in their study sample show a tendency to buy stocks that have increased in price over the previous quarter. Also Grinblatt, Titman, and Wermers (1994) show that about 77% of the 155 mutual funds in their sample follow momentum strategies.\(^{51}\) In addition, the Value Line rankings are known to be based in large part on past relative strength\(^{52}\).

\(^{49}\) Jegadeesh and Titman (1993) p. 65  
\(^{50}\) Jegadeesh and Titman (1993) p. 66  
\(^{52}\) Value Line, Inc. is a New York corporation best known for publishing the The Value Line Investment Survey; a weekly stock analysis newsletter. In 1965, Value Line introduced a mathematical formula called the Timeliness Ranking System, which serves as the basis for its survey picks.
The success of many of the mutual funds in the above studies, and the predictive power of the Value Line rankings\textsuperscript{53}, seems difficult to reconcile with the academic literature favouring contrarian strategies. A closer look at the strategies, however, reveals that the different trading rules turn out profitable over different time horizons. Where the evidence favouring contrarian strategies focuses on strategies based on either very short term reversals (1 to 4 weeks) or long term reversals (3 to 5 years), practitioners using relative strength rules seem to base their selections on price movements over the past 3 to 12 months.\textsuperscript{54} Having discovered this, Jegadeesh and Titman (1993) conduct one of the most important academic studies of momentum strategies, followed by numerous others.

The next chapter is a literature review of what has so far been documented in relation to price momentum strategies.

\textsuperscript{53} Value Line themselves state that: “A portfolio of #1 ranked stocks for Timeless from The Value Line Investment Survey, beginning 1965 and updated at the beginning of each year, would have shown a gain (i.e. a cumulative return) of 28,913% through the month end of December 2008. That compares with a gain of 1,355% in the Dow Jones Industrial Average over the same period”; www.valueline.com.

\textsuperscript{54} Jegadeesh and Titman (1993) p. 67
4. Literature Review of Price Momentum Strategies

The following chapter is going to present various researchers’ studies of price momentum. The first section describes the most commonly used methodology when testing the momentum strategies, whereas the second section goes through the empirical findings from a large number of studies covering markets all around the world.

4.1. Commonly Used Test Methodology

Momentum investing basically involves investing on the basis of a past trend, where the most common type of momentum, price momentum, involves investing on the basis of historical stock prices. Specifically, it is suggested that if recent trends in stock prices are maintained into the near future, then an investment approach that buys stocks that have realised high returns in recent times and short-sells stocks that have realised poor returns will outperform the market. The following presents the most commonly used method when testing the profitability of momentum strategies. It should be noticed that this method is very similar to the one used by Jegadeesh and Titman (1993), as they provided the pioneering academic work on momentum strategies, and other researchers to a large extent have adopted their methodology.\[55\]

The most commonly used test methodology is as follows: At the beginning of each month throughout the selected sample period, stocks are ranked in ascending order on the basis of their returns in the past $J$ months, where $J$ is the formation period usually set to 3, 6, 9, or 12 months. Based on these rankings, stocks are divided into ten decile portfolios, or in some cases five quintile portfolios depending on the amount of data available. The portfolio containing the stocks with the highest past returns is called the winner portfolio, whereas the portfolio containing the stocks with the lowest past returns is called the loser portfolio. The stocks in the portfolios are, in the majority of the studies, equally-weighted at the formation date.

In each month $t$, the portfolios are bought and held for $K$ months, where $K$ is the holding period; again usually set to 3, 6, 9, or 12 months. In addition, the position initiated in month $t-K$ is closed out. Thus, in any given month, the strategies hold a series of portfolios selected in the current month as well as in the previous $K-1$ months.\[56\] The monthly return for a $K$-month

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\[55\] The main source for the description of the most commonly used methodology is the article by Jegadeesh and Titman (1993).

\[56\] Jegadeesh and Titman (1993) p. 68
holding period is calculated as an equally-weighted average of portfolio returns in the current month and in the previous $K-1$ months. The method of examining strategies including portfolios with overlapping holding periods is sometimes referred to as partial rebalancing (as opposed to full rebalancing) and has the advantage of increasing the power of the tests in that more observations are obtained\footnote{A discussion of full versus partial rebalancing can be found in subsection 5.1.3.1.3.}

At the end of the sample period, the momentum return for a given strategy is calculated as the average monthly return of the winner portfolio minus the average monthly return of the loser portfolio over the sample period. The momentum return is often referred to as the return of the zero-cost portfolio, since a strategy that short-sells the loser portfolio and buys the winner portfolio for the proceeds is, when disregarding transaction costs, approximately free of costs to the investor\footnote{The zero-cost portfolios can also be referred to as zero-investment arbitrage portfolios; De Bondt et al. (1999) p. 107.}.

Obviously, the momentum strategy has proven profitable, whenever the momentum return, or the return of the zero-cost portfolio, turns out to be positive and statistically significant.

The above method using four different formations periods and four different holding periods, sums up to a total of 16 momentum strategies. In addition, a number of authors choose to investigate a set of 16 strategies that skip a week between the formation and holding period. The method of skipping a week, or in some cases a month\footnote{See for example Rouwenhorst (1998).}, between the formation and the holding periods is commonly used in order to avoid bid-ask spreads and short term reversal effects, as documented by Jegadeesh (1990) and Lehman (1990).\footnote{Jegadeesh and Titman (1993) p. 68}

### 4.2. Empirical Findings of Momentum Strategies

The following presents the empirical findings from a number of studies of price momentum strategies. The section is divided into three subsections; empirical studies of the American market, empirical studies of other international markets (further divided into European, emerging, and Asian markets), and last a worldwide study of momentum strategies.

Focus throughout the literature review is on the degree and the robustness of price momentum, whereas possible explanations for the momentum effect are treated in a separate chapter.

\footnotesize{\textsuperscript{57} A discussion of full versus partial rebalancing can be found in subsection 5.1.3.1.3.}
\footnotesize{\textsuperscript{58} The zero-cost portfolios can also be referred to as zero-investment arbitrage portfolios; De Bondt et al. (1999) p. 107.}
\footnotesize{\textsuperscript{59} See for example Rouwenhorst (1998).}
\footnotesize{\textsuperscript{60} Jegadeesh and Titman (1993) p. 68}
4.2.1. Empirical Studies of the American Stock Market

The first academic paper documenting that momentum strategies are able to generate significantly positive returns over 3 to 12 months holding periods is published by Jegadeesh and Titman in 1993. Jegadeesh and Titman conduct an analysis of NYSE and AMEX stocks during the sample period from 1965 to 1989 and find the momentum returns from all the 32 examined strategies to be positive. Also the returns are statistically significant, except for the 3-month/3-month strategy that does not skip a week between the formation and the holding periods. The most successful momentum strategy turns out to be the 12-month/3-month strategy, which yields 1.31% per month (t=3.74) when there is no time lag between the formation and the holding periods and 1.49% per month (t=4.28) when there is a 1-week lag between the two. The worst performing strategy, with average monthly returns of 0.32% (t=1.10) and 0.73% (t=2.61), without and with a 1-week lag respectively, is the 3-month/3-month strategy. In general, it seems that strategies with long formation periods of 9 or 12 months and short holding periods of 3 or 6 months perform somewhat better than the remaining strategies.

In 1998, Conrad and Kaul examine momentum strategies for which the length of the formation and the holding periods are identical; ranging between 1 week and 36 months. To make their study comparable with the one by Jegadeesh and Titman (1993), Conrad and Kaul initially investigate stocks listed on the NYSE and AMEX during the period from 1962 to 1989. They find that, with the exception of the 1-week/1-week strategy, all other strategies show profitable up to and including the 18-month/18-month strategy. The results by Conrad and Kaul thus confirm the momentum effect documented by Jegadeesh and Titman.

In the study by Jegadeesh and Titman (1993), the 6-month/6-month strategy with no time lag between the formation and the holding periods is considered the most representative strategy with an average monthly momentum return of 0.95% (t=3.07). Based on this strategy, Jegadeesh and Titman test the effect of risk and transaction costs and find the risk-adjusted return after considering a 0.5% one-way transaction cost to be 9.29% per year, which is

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61 That is the strategy that selects stocks based on the previous 3 months’ returns and holds the portfolio for 3 subsequent months.
62 Jegadeesh and Titman (1993) p. 69
63 Jegadeesh and Titman (1993) p. 70, table I
64 Jegadeesh and Titman (1993) p. 70, table I
65 The exact formation and holding periods are: 1 week, 3, 6, 9, 12, 18, 24, and 36 months.
67 Jegadeesh and Titman (1993) p. 70, Table I, panel A
significantly different from zero. Thus, the momentum strategies seem profitable even after accounting for risk and transaction costs. That momentum returns are robust to the inclusion of transaction costs is also found by Korajczyk and Sadka (2004). In addition, they find that value-weighted strategies perform better after cost than equally-weighted strategies, in that value-weighted portfolios place a greater weight on larger and more liquid stocks, which are cheaper to trade.

Jegadeesh and Titman further test the profitability of the 6-month/6-month strategy within subsamples stratified on the basis of firm size (small, medium, and large cap stocks) and ex ante beta estimates (low, medium, and high beta stocks) to examine whether the profitability of the momentum strategies are confined to particular subsamples of stocks. The average monthly momentum return for all stocks combined is found to be 0.95% (t=3.07). In comparison, the returns of the size-based subsamples are 0.99% (small cap), 1.26% (medium cap), and 0.75% (large cap) and the returns of the beta-based subsamples are 0.62% (low beta), 0.79% (medium beta), and 1.08% (high beta)\(^7\). Thus, although the returns seem to be somewhat related to firm size and especially beta, all the returns are positive and appear to be of approximately the same magnitude when the strategy is implemented on the various subsamples of stocks as when it is implemented on the entire sample. The profitability of the momentum strategies does therefore not seem to be confined to any particular subsamples of stocks.\(^7\)

The momentum strategies do not seem to be confined to any sub-periods either. Jegadeesh and Titman examine the returns of the 6-month/6-month zero-cost portfolio in each of the 5-year sub-periods within the 1965 to 1989 sample period. They find the strategy to produce positive returns in all but one 5-year period (1975 to 1979). Furthermore, when examining the results in greater detail, it turns out that the negative return in the 1975 to 1979 sub-period is primarily due to the January returns of small firms. Thus, when implemented only on large- and medium-sized firms, the returns are positive in all five sub-periods. Likewise, when the

\(^6\) Jegadeesh and Titman (1993) p. 77
\(^6\) Korajczyk and Sadka (2004) p. 1071
\(^7\) The corresponding t-values are (t=2.77), (t=4.57), and (t=3.03) for the size-based subsamples and (t=2.05), (t=2.64), and (t=3.35) for the beta-based subsamples.
\(^7\) Jegadeesh and Titman (1993) p. 78, table III, panel A
\(^7\) Jegadeesh and Titman (1993) p. 77
\(^7\) Jegadeesh and Titman (1993) p. 82
month of January is excluded, the returns are positive in all five sub-periods as well as in each size-based subsample.  

Jegadeesh and Titman indeed observe a strong January effect. By examining the returns in different months, they find that the momentum strategy loses 6.86% (t=-3.52), on average, in each January but achieves positive abnormal returns in each of the other months. The average return in non-January months is 1.66% per month (t=6.67), where returns are found to be particularly high in April, November, and December. Similar results are found by Grundy and Martin (2001). By analysing NYSE and AMEX stocks over the period from 1926 to 1995, using a 6-month/1-month momentum strategy, they observe average monthly returns of -5.85% (t=-4.93) and 1.01% (t=4.44) in Januaries and non-Januaries, respectively. The negative returns in Januaries, furthermore, correspond to De Bondt and Thaler’s (1985) finding that the profitability of contrarian strategies is especially pronounced in Januaries.

In order to evaluate whether the observed price pattern is persistent over time, Jegadeesh and Titman (1993) track the average portfolio returns in each of the 36 months following the formation date. With the exception of the first month, the average return of the zero-cost portfolio turns out to be positive in each month during the first year, but negative in each month during the second year as well as in the first half of the third year and virtually zero hereafter. Consequently, the cumulative return reaches a maximum of 9.51% (t=3.67) at the end of month 12 and declines to 4.06% (t=0.67) at the end of month 36, indicating that the observed price pattern during the 3 to 12 months holding period is not permanent. The negative returns of the zero-cost portfolio in years 2 and 3 are, however, not statistically significant.

In 1996, Chan, Jegadeesh, and Lakonishok examine the 6-month/6-month momentum strategy over a sample period from 1977 to 1993 using primarily stocks listed on the NYSE,

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74 Jegadeesh and Titman (1993) p. 83
75 It turns out that by reversing buy and sell portfolios in the month of January (i.e. taking long positions in past losers and short positions in past winners), the abnormal returns would be close to 25% per year. Such strategy would lose money in only 1 out of 25 years in the sample period; Jegadeesh and Titman (1993) p. 79.
76 Jegadeesh and Titman (1993) p. 80, table IV
77 Grundy and Martin (2001) p. 30
78 De Bondt and Thaler (1985) p. 799
79 Many researchers suggest that the January effect is due to tax-loss selling of stocks. That is, investors may sell losing stocks at the end of the year to realise the losses for tax purposes. This selling pressure pushes stock prices below their fundamental values in December after which the prices rebound strongly in January; Haugen (2001) p. 610. This explanation, however, cannot be used for countries like Japan and Belgium where capital gains historically have not been taxed, but where the January effect nevertheless has still been documented.
80 Up to and including the 31st month after the formation date.
81 Jegadeesh and Titman (1993) p. 84, table VII
82 Jegadeesh and Titman (1993) p. 83
AMEX, and NASDAQ.\textsuperscript{83} Their results show a momentum return of 8.8% over the first 6 months following the portfolio formation date and a return of no less than 15.4% over the first year. In years 2 and 3, the momentum returns are \(-0.6\%\) and \(1.2\%\), respectively.\textsuperscript{84} The cumulative return from Chan et al.’s study thus increases throughout the first year but stays virtually unchanged hereafter.

In 2001, Jegadeesh and Titman extend the 6-month/6-month strategy from their original study with eight additional years. Using data over the 1990 to 1998 sample period, they find that the momentum strategy continues to be profitable with an average monthly return of 1.39\% (\textit{t}=4.71) over the 8-year period.\textsuperscript{85} Furthermore, momentum continues to exist in both small cap and large cap stocks, although it is found to be stronger in the former.\textsuperscript{86} In general, the findings in Jegadeesh and Titman’s second article appear to be very similar to those in their original study.

Also Chan, Jegadeesh, and Lakonishok (1999) extend their original study with five additional years from 1994 to 1998 to see whether the findings from their previous study hold outside the initially selected sample period. The results show that the 6-month/6-month strategy generates an average yearly momentum return of 7.74\% during the 5-year period.\textsuperscript{87} As Jegadeesh and Titman (2001), Chan et al. therefore conclude that the momentum strategies continue to be profitable during the 1990’s.

In addition to the above, Lee and Swaminathan (2000) test the momentum effect over the 1965 to 1995 sample period using all firms listed on the NYSE and AMEX. Lee and Swaminathan deliberately choose to exclude NASDAQ stocks from their sample, as NASDAQ firms tend to be smaller and thus more difficult to trade in momentum strategies.\textsuperscript{88} The results appear to be very similar to those obtained by Jegadeesh and Titman (1993). Lee and Swaminathan investigate 16 different strategies and find the returns of all zero-cost portfolios to be positive and statistically significant\textsuperscript{89}. As in the study by Jegadeesh and Titman, the 12-month/3-month strategy turns out to be the most successful with an average monthly return of 1.54\% (\textit{t}=5.63) over the sample period, whereas the worst performing strategy turns out to be the 3-month/3-month strategy with an average monthly return of

\textsuperscript{83} Chan et al. (1996) p. 1684
\textsuperscript{84} Chan et al. (1996) p. 1688, table II
\textsuperscript{85} Jegadeesh and Titman (2001) p. 705
\textsuperscript{86} The average monthly momentum returns of the small cap and large cap subsamples are \(1.65\%\ (\textit{t}=5.74)\) and \(0.88\%\ (\textit{t}=2.59)\), respectively; Jegadeesh and Titman (2001) p. 704, table I.
\textsuperscript{87} Chan et al. (1999) p. 86
\textsuperscript{88} Lee and Swaminathan (2000) p. 2021
\textsuperscript{89} Lee and Swaminathan (2000) pp. 2025-2026
0.66% (t=3.06).\(^{90}\) Hence, also here the general pattern seems to be that strategies with relatively long formation periods and short holding periods are to prefer.

Lee and Swaminathan further report the annual returns of the four different formation period portfolios\(^{91}\) in the five years following the portfolio formation date\(^{92}\). In year 1, they find the four zero-cost portfolios to yield statistically significant returns between 10.62% (3-month formation period) and 12.70% (9-month formation period) per year\(^{93},^{94}\). Consistent with Jegadeesh and Titman (1993), Lee and Swaminathan observe a modest reversal in momentum profits in years 2 and 3, but again the negative returns are not statistically significant and not sufficient to account for the initial momentum gains in year 1.\(^{95}\) By extending the study to years 4 and 5 after the portfolio formation date, a pattern of price reversal, however, begins to emerge. In years 4 and 5, all the returns of the zero-cost portfolios are negative, and it is found that the reversal effect becomes stronger as the formation period increases. For the longest formation period of 12 months it is found that the sum of the losses in years 2 through 5 (-10.95%) almost offsets the entire gain from year 1 (11.56%).\(^{96}\) Lee and Swaminathan are thereby the first to document that, at least based on their American study, momentum in stock prices does reverse over longer horizons.

### 4.2.2. Empirical Studies of Other International Stock Markets

#### 4.2.2.1. European Markets

Rouwenhorst (1998) is one of the first to acknowledge that, at the time of his study, return continuation has alone been documented by researchers using substantially the same database of U.S. stocks. To rule out the possibility that the observed momentum phenomenon is simply an outcome of data snooping, Rouwenhorst decides to study the return pattern in an international context.\(^{97}\) In his article from 1998, he investigates the momentum effect using sample data for 2,190 companies from 12 European countries\(^{98}\) over the period from 1980 to 1995.\(^{99}\)

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\(^{90}\) Lee and Swaminathan (2000) p. 2025, table I

\(^{91}\) That is portfolios with formation periods of 3, 6, 9, and 12 months.

\(^{92}\) The annual returns are computed as event time returns for five 12-month periods following the formation date.

\(^{93}\) The corresponding t-values are (t=5.77) and (t=5.10).

\(^{94}\) Lee and Swaminathan (2000) p. 2026

\(^{95}\) Lee and Swaminathan (2000) p. 2026

\(^{96}\) Lee and Swaminathan (2000) p. 2026

\(^{97}\) Rouwenhorst (1998) p. 267

\(^{98}\) Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom.

When testing the momentum strategies, using the combined data from all 12 countries, Rouwenhorst finds the returns of all the 16 zero-cost portfolios that do not skip time between the formation and the holding periods to be positive and statistically significant at the 5% level. The average monthly returns range from 0.70% (t=2.59) using the 3-month/3-month strategy to 1.35% (t=3.97) using the 12-month/3-month strategy. Interestingly, the worst performing and the best performing strategies turn out to be exactly the same as when the momentum effect was investigated by Jegadeesh and Titman (1993) on the U.S. market. From the combined data, Rouwenhorst also finds that momentum strategies using long formation periods of 9 or 12 months and short holding periods of 3 or 6 months tend to perform better than the remaining strategies. The 16 strategies skipping a month between the formation and the holding periods provide very similar results to above. Also here, the returns of all zero-cost portfolios turn out to be significantly positive.

In the second part of his study, Rouwenhorst examines a country-neutral portfolio, based on the 6-month/6-month strategy that does not skip a month between the formation and the holding periods, to rule out the possibility that the observed momentum effect is simply caused by country momentum; that is persistence in country-specific market performance. The results show that controlling for country composition only slightly reduces the average monthly return of the zero-cost portfolio from 1.16% (t=4.02) to 0.93% (t=5.36). Moreover, the standard deviation is also reduced from 3.97% to 2.39% per month.

When examining the momentum strategies in individual countries, Rouwenhorst finds a positive return of the zero-cost portfolios for all 12 countries included in the study. Furthermore, with the exception of Sweden, all the country-specific returns are statistically significant. The strongest momentum effect is found in Spain, followed by the Netherlands, Belgium, and Denmark.

By investigating the portfolios in greater detail, Rouwenhorst finds the firms in the winner and loser portfolios to be smaller than the average firm in the sample, which raises the question whether the momentum effect is limited to small cap stocks only. Based on size-neutral deciles, Rouwenhorst, however, finds that, although there is a negative relation between firm size (measured by market capitalisation) and the profitability of the momentum

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100 Rouwenhorst (1998) p. 269  
103 Rouwenhorst (1998) p. 275  
104 Rouwenhorst (1998) p. 275  
105 Rouwenhorst (1998) p. 275  
106 The average monthly momentum returns, based on a 6-month/6-month strategy, in these countries are found to be 1.32% (t=2.28), 1.26% (t=3.51), 1.10% (t=3.42), and 1.09% (t=3.16), respectively; Rouwenhorst (1998) p. 274, table III, panel A.
strategies, past winners continue to significantly outperform past losers regardless of the size of the stocks. This result is consistent with the one found by Jegadeesh and Titman (1993) on the U.S. market.

Last, in order to obtain information about the persistence of the momentum effect, Rouwenhorst examines the returns in each month during the two years following the portfolio formation date. The results show that the momentum returns are positive up to and including month 11, after which they turn negative. The negative momentum returns are, however, never statistically significant. That the momentum effect shows some sign of reversal in the second year is consistent with the finding by Jegadeesh and Titman (1993) on the U.S. market. The reversal effect is, however, slightly more pronounced in the European sample.

The momentum effect observed by Rouwenhorst (1998) is supported in a subsequent study by Dijk and Huibers in 2002. Dijk and Huibers examine 15 European countries in the period from 1987 to 1999, using strategies with 12-month formation periods and holding periods of 1, 3, 6, or 12 months. Similar to Rouwenhorst, Dijk and Huibers find the momentum strategies to be profitable for all the examined holding periods. In addition, all strategies are found to generate a risk-adjusted return in excess of the equally-weighted index throughout the full sample period. Finally, Dijk and Huibers perform a sub-period analysis by dividing the sample period into two equally-sized periods, and find momentum to be present in both sub-periods using all four strategies.

In 1999, De Bondt, Schiereck, and Weber examine the momentum effect over the period 1961 to 1991 based on a sample of all major German companies listed on the Frankfurt Stock Exchange (FSE). Slightly different from other studies, De Bondt et al. report the cumulative excess returns of the momentum strategies, where the excess return is calculated as the return of the zero-cost portfolio minus the index return. Their study generally confirms the momentum effect. Based on formation periods of 1, 3, 6, and 12 months, the cumulative excess returns of the zero-cost portfolios 12 months after the

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106 Winners from the smallest size decile outperform the losers by, on average, 1.45% per month (t=3.42), while winners from the largest decile outperform the losers by, on average, 0.73% (t=2.13); Rouwenhorst (1998) p. 274, table III, panel B.
107 Rouwenhorst (1998) p. 276
109 Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.
109 De Bondt et al. (1999) p. 106
110 Dijk and Huibers (2002) p. 100
111 Dijk and Huibers (2002) p. 101
113 De Bondt et al. (1999) p. 106
formation date turn out to be 1.49% (t=6.35), 5.52% (t=5.57), 8.07% (t=4.95), and 5.21% (t=1.87), respectively.\(^{114}\) Thus, similar to other studies it is found that the magnitude of the momentum returns increases with the length of the formation period; here with the exception of the formation period as long as 12 months.

In general, De Bondt et al. find that momentum strategies outperform a passive approach that invests in the market index.\(^{115}\) Also it is found that the results for Germany match the findings for the United States relatively well; although the cumulative returns on the U.S. market would have been larger.\(^{116}\) The similarities are interesting, since, as argued by De Bondt et al., the German and the U.S. equity markets are organised very differently, and since the countries have profound differences in their social, cultural, and economic environment.\(^{117}\)

In a paper from 2003, Bird and Whitaker argue that most studies of momentum strategies have focused on the U.S. market throughout a period with a consistent upward trend in stock prices\(^{118}\). Bird and Whitaker therefore examine a wide selection of momentum strategies applied to seven of the major European markets\(^{119}\) over the period from 1990 to 2002\(^{120}\); a period which captures a large upward movement followed by a significant correction.\(^{121}\) The formation periods are set to 6 or 12 months, whereas the holding periods vary from 1 to 48 months (more precisely 1, 3, 6, 9, 12, 24, 36, or 48 months). Bird and Whitaker use a partially rebalanced quintile strategy and examine the momentum effect on each of the seven markets separately as well as in combined portfolios incorporating stocks from all seven countries. In order to minimise the impact of any country bias on the combined portfolios, these are also constructed on a country-corrected basis.\(^{122}\)

For the combined equally-weighted portfolios, Bird and Whitaker find that, with the 6-month formation period, the momentum strategy continues to provide good results for holding periods of up to 9 months. The excess return of past winners over past losers during this period is more than 7%. In case of the 12-month formation period, the optimal holding period is less than 6 months, with the outperformance of past winners over past losers being around

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115 De Bondt et al. (1999) p. 114  
117 De Bondt et al. (1999) p. 114  
118 Primarily the 1980’s and the 1990’s.  
119 France, Germany, Italy, the Netherlands, Spain, Switzerland, and the United Kingdom.  
120 Bird and Whitaker (2003) p. 225  
121 Bird and Whitaker (2003) p. 221  
4% for the 6-month holding period. No matter the length of the formation period the greatest and most significant returns are found for holding periods of 3 months or less.\textsuperscript{123}

Similar to other studies, the positive performance of the momentum strategies reverses and becomes negative over longer holding periods. Bird and Whitaker find negative momentum returns for holding periods beyond 24 months using a 6-month formation period and beyond 12 months using a 12-month formation period.\textsuperscript{124}

In addition to the equally-weighted returns, Bird and Whitaker calculate market-weighted returns and find the performance of the momentum strategies to be slightly lower over holding periods of up to 3 months, but considerably higher for holding periods beyond 3 months.\textsuperscript{125} Forming market-weighted portfolios is, furthermore, found to prolong the time in which past winners continue to outperform past losers. Bird and Whitaker therefore conclude that controlling for size biases actually improves the performance of the price momentum strategies.\textsuperscript{126 127}

The results from the country-corrected portfolios turn out to be rather similar to the above; hence suggesting that the profitability of the momentum strategies stems from stock selection rather than from a country bias where the outperformance of winners over losers is simply a result of the winner portfolio including stocks from the best performing markets.\textsuperscript{128}

Finally, Bird and Whitaker examine the profitability at the individual country level. They use a formation period of 6 months and holding periods of 6, 9, or 12 months. The momentum strategies show profitable in all countries for all holding periods; however, with a relatively low return on the French and Spanish markets.\textsuperscript{129} These results support the above finding that the profitability of the momentum strategies is largely attributable to the performance of price momentum within the individual markets.

### 4.2.2.2. Emerging Markets

Rouwenhorst (1999) is one of the first to investigate the momentum effect on emerging markets. From the perspective of collecting independent samples, emerging market countries are particularly interesting because of their relative isolation from the capital markets of other

\textsuperscript{123} Bird and Whitaker (2003) p. 237
\textsuperscript{124} Bird and Whitaker (2003) p. 237
\textsuperscript{125} Bird and Whitaker (2003) p. 238
\textsuperscript{126} An interesting observation is that most of the added value comes from buying the winners in the equally-weighted portfolio, but from shorting the losers in the market-weighted portfolio; Bird and Whitaker (2003) pp. 237-238.
\textsuperscript{127} Bird and Whitaker (2003) p. 238
\textsuperscript{128} Bird and Whitaker (2003) p. 239
\textsuperscript{129} Bird and Whitaker (2003) p. 240, table 13
Rouwenhorst examines a sample of 1,705 companies from 20 emerging market countries over the period from 1982 to 1997. He uses a 6-month/6-month strategy, which at the beginning of each month ranks stocks into one of three portfolios; top 30%, middle 40%, and bottom 30%. The results show that past winners outperform past losers in 17 of the 20 countries. The average monthly momentum returns range from -0.79% (t=-0.95) in Argentina to 2.09% (t=3.27) in Colombia. Implemented simultaneously across all 20 emerging markets, the average monthly momentum return is 0.39% (t=2.68) when stocks are equally-weighted, and 0.58% (t=3.96) when countries are equally-weighted.

At a first glance, the average momentum returns from the emerging market study seem lower than those reported for the developed markets by Jegadeesh and Titman (1993) and Rouwenhorst (1998). However, the winner and loser portfolios in these latter studies are formed based on a decile strategy and thus contain the ranking period’s 10% best and worst performing stocks, respectively. In contrast, the winner and loser portfolios in the emerging market study contain the ranking period’s 30% best and worst performing stocks, which could have the effect of somewhat decreasing the momentum returns. In general, although the results by Rouwenhorst (1999) indicate a lower momentum return in emerging markets than in developed markets, they still confirm the existence of a momentum effect.

4.2.2.3. Asian Markets

In 2000, Chui, Titman, and Wei examine the momentum effect on eight Asian markets during the period from 1976 to 2000. They examine the profitability of a 6-month/6-month value-weighted strategy, in which the momentum portfolios consist of the top and bottom 30% stocks. Although there is some overlap between the countries examined by Chui et al. and those examined by Rouwenhorst (1999), Rouwenhorst obtains his data from a database that typically includes mainly the stocks with the largest market capitalisations, whereas

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130 Compared to developed markets, Harvey (1995) find that the correlation between most emerging markets and other stock markets has historically been low; Rouwenhorst (1999) p. 1440.
131 Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, and Zimbabwe.
132 Rouwenhorst (1999) p. 1445
133 Rouwenhorst (1999) p. 1450, table III
134 Rouwenhorst (1999) p. 1449
135 Hong Kong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan, and Thailand.
136 Chui et al. (2000) p. 9
137 A value-weighted strategy is chosen due to the illiquidity of the smaller Asian stocks; Chui et al. (2000) p. 9
138 The Emerging Markets Database of the IFC.
Chui et al. include all common stocks listed on the eight Asian stock markets. Furthermore, Chui et al. examine a longer time period, including the period of the Asian financial crisis.\textsuperscript{139} The results obtained by Chui et al. indicate that the momentum effect is present in all of the Asian countries, except Korea and Indonesia, but that it is generally weak; and statistically significant in Hong Kong only.\textsuperscript{140} A further analysis, however, shows that the lack of statistical significance in some countries is due to the volatility of the momentum portfolio during the financial crisis.\textsuperscript{141}

When stocks from all eight countries are included in one aggregate sample, the momentum effect is still weak with an average monthly momentum return of 0.38%, being statistically insignificant.\textsuperscript{142} However, this aggregate sample is dominated by Japanese stocks, which exhibit a very weak momentum effect. For the sample including all countries except Japan, the momentum effect is quite strong and statistically significant.\textsuperscript{143} In general, Chui et al. find the momentum effect to be relatively stronger for firms with small market capitalisations, low book-to-market values, and high turnover ratios.\textsuperscript{144}

When analysing the long-run performance of the momentum strategy in the aggregate sample excluding Japan, as well as in a country-neutral portfolio\textsuperscript{145}, it is found that the positive momentum profits last for about 9 or 10 months following the portfolio formation date. The profits of the momentum portfolio thus reverse and become negative from month 10 through year 5, indicating that the momentum phenomenon does not persist over longer horizons.\textsuperscript{146} This finding is consistent with the U.S. evidence obtained by Lee and Swaminathan (2000). However, the reversal effect appears to be somewhat stronger on the Asian markets.\textsuperscript{147}

\textsuperscript{139} Chui et al. (2000) p. 3
\textsuperscript{140} Chui et al. (2000) p. 4
\textsuperscript{141} Chui et al. (2000) p. 14
\textsuperscript{142} Chui et al. (2000) p. 10
\textsuperscript{143} Chui et al. (2000) p. 4.
\textsuperscript{144} Chui et al. (2000) p. 5.
\textsuperscript{145} Eight country-specific value-weighted momentum portfolios are equally-weighted to form the country-neutral momentum portfolio; Chui et al. (2000) p. 11.
\textsuperscript{146} Chui et al. (2000) p. 4
\textsuperscript{147} Chui et al. (2000) p. 13
4.2.3. Worldwide Study of Momentum Strategies

In 2003, Griffin, Ji, and Martin conduct a large worldwide study of momentum strategies. Their study includes a total of 40 countries from the following five regions: Africa, Americas (ex. the U.S.), Asia, Europe, and the United States. Due to different data availability, the sample periods for the different countries varies considerably. For the United States, data is available from 1926, for 10 markets, coverage begins in 1975, by 1990 data from 23 countries are available, and all countries, except Egypt, have coverage primo 1995. The sample periods end ultimo 2000. Griffin et al. examine a 6-month/6-month quintile strategy that skips a month between the formation and the holding periods.

The study shows that momentum strategies are, on average, largely profitable all around the world, with the Asian countries displaying the weakest momentum profits; consistent with the Asian study by Chui, Titman, and Wei (2000). More precisely, Griffin et al. find positive momentum profits in 2 out of 2 African countries, 7 out of 7 American countries, 10 out of 14 Asian countries, and 14 out of 17 European countries.

To allow for noise in individual country data, Griffin et al. further calculate the regional averages as the equally-weighted average of all countries in a given region. The average monthly momentum profits are 1.63% (t=3.89), 0.78% (t=3.13), 0.32% (t=1.64), and 0.77% (t=8.15) in Africa, Americas (ex. the U.S.), Asia, and Europe, respectively. The profits are found to be highly significant in all regions except Asia. The regional momentum profits are, furthermore, reported for strategies that do not skip a week between the formation and the holding periods. As expected, these results turn out slightly lower with average monthly profits of 1.42% (t=3.36), 0.50% (t=1.89), 0.13% (t=0.64), and 0.70% (t=6.86) in Africa, Americas (ex. the U.S.), Asia, and Europe, respectively. Still, however, the momentum profits are statistically significant in all regions except Asia.

Similar to Rouwenhorst (1999), Griffin et al. find weaker momentum profits for emerging markets than for developed markets. The average momentum profit for all non-U.S. developed markets is a statistically significant 0.73% per month (8.74% per year) compared

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148 Africa: Egypt and South Africa. Americas (ex. the U.S.): Argentina, Brazil, Canada, Chile, Mexico, and Peru. Asia: Australia, China, Hong Kong, India, Indonesia, Japan, Malaysia, New Zealand, Pakistan, Philippines, Singapore, South Korea, Taiwan, and Thailand. Europe: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. America: the United States.
149 Griffin et al. (2003) p. 2518
150 Griffin et al. (2003) p. 2518
151 Griffin et al. (2003) p. 2519, table I
152 Griffin et al. (2003) pp. 2519-2520, table I, panel A
153 Griffin et al. (2003) p. 2522
154 Griffin et al. (2003) p. 2521, table I, panel B
to a statistically insignificant 0.27% per month (3.24% per year) for emerging markets\textsuperscript{155}\textsuperscript{156}. The overall conclusion by Griffin et al. is, however, that momentum strategies, in general, prove profitable and statistically significant all around the world\textsuperscript{157}.

4.2.4. Summary

The above literature review seems to prove that the momentum effect does indeed exist on the stock market. Ever since it was first documented by Jegadeesh and Titman in 1993, numerous researchers have documented it across different markets and time periods. The momentum return appears to be around 1% per month, and the momentum strategies show profitable even after accounting for transaction costs. The momentum effect does not seem to be confined to any particular types of stocks or any sub-periods. In general, the momentum strategies with long formation periods and short holding periods are found to perform better than the remaining strategies. However, all strategies, regardless of the formation and the holding periods provide significantly positive momentum returns. When looking at the monthly momentum returns following the formation date, it appears that the strategies are profitable only for about 12 months. Thus, in years 2 and 3, the momentum returns turn slightly negative and in years 4 and 5 a significant pattern of mean reversion appears. As a consequence, the cumulative momentum return after year 5 is just slightly above zero. In terms of countries, the momentum effect is found to be stronger on the developed markets, than on the emerging and Asian markets. However, even though the momentum effect varies in strength, it is found to be a worldwide phenomenon.

The next chapter investigates the profitability of momentum strategies on the Danish stock market. Although the momentum effect has already been documented on the Danish market by Rouwenhorst (1998) and Dijk and Huibers (2002), these studies are not completely up to date and, furthermore, only include Denmark as part of two larger studies of the European market. The below chapter focuses on the Danish stock market only, and investigates the most recently available time period.

\textsuperscript{155} The corresponding t-values are (t=7.04) and (t=1.21).
\textsuperscript{156} Griffin et al. (2003) p. 2522
\textsuperscript{157} Griffin et al. (2003) p. 2522
5. An Empirical Study of the Danish Stock Market

The following chapter is the empirical part of the thesis, which investigates the momentum effect on the Danish stock market. The chapter is divided into four main sections; the first section contains information about the sample period and data, the methodology, and the statistical issues related to the tests, the second section presents the results of the overall test of momentum, the third section presents the results of various robustness tests across different types of stocks and sub-periods, and finally the fourth section looks into some practical implementation issues regarding the momentum strategies.

5.1. Fundamentals Preceding the Empirical Analysis

5.1.1. Sample Period

As mentioned above, the momentum effect on the Danish stock market has already been tested and documented by Rouwenhorst (1998) as well as by Dijk and Huibers (2002) as part of two larger studies of the European market. Rouwenhorst and Dijk and Huibers use the sample periods 1980 through 1995 and 1987 through 1999, respectively, and it is therefore found sensible to test a period that lies beyond this point. This has the advantage of investigating not only whether the momentum effect has been present on the Danish stock market, but also whether it has been present during more recent times than those already tested. In fact, most of the empirical studies of momentum date a few years back, why it seems appealing to test a newer period to see whether the momentum effect is still as significant as it previously was. The sample period is therefore chosen to run from January 1996 through December 2009. This period captures all the years following the early study of the Danish stock market by Rouwenhorst (1998) and up till today. Furthermore, the length of the sample period amounts to 14 years, which is in accordance with the length of the sample periods in previously conducted studies. Last, the selected period is interesting to analyse since it includes a relatively stable period from 1996 to 2003, a significant market increase from 2003 to the second half of 2007, and the recent financial crisis, initiated by the U.S. subprime crisis, from the second half of 2007 to the beginning of 2009.

5.1.2. Sample Data

The KAX Index, currently consisting of 201 Danish stocks, is used as the starting point for the empirical data set. The KAX Index is the Copenhagen Stock Exchange’s all share index and is selected since it contains both small cap, mid cap, and large cap companies, giving a representative sample of the Danish stock market. Only stocks that are currently listed on the KAX Index are considered. Hence, stocks that have been de-listed or gone bankrupt during the period from 1996 through 2009 are disregarded from the start. The initial data set, thus, consists of monthly closing prices (used to calculate monthly returns), market capitalisations, price-to-book ratios (used to calculate book-to-market values), and trading volumes from all stocks currently listed on the KAX Index. All data is collected from Bloomberg.

5.1.2.1. Selection of the Final Data Set

While the starting point for the empirical data set is all stocks currently listed on the KAX Index, a more detailed selection is required before the final data set can be introduced. It is decided to screen the above selected data based on three different criteria. The first screening criterion is commonly used when testing the momentum effect, whereas the other two are merely found sensible by the writer.

First, in accordance with common practice, real estate investment trusts, real estate development companies, mutual funds, and investment funds are excluded from the sample. The main reason for excluding these types of companies is that they represent diverse and often-changing investments in other stocks, making them unsuitable for analytical purposes.

Secondly, all A-shares are removed from the sample, since these are typically held by funds and stakeholders with long term interests in the companies, making the shares less liquid than the equivalent B-shares. Hence, by excluding A-shares from the sample, the results of the empirical analysis seem more useful to the private investor.

The third, and last, screening criterion in selecting the final data set is that in order for a stock to be selected it must have data available for all four variables (price, market cap, price-to-book value, and volume) for at least four continuous years. There is no essential reason for

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159 Ultimo December 2009.
160 It is not possible to obtain historical data for the so-called dead stocks using Bloomberg. This could introduce some survivorship bias on the data. Whether the results would have turned out differently with the inclusion of dead stocks is, however, impossible to say.
161 Adjusted for stock splits and with re-invested dividends.
162 The formula used to calculate returns is: \((P_1 - P_0)/P_0\).
163 The formula used to calculate book-to-market values is: \(1/\text{price-book ratio}\).
164 Bloomberg definitions of the four variables can be found in Appendix 3.
screening based on this criterion, however, it is found sensible only to include stocks that have a certain amount of data available.

Having sorted the obtained data based on the three screening criteria, the final data set consists of 108 Danish stocks. The companies selected for the empirical analysis can be found in Appendix 4.

5.1.2.2. Sample Period Alterations

Although it has just been argued that the sample period should run from 1996 through 2009, limited data availability requires some corrections to be made.

As can be seen from the below table, the amount of data for the selected companies varies significantly on a year-to-year basis:

<table>
<thead>
<tr>
<th>Year</th>
<th>Return</th>
<th>Market Cap</th>
<th>Book-to-Market</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>82-91</td>
<td>0</td>
<td>1</td>
<td>86-91</td>
</tr>
<tr>
<td>1997</td>
<td>91-93</td>
<td>0</td>
<td>1-15</td>
<td>91-93</td>
</tr>
<tr>
<td>1998</td>
<td>93-98</td>
<td>0</td>
<td>15</td>
<td>93-98</td>
</tr>
<tr>
<td>1999</td>
<td>98-99</td>
<td>0</td>
<td>15-19</td>
<td>98-99</td>
</tr>
<tr>
<td>2000</td>
<td>99-103</td>
<td>0-104</td>
<td>19-27</td>
<td>99-104</td>
</tr>
<tr>
<td>2001</td>
<td>104-107</td>
<td>105-107</td>
<td>27-39</td>
<td>105-107</td>
</tr>
<tr>
<td>2002</td>
<td>107</td>
<td>107</td>
<td>39-52</td>
<td>107</td>
</tr>
<tr>
<td>2003</td>
<td>107</td>
<td>107</td>
<td>52-55</td>
<td>107</td>
</tr>
<tr>
<td>2004</td>
<td>107</td>
<td>107</td>
<td>55-85</td>
<td>107</td>
</tr>
<tr>
<td>2006</td>
<td>108</td>
<td>108</td>
<td>108</td>
<td>108</td>
</tr>
<tr>
<td>2007</td>
<td>108</td>
<td>108</td>
<td>108</td>
<td>108</td>
</tr>
<tr>
<td>2008</td>
<td>108</td>
<td>108</td>
<td>108</td>
<td>108</td>
</tr>
<tr>
<td>2009</td>
<td>108</td>
<td>108</td>
<td>108</td>
<td>108</td>
</tr>
</tbody>
</table>

Since a certain amount of data is considered necessary in order to conclude on the test results, the overall momentum test as well as the robustness tests will be carried out only in months where the relevant data is available on at least 50 stocks. From the table above, this means that the different tests will be conducted throughout the following periods:

<table>
<thead>
<tr>
<th>Testing Periods</th>
<th>1/1-96 to 31/12-09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Momentum Test</td>
<td></td>
</tr>
<tr>
<td>Size-Based Subsample</td>
<td>1/7-00 to 31/12-09</td>
</tr>
<tr>
<td>Value-Based Subsample</td>
<td>1/7-02 to 31/12-09</td>
</tr>
<tr>
<td>Volume-Based Subsample</td>
<td>1/1-96 to 31/12-09</td>
</tr>
<tr>
<td>Sub-Period Analysis</td>
<td>1/1-96 to 31/12-09</td>
</tr>
</tbody>
</table>
5.1.3. Test Methodology

The test methodology describes how the selected data is used to test for momentum on the Danish stock market. The pros and cons of different methods are considered before selecting the final methodology.

5.1.3.1. Methodology Considerations

5.1.3.1.1. Decile versus Weighted Relative Strength Strategy

Over the years, several methods to investigate the momentum effect have been proposed. The two most common methods are the decile strategy and the weighted relative strength strategy (WRSS). The decile strategy, which is the one presented in the literature review, ranks stocks based on their past returns over a given period and divides them into ten portfolios based on this ranking. The momentum portfolio then consists of a long position in the portfolio containing the 10% best performing stocks and a short position in the portfolio containing the 10% worst performing stocks. The stocks in the portfolios are either equally-weighted or value-weighted. In contrast to the decile strategy, the WRSS measures the performance of a stock relative to the average performance of all stocks in the sample.\(^{(165)}\) Thus, the momentum portfolio consists of a long position in the stocks that have outperformed the sample average over a given period and a short position in the stocks that have underperformed the sample average during the same period. Under the WRSS assets are held in proportion to their market-adjusted returns. Hence, the weight of asset \(i\) in a portfolio is given by\(^{(166)}\):

\[
    w_i = \frac{1}{n} \left( r_i - \bar{r} \right)
\]

where: \(r_i\) = the return of asset \(i\); \(\bar{r}\) = the average return of all stocks in the sample; \(n\) = the number of stocks in the sample.

Whereas both methods have individual advantages and disadvantages, an important disadvantage of the WRSS is the weighting scheme. This is so, since the momentum portfolios, following a WRSS, will be dominated by stocks with extreme past returns regardless of their market capitalisations. As a result, the WRSS may lack robustness in that the dominant stocks tend to be small in size. Furthermore, the transaction costs are significantly higher for the WRSS than for the decile strategy due to a considerably larger portfolio size, making the WRSS unattractive to private investors with less capital available.

\(^{(165)}\) Conrad and Kaul (1998) p. 493
\(^{(166)}\) Conrad and Kaul (1998) p. 493
Perhaps for these reasons, the decile strategy (sometimes altered to a quintile strategy) seems to be the preferred method in the academic studies of the momentum effect. The quintile strategy is also selected for the empirical study of the Danish stock market.

5.1.3.1.2. Equally-Weighted versus Value-Weighted Portfolios

Having decided on the quintile strategy, the next thing to consider is whether to use equally-weighted or value-weighted portfolios. As indicated by its name, an equally-weighted portfolio means that stocks in the portfolio are given the same weight, regardless of their individual market capitalisations, and thus all stocks contribute equally to the portfolio return. In contrast, stocks in a value-weighted portfolio are weighted according to their market capitalisations so that large cap stocks have the greatest influence on the portfolio return. Since small cap stocks are typically considered more expensive to trade, the result of using value-weighted portfolios should be to improve the overall performance of the momentum strategies through a reduction of transaction costs. On the other hand, using value-weighted portfolios makes it more difficult to conclude, whether momentum is present in all types of stocks or in large cap stocks only.

It seems that most of the existing studies of momentum strategies use equally-weighted portfolios. This type of weighting is also selected for the empirical study of the Danish stock market.

5.1.3.1.3. Full versus Partial Rebalancing

The last issue to consider is whether to use full or partial rebalancing of the portfolios. With full rebalancing, the portfolios are rebalanced at the beginning of each holding period, whereas partial rebalancing involves monthly rebalancing regardless of the length of the holding period.

The method of partial rebalancing is the one described in the literature review. Following this method, the momentum strategy, in short, buys the winner portfolio and sells the loser portfolio in each month \( t \), holding this position for \( K \) months; where \( K \) is the holding period. In addition, the strategy closes out the position initiated in month \( t-K \). Hence, in any given

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167 It should, furthermore, be mentioned that Swinkels (2004) find the variation in the test results from the two different methods to be insignificant.


169 Under this strategy effectively the weights of \( 1/K \) of the stocks in the portfolio is revised, while the rest is carried over from the previous month; Jegadeesh and Titman (1993) p. 68. This means that with a 1-month holding period, the portfolios are fully rebalanced each month, whereas with, say, a 6-month holding period, effectively 1/6 of the portfolio is rebalanced each month.
month, the strategy holds a series of portfolios selected in the current month as well as in the previous $K-1$ months.

The below figure illustrates the difference between full and partial rebalancing for a 6-month/6-month strategy. One should imagine being in months 12, going into month 13. As can be seen, the method of full rebalancing rebalances the entire portfolio in the beginning of month 13, whereas the method of partial rebalancing effectively rebalances 1/6 of the portfolio in the beginning of each month, including month 13:

<table>
<thead>
<tr>
<th>Formation Period</th>
<th>Holding Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Partial</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Compared to full rebalancing, the method of partial rebalancing has the advantage of increasing the significance of the results in that considerably more observations are obtained. Whether the magnitude of the results is affected seems to be a bit unclear. Some argue that partial rebalancing does not affect the magnitude of the results, since the overlapping formation periods will have a tendency to rank stocks in the same manner unless stock returns have changed significantly over the month. Others, on the other hand, argue that it would seem natural to find higher returns using partial rebalancing, since stocks are ranked more often according to their past performance. When comparing returns obtained from full and partial rebalancing, one important thing to keep in mind is, however, that the two methods cannot be fairly compared without considering the trading costs involved, and this is where
the major disadvantage of partial rebalancing appears. Since this method involves considerably more rebalancings than the method of full rebalancing, the trading costs too are significantly higher. Take for example the 6-month/6-month strategy. Following the method of full rebalancing, this strategy involves two rebalancings a year. However, when using the method of partial rebalancing, the strategy requires no less than 12 rebalancings a year. This indeed will reduce the after-cost returns from partial rebalancing significantly.

It seems that most academic studies use the method of partial rebalancing to increase the statistical significance of the results. The method of full rebalancing is, however, chosen for the empirical test of the Danish stock market, since this method is considered more feasible to the private investor, who is unlikely to benefit from following the market on a monthly basis and rebalance portfolios accordingly.

5.1.3.2. Test Methodology

Based on the above, the chosen methodology for the empirical analysis of the Danish stock market is the equally-weighted quintile strategy with full rebalancing.

The quintile strategy, as opposed to the WRSS, is chosen to avoid the unfavourable weighting scheme. Furthermore, it is considered necessary to rank stocks into more than two portfolios in order to capture the full effect of winners versus losers. The quintile strategy is selected instead of the decile strategy to ensure that a reasonable amount of stocks are included in each of the portfolios.

The method of equally-weighting stocks in the portfolios is chosen since there are some big players on the Danish market, which would dominate the analysis in case value-weighted portfolios were selected\(^{170}\). Hence, since it is found interesting to explore not only whether the momentum effect exists on the Danish stock market, but also whether it exists in different type of stocks regardless of size, value and liquidity, the equally-weighted portfolios seem more sensible to select.

Finally, full rebalancing is chosen since this method is considered more feasible to the private investor than partial rebalancing, due to significantly fewer rebalancings.

In greater detail, the methodology used for testing the momentum effect on the Danish stock market is as follows: At the beginning of each holding period, stocks are ranked according to

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\(^{170}\) For example, when calculating the average market capitalisations for all companies over the four years from 2006 through 2009 (where all stocks must have available data), it is found that the average market capitalisation of the 15 largest companies account for 80% of the average market capitalisation of all 108 companies in the sample. The average market capitalisation for the 5 largest companies account for nearly 60% of the entire sample.
their geometric average monthly returns over the past 3, 6, 9, or 12 months; these are the formation periods. Only stocks with data available throughout the entire formation period are considered. Based on the ranking, stocks are divided into five equally-weighted portfolios. Stocks with the highest formation period returns are placed in portfolio 1 (the winner portfolio), stocks with the next highest formation period returns are placed in portfolio 2 and so forth. Thus, stocks with the lowest formation period returns are placed in portfolio 5, also called the loser portfolio. The five equally-weighted portfolios are held over the next 3, 6, 9, or 12 months; these are the holding periods.

The process can be illustrated as follows:

<table>
<thead>
<tr>
<th>Trading Strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td>t - 3, 6, 9, or 12 months</td>
</tr>
<tr>
<td>Formation Period</td>
</tr>
</tbody>
</table>

At the end of each holding period, the above process is repeated.

When the sample period expires, the geometric average monthly return for the entire period is calculated for each of the five equally-weighted portfolios in a given strategy. The difference between the average monthly return of the winner portfolio and the loser portfolio constitutes the strategy’s momentum return over the sample period. Since there are four different lengths for the formation period and four different lengths for the holding period, a total of 16 momentum strategies are investigated.

In addition to the overall test of momentum, using the entire data set as a whole, several robustness tests are conducted. The above methodology is used for these tests in almost the same manner as for the overall test of momentum. However, when conducting the robustness tests, the sample data is initially divided into smaller sub-groups. Furthermore, a tercile strategy, as opposed to the above quintile strategy, is used for the first three robustness tests, where it is found necessary in order to ensure a reasonable amount of stocks in the portfolios.

The first three robustness tests in the empirical analysis are also referred to as two-dimensional tests in that they first rank stocks into subsamples according to an initial factor (in this case either size, value, or volume) and then rank stocks into portfolios based on past returns, as illustrated below:

171 The five portfolios being: the winner portfolio, the three middle portfolios, and the loser portfolio.
The two-dimensional tests are able to capture whether the momentum effect is a general phenomenon or whether it is limited to particular types of stocks such as for example small stocks, value stocks or illiquid stocks.

The last robustness test in the empirical study is a sub-period analysis. Here the selected sample period from 1996 through 2009 is initially divided into shorter sub-periods, after which the methodology is identical to the one applied for the overall test of momentum. The sub-period analysis is conducted to test whether the momentum effect is a general phenomenon in terms of time periods or whether it is confined to specific sub-periods or market conditions.

For computational reasons, the robustness tests are carried out for the 6-month/6-month strategy only. The 6-month/6-month strategy is commonly chosen to be investigated in greater detail, since the length of both the formation and the holding periods are considered reasonably representative for the remaining 15 strategies.  

5.1.4. Statistical Issues

In order to evaluate the statistical significance of the results, a one-sample one-tailed t-test is calculated. The reason for choosing a one-tailed test is to evaluate whether the results are significantly positive for the winner and zero-cost portfolios and significantly negative for the loser portfolios, as opposed to merely evaluating whether the results are significantly different from zero.  

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172 See for example Jegadeesh and Titman (1993).
173 Significance tests are only calculated for winner, loser, and zero-cost portfolios.
The one-sample t-test with n-1 degrees of freedom is calculated as follows:

\[ t_{n-1} = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \]

where: \( \bar{x} \) = the average of the observations in the sample (i.e. the arithmetic average of the portfolio returns); \( \mu_0 \) = the average to be tested whether \( x \) is greater or smaller than (in this case 0); \( s \) = the standard deviation of the sample (i.e. the standard deviation of the portfolio returns); \( n \) = the number of observations in the sample (i.e. the number of portfolio returns in a given strategy).

To determine the significance of the results, the t-values are compared with the critical values of the Student’s t-distribution at the 10%, 5%, and 1% significance level. In order to reject the null hypothesis in favour of the alternative hypothesis, i.e. that a given momentum return is significantly above (below) 0, the calculated t-values must be larger (smaller) than the corresponding positive (negative) critical values.

The t-values are presented in brackets below the returns of the winner, loser, and zero-cost portfolios. Next to the returns it is indicated whether, and to what extent, the results can be considered statistically significant. *, **, and *** indicate that the result is significantly positive or negative at the 10%, 5% or 1% level, respectively.

5.2. The Momentum Effect on the Danish Stock Market

This section presents the results from the price momentum strategies implemented on the Danish stock market during the period from 1996 through 2009. In accordance with common practice, the strategies are evaluated based on average monthly returns. The annualised returns of the zero-cost portfolios can be found in Appendix 5A.

For each of the 16 investigated momentum strategies, the following table shows the average monthly returns of the five individual portfolios (winner, 2, 3, 4, and loser), as well as the average monthly return of the momentum, or zero-cost, portfolio. The t-values are shown in brackets below the returns of the winner, loser, and zero-cost portfolios.\(^{174}\)

\(^{174}\) The critical values used to evaluate the statistical significance of the returns are shown in Appendix 6A.
The results document that the momentum effect has indeed existed on the Danish stock market in the period from 1996 through 2009 in that the returns of all 16 zero-cost portfolios are positive. Out of the 16 zero-cost portfolios, 3 results are significant at the 10% level, 9 results are significant at the 5% level, and 4 results are significant at the 1% level. Thus, all
strategies earn a positive return and all momentum returns are statistically significant at least at the 10% level.

The two most profitable strategies are the 12-month/3-month strategy and the 12-month/6-month strategy, which yield average monthly returns of 1.55% and 1.54%, respectively; both significant at the 1% level. The strategy with the worst performance is the 9-month/12-month strategy with an average monthly return of 0.61%, being statistically significant at the 10% level. The general finding from the above table seems to be that strategies with long formation periods and short holding periods perform better than the remaining strategies. Noteworthy, this is exactly the same conclusion reached by Jegadeesh and Titman (1993) and Lee and Swaminathan (2000) in investigating the American market and by Rouwenhorst (1998) in investigating the European market. More broadly, and consistent with the finding by Bird and Whitaker (2003), it can be said that strategies with short holding periods tend to outperform strategies with long holding periods, regardless of the length of the formation period.

In general, the magnitude of the results fit well with the result by Rouwenhorst (1998), who finds the 6-month/6-month strategy to generate an average monthly momentum return of 1.09% (t=3.16) on the Danish market over the period from 1980 to 1995.175

Looking at the returns in the above table, it becomes clear that the success of the momentum strategies comes from both buying the winner portfolios and short-selling the loser portfolios. To have invested in the winner portfolios alone would not have been an attractive alternative, since the zero-cost portfolio, by far, outperforms the winner portfolio in each of the 16 strategies. This is an important finding, as many private investors may want to avoid short-selling and therefore could be interested in the performance of the winner portfolios on their own.176

Apart from evaluating the momentum returns in isolated settings, it is interesting to see how the strategies perform compared to an investment in the index portfolio; in this case the KAX Index. The average monthly return of the entire index over the sample period amounts to 0.66%, being statistically significant at the 5% level. Thus, the momentum portfolio outperforms the index portfolio in 15 out of 16 cases. It further appears that it is the short-selling of the loser portfolios that contributes most to the momentum portfolios’ outperformance. This being the case since the loser portfolio, in all 16 strategies,

175 Rouwenhorst (1998) p. 275
176 Furthermore, some institutional investors might be restricted from short-selling.
underperforms the index portfolio to a greater extent than the winner portfolio outperforms the index portfolio.\textsuperscript{177,178}

\section*{5.2.1. Summary}

The empirical test of the Danish stock market from 1996 through 2009 confirms the observed momentum effect from previous studies, as the momentum returns from all 16 strategies turn out to be positive and statistically significant. It shows that both winner and loser portfolios contribute to the success of the momentum strategies, which are able to outperform both the winner portfolios on their own and the index portfolio.

The next section investigates the robustness of the momentum strategies across different types of stocks and sub-periods.

\section*{5.3. Robustness Tests}

The above test of momentum is conducted using the full sample of stocks selected for the empirical analysis. However, it is also found interesting to investigate whether the momentum effect is limited to, or at least more severe in, specific types of stocks. It is determined to examine the momentum strategies in subsamples based on size (market capitalisations), value (book-to-market values), and liquidity (trading volume). Size and liquidity are selected since some researchers suggest that the momentum effect is likely to be limited to small and illiquid stocks.\textsuperscript{179} Value and, again, size are selected since these variables have the advantage of showing, not only whether the momentum effect is limited to high book-to-market and small cap stocks, as suggested by some researchers, but also whether the momentum phenomenon is essentially caused by stocks in the winner portfolios being more risky than stocks in the loser portfolios, which would be the natural explanation according to the traditional finance theory.

In addition to the above, it has been questioned whether the momentum effect is a broad phenomenon or confined to particular sub-periods. Hence, a sub-period analysis is going to investigate whether the momentum effect is robust when tested across different time periods and markets with very distinct stock price behaviour.

The robustness tests are, as previously stated, carried out for the 6-month/6-month strategy only. As with the overall test of momentum, it is the average monthly returns that are

\textsuperscript{177} In fact the winner portfolios only outperform the index portfolio in 6 out of 16 cases.

\textsuperscript{178} The methodology of measuring which portfolios contribute most to the momentum portfolio’s outperformance of the index portfolio is adapted from Jegadeesh and Titman (2001) p. 705.

presented. The annualised returns can be found in Appendix 5B-D for the two-dimensional tests and in Appendix 5E-F for the sub-period analysis.\textsuperscript{180}

5.3.1. Size-Based Subsamples

The reason for studying size-based subsamples is the assumption by some researchers that the momentum effect is limited to, or at least more severe in, small cap stocks. The researchers argue that inefficiencies, and thereby momentum, are more likely to be observed in small cap stocks, since these are less covered by analysts, and the media in general, and since trading in small cap stocks is often associated with higher costs. The second argument is consistent with the conventional wisdom that, with learning, profit opportunities will be sustained longer when there are higher costs of implementing the trading strategies.\textsuperscript{181}

To test whether the momentum effect is robust regardless of firm size, stocks are ranked according to their average monthly market capitalisations during the formation period and placed in one of three equally-sized subsamples at the beginning of each holding period. Using a tercile strategy, as explained previously, the momentum return is now calculated for each of the three size groups; small cap, mid cap, and large cap stocks.

Apart from measuring whether momentum is more pronounced in small cap stocks, the method has the advantage of making the stocks in each group size-neutral to one another. This is convenient since proponents of traditional finance argue that the momentum effect is presumably due to stocks in the winner portfolios being riskier than stocks in the loser portfolios, thereby justifying the outperformance of winners over losers. Given that size is considered one of the most important risk measures in the traditional finance theory\textsuperscript{182}, eliminating the size difference in each of the three groups should diminish momentum returns considerably, if risk is to account for the momentum effect.

\textsuperscript{180} The critical values used to evaluate the statistical significance of the returns can be found in Appendix 6B and Appendix 6C-D for the two-dimensional tests and the sub-period analysis, respectively.
\textsuperscript{181} Jegadeesh and Titman (2001) p. 706
\textsuperscript{182} According to Fama and French’s (1993) Three-Factor Model small cap stocks are riskier than large cap stocks and should, as a consequence, provide a greater return.
The results from the size-based subsamples are as follows:

<table>
<thead>
<tr>
<th>Size-Based Subsamples</th>
<th>Small Cap</th>
<th>Mid Cap</th>
<th>Large Cap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner (1)</td>
<td>0,52%</td>
<td>0,60%</td>
<td>0,79%</td>
</tr>
<tr>
<td></td>
<td>(0,718)</td>
<td>(0,857)</td>
<td>(1,020)</td>
</tr>
<tr>
<td>Loser (3)</td>
<td>0,39%</td>
<td>0,09%</td>
<td>0,06%</td>
</tr>
<tr>
<td></td>
<td>(-0,622)</td>
<td>(-0,559)</td>
<td>(-0,124)</td>
</tr>
<tr>
<td>Zero-Cost</td>
<td><strong>1,07%</strong></td>
<td><strong>1,46%</strong></td>
<td><strong>0,97%</strong></td>
</tr>
<tr>
<td></td>
<td>(1,705)</td>
<td>(1,846)</td>
<td>(2,018)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

Most importantly, the table shows that the momentum returns are all positive and statistically significant at the 5% or 10% level. The results thus indicate that the momentum effect is not confined to small stocks only. In fact, the momentum returns from all size-based subsamples outperform the momentum return from the full sample, which amounts to 0.91% for the 6-month/6-month strategy, being statistically significant at the 5% level. That the momentum effect is not limited to small cap stocks is supported by a number of researchers.¹⁸³ The majority of these, however, find that size does have an effect on the magnitude of the momentum returns; with small cap stocks leading to a somewhat greater return. Whether this is the case in this sample is a bit difficult to conclude, since the above test finds the strategy from the mid cap subsample to be the most profitable¹⁸⁴. It is true, though, that the large cap sample provides the lowest momentum return of the three subsamples¹⁸⁵.

Last, the fact that the momentum returns are significantly positive for all the size-neutral subsamples indicates that size as a risk measure is not able to account for the observed momentum effect.

### 5.3.2. Value-Based Subsamples

The second robustness test divides the full sample into three equally-sized subsamples based on the stocks’ average monthly book-to-market values over the formation period, after which the tercile strategy is carried out separately in each of the three value groups. Thus, from this test, it is possible to evaluate, whether the momentum exists in both value stocks (high book-to-market values) and growth stocks (low book-to-market values).

¹⁸³ See for example Jegadeesh and Titman (1993, 2001) and Chui et al. (2000).
¹⁸⁴ That the mid cap sample provides the greatest return followed be the small cap and the large cap samples is also found by Jegadeesh and Titman (1993).
¹⁸⁵ An interesting observation is that the large cap stocks actually generate the greatest return when looking at the winner portfolios only. Thus, the lower performance of the zero-cost portfolio for large cap stocks is caused by a greater return of the large cap loser portfolio relative to the loser portfolios in the two other size samples.
Since the book-to-market value, along with the above market capitalisation, is considered one of the most important risk measures in the Three-Factor Model developed by Fama and French (1993), also this test has the advantage of simultaneously measuring whether the momentum effect is merely a result of stocks in the winner portfolios being riskier than stocks in the loser portfolios. Again, if this is so, the momentum returns should decrease, or completely disappear, as a consequence of the value-neutral subsamples.

The results from the value-based subsamples are as follows:

<table>
<thead>
<tr>
<th>Value-Based Subsamples</th>
<th>Low Book-to-Market</th>
<th>Mid Book-to-Market</th>
<th>High Book-to-Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner (1)</td>
<td>0.99% (1,022)</td>
<td>0.58% (0,624)</td>
<td>0.79% (0,759)</td>
</tr>
<tr>
<td>2</td>
<td>0.66% (0,475)</td>
<td>0.60% (0,315)</td>
<td>0.78% (-0,104)</td>
</tr>
<tr>
<td>Loser (3)</td>
<td>0.41% (-0,44%)</td>
<td>-0.44% (-0,315)</td>
<td>-0.28% (-0,104)</td>
</tr>
<tr>
<td>Zero-Cost</td>
<td>0.58% (0,813)</td>
<td>1.02%* (1,765)</td>
<td>1.07%** (1,889)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

The momentum returns in the above table are all positive; again suggesting that the momentum effect is not confined to particular types of stocks. However, the fact that the returns, as well as the significance of the returns, are monotonically increasing with the stocks’ book-to-market values, indicate that at least the magnitude of the momentum returns is affected by the value of the stocks. The results show that the momentum returns from both the mid and the high book-to-market subsamples outperform the momentum return from the full sample (0.91%), whereas the momentum return from the low book-to-market subsample underperforms, due to a positive return of the loser portfolio. Looking at the winner portfolios alone, the subsample with the low book-to-market value stocks has outperformed the other two subsamples as well as the winner portfolio constructed from the full sample, meaning that the growth stocks, in general, have performed better than the remaining stocks. Whether the positive return of the loser portfolio is restricted to the stocks or the sample period in question is difficult to say. One fact, however, is that the majority of other studies of the momentum effect find the low book-to-market subsample to generate the highest momentum return.

This implies that at least one should be careful with concluding on the above result for the low book-to-market zero-cost portfolio.

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186 According to Fama and French’s (1993) Three-Factor Model high book-to-market value stocks are riskier than low book-to-market value stocks and should, as a consequence, provide a greater return.

187 See for example Chui et al. (2000) and Grinblatt and Moskowitz (2003).
Last, the finding that the momentum strategies are able to generate significantly positive momentum returns in two out of the three value-neutral subsamples suggests that neither value as a risk measure can account for the observed momentum effect.

### 5.3.3. Volume-Based Subsamples

Similar to the above argumentation regarding small cap stocks, it is argued that momentum is likely to be more pronounced in illiquid than in liquid stocks, as the low trading activity in the illiquid stocks makes it easier for inefficiencies, and thus the momentum effect, to persist. To test whether the momentum effect is robust regardless of the stocks’ liquidity, stocks are ranked according to their average monthly trading volume over the formation period and placed in one of three equally-sized subsamples, after which the tercile strategy is used to calculate the momentum returns in each of the three volume groups. In case the momentum effect is primarily driven by illiquid stocks, the momentum return should appear to be significantly less pronounced, or non-existing, in the high volume subsample.

The results from the volume-based subsamples are as follows:

<table>
<thead>
<tr>
<th>Volume-Based Subsamples</th>
<th>Low Volume</th>
<th>Mid Volume</th>
<th>High Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Winner (1)</strong></td>
<td>0,00%</td>
<td>0,47%</td>
<td>1,39%***</td>
</tr>
<tr>
<td>(0,082)</td>
<td>(1,011)</td>
<td>(2,064)</td>
<td></td>
</tr>
<tr>
<td><strong>Loser (3)</strong></td>
<td>-0,23%</td>
<td>0,64%</td>
<td>0,06%</td>
</tr>
<tr>
<td>(-0,243)</td>
<td>(-0,09%)</td>
<td>(-0,56%)</td>
<td></td>
</tr>
<tr>
<td><strong>Zero-Cost</strong></td>
<td>0,23%</td>
<td>0,57%</td>
<td>1,95%***</td>
</tr>
<tr>
<td>(0,500)</td>
<td>(1,059)</td>
<td>(4,104)</td>
<td></td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

The results show that the momentum return is insignificantly positive in the low and the mid volume subsamples, but significantly positive in the high volume subsample, with an average monthly momentum return of no less than 1.95%, being statistically significant at the 1% level. The lowest momentum return is found for the low volume stocks, which generate a statistically insignificant momentum return of only 0.23%. Thus, the suggestion by some researchers that the momentum effect is likely to be confined to illiquid stocks is not supported by the above results. In fact, the conclusion seems to be the exact opposite; that the momentum is limited to, or at least more severe in, liquid high volume stocks.

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188 See for example Daniel et al. (1998) p. 1866.
That high volume, or high turnover, stocks exhibit stronger momentum is also found by Chui, Titman and Wei (2000)\(^\text{189}\), Lee and Swaminathan (2000), and Grinblatt and Moskowitz (2003)\(^\text{190}\). These researchers, however, find evidence of momentum in both low and high volume stocks.

### 5.3.4. Sub-Period Analysis

Apart from the two-dimensional tests, investigating the extent to which the momentum effect is present across different types of stocks, it is interesting to examine whether the momentum effect is a general phenomenon in terms of time periods or whether it is confined to particular sub-periods. The first part of the sub-period analysis looks into this issue by dividing the sample period into two equally-sized sub-periods. As will be seen, the first period is relatively stable in terms of stock price movements, whereas the second period is more volatile. The second part of the sub-period analysis tests the momentum strategies in three periods with very distinct stock price behaviour; in particular this part of the analysis tests the performance of the strategies during a bull market, a bear market, and a market that is mean reverting.

The below graph illustrates the movement of the average price for all stocks in the sample over the entire sample period from 1996 through 2009\(^\text{191}\). The grey dot divides the sample period into two equally-sized sub-periods:

\[\text{Average Sample Price}\]

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\(^{189}\) Chui et al. (2000) p. 5  
\(^{190}\) Griffin et al. (2003) p. 2516  
\(^{191}\) As can be seen in Appendix 7, the average price of the 108 sample stocks moves very similar to the overall KAX Index consisting of 201 stocks; however, at a higher price level.
The results from the first sub-period analysis are presented in the table below:

<table>
<thead>
<tr>
<th>Sub-Period Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/7-96 to 31/12-02</td>
</tr>
<tr>
<td><strong>Winner (1)</strong></td>
</tr>
<tr>
<td>0.55%</td>
</tr>
<tr>
<td>(0.935)</td>
</tr>
<tr>
<td><strong>2</strong></td>
</tr>
<tr>
<td>0.26%</td>
</tr>
<tr>
<td><strong>3</strong></td>
</tr>
<tr>
<td>-0.23%</td>
</tr>
<tr>
<td><strong>4</strong></td>
</tr>
<tr>
<td>-0.19%</td>
</tr>
<tr>
<td><strong>Loser (5)</strong></td>
</tr>
<tr>
<td>-0.23%</td>
</tr>
<tr>
<td>(0.541)</td>
</tr>
<tr>
<td><strong>Zero-Cost</strong></td>
</tr>
<tr>
<td><strong>1.24%</strong>**</td>
</tr>
<tr>
<td>(2.636)</td>
</tr>
<tr>
<td><strong>0.59%</strong></td>
</tr>
<tr>
<td>(0.884)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

The results show a momentum return of 1.24%, being statistically significant at the 5% level, during the first, stable, period and a momentum return of 0.59%, being statistically insignificant, during the second, volatile, period. This can be compared to the results of the index portfolio, which is found to generate returns of 0.61% and 0.71%, both significant at the 10% level, during sub-period one and two, respectively.

Overall, the results seem to suggest that momentum strategies perform best under more stable market conditions, and that the profitability of the strategies is, therefore, affected by the selected sample period. This last finding is supported by a test dividing the sample period into four equally-sized sub-periods as opposed to the above two. Here the momentum returns turn out to be 0.48%, 1.89%, 0.93%, and 0.26% for the four periods respectively, where only the second return is statistically significant.\(^{192}\)

That the profitability of momentum strategies seems to depend on the choice of sample period is somewhat surprising in that many researchers find the strategies to be equally profitable regardless of the selected period.\(^ {193}\) A closer look at the above results reveals that the poor performance of the strategy during the second, volatile, sub-period can be explained by the initial long period of rising stock prices, as this has the effect of making the returns of both winner and loser portfolios positive, whereby the short-selling of the loser portfolio contributes negatively to the momentum return. Also the poor returns of 0.48% and 0.93% from the four-period analysis turn out to be caused by rising stock markets, and thus positive returns of the loser portfolios. In a similar vein, the result of only 0.26% appears to be caused

\(^{192}\) The sub-period analysis dividing the entire sample period into four equally-sized periods (including average monthly returns for winner, loser and zero-costs portfolios, annualised returns, and critical values) can be found in Appendix 8.

\(^{193}\) See for example Jegadeesh and Titman (1993) and Dijk and Huibers (2002).
by a large fall in the market, causing the returns of both winner and loser portfolios to be negative, whereby the winner portfolio contributes negatively to the momentum return.

The second part of the sub-period analysis investigates the effect of different market conditions further. Instead of including data from the entire sample period, as above, this analysis focuses on three specifically chosen periods with very distinct market behaviour. More precisely, the momentum effect is tested on a bull market (1/1-03 to 31/12-05), a bear market (1/7-07 to 31/12-08), and a market in which prices mean revert (1/7-04 to 31/12-08):

The results of the second sub-period analysis are presented in the table below:

<table>
<thead>
<tr>
<th>Sub-Period Analysis</th>
<th>Bull Market</th>
<th>Bear Market</th>
<th>Mean Reversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner (1)</td>
<td>3.33%***</td>
<td>-4.70%</td>
<td>-0.24%</td>
</tr>
<tr>
<td></td>
<td>(7.977)</td>
<td>(-1.738)</td>
<td>(-0.109)</td>
</tr>
<tr>
<td>2</td>
<td>3.25%</td>
<td>-4.61%</td>
<td>0.82%</td>
</tr>
<tr>
<td>3</td>
<td>2.57%</td>
<td>-5.61%</td>
<td>0.26%</td>
</tr>
<tr>
<td>4</td>
<td>2.12%</td>
<td>-6.71%</td>
<td>-0.32%</td>
</tr>
<tr>
<td>Loser (5)</td>
<td>1.77%</td>
<td>-6.52%*</td>
<td>-0.66%</td>
</tr>
<tr>
<td></td>
<td>(2.649)</td>
<td>(-2.091)</td>
<td>(-0.302)</td>
</tr>
<tr>
<td>Zero-Cost</td>
<td>1.56%*</td>
<td>1.81%*</td>
<td>0.42%</td>
</tr>
<tr>
<td></td>
<td>(1.827)</td>
<td>(2.368)</td>
<td>(0.663)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

As in the analysis above, it is found that the returns of both winner and loser portfolios are positive during the bull market and negative during the bear market, meaning that, if one could predict the direction of the market, the most attractive investment strategy would be to buy the winner portfolio when expecting a bull market and short-sell the loser portfolio when expecting a bear market. This finding is not that surprisingly. What is surprisingly, however, is that the momentum strategy shows capable of providing significantly positive returns during both bull and bear markets, with average monthly returns of 1.56% and 1.81% in the
two periods, respectively\textsuperscript{194}. The fact the very same strategy proves profitable in both strong bull and bear markets, makes it appear a very safe and attractive investment strategy. Also the results can be compared to an investment in the index portfolio, which would have generated average monthly returns of 2.22\% and -4.01\% during the two periods. Thus, although the index portfolio outperforms the zero-cost portfolio in the bull market, the momentum strategy, overall, generates the best result.

The momentum return from the last period, in which the market mean reverts, is a bit more questionable being positive at 0.42\%, but statistically insignificant. The low return of the zero-cost portfolio during this period is caused by both winner and loser portfolios generating returns that are negative but close to zero. Nevertheless, the momentum strategy is still to prefer over an investment in the index portfolio, which would have generated an average monthly return of -0.30\% in the mean reverting market. That momentum strategies seem to prove less successful during very volatile and mean reverting periods is also found by Jegadeesh and Titman (1993) in back-testing their 6-month/6-month strategy during the periods 1927 to 1940 and 1941 to 1964. Here, the early period is characterised by extreme volatility and a high degree of mean reversion, and the returns are found to be significantly lower for this period than for the 1941 to 1964 period.\textsuperscript{195} Jegadeesh and Titman argue that large market movements and negative serial correlation reduce momentum profits, since momentum strategies tend to select high beta stocks following market increases and low beta stocks following market decreases and as a consequence perform poorly during market reversals.\textsuperscript{196}

\textbf{5.3.5. Summary}

The above robustness tests are divided into three two-dimensional tests and a sub-period analysis. From the first two two-dimensional tests, it is found that the momentum effect is, in general, robust across different types of stocks, both when examined within size-based and value-based subsamples. These two-dimensional tests further indicate that neither size nor value, being the two most important risk measures identified by Fama and French (1993), are able to account for the observed momentum effect. The third two-dimensional test shows that momentum is by far strongest in liquid, high volume, stocks. This finding is supported by

\textsuperscript{194} The perhaps most noteworthy result is the return of 1.81\%, being significant at the 10\% level, during the recent subprime crisis, where all other investment strategies seemed to fail.

\textsuperscript{195} Jegadeesh and Titman (1993) p. 86, table VIII, panels A and B

\textsuperscript{196} Jegadeesh and Titman (1993) p. 85
many researchers, but is at stake with the conventional theory stating that the most actively traded stocks should be better arbitraged and thus more rationally priced. The sub-period analysis indicates that momentum strategies tend to perform better under more stable, as opposed to more volatile, market conditions. Particularly, the investigated 6-month/6-month strategy seems to have difficulties in generating significantly positive returns during market reversals. The strategy, however, shows capable of generating significantly positive returns during both strong bull and bear markets. Most noteworthy is the statistically significant momentum return of 1.81% during the recent financial crisis.

5.4. Practical Implementation Issues

Although the above tests seem to document that the momentum effect has existed on the Danish stock market in more recent times, there are two important practical issues, which have not yet been touched upon; namely how transaction costs and possible restrictions on short-selling influence the profitability of the momentum strategies.

5.4.1. Transaction Costs

The first practical issue to be investigated is whether the momentum strategies remain profitable when adjusting the returns for transaction costs. The influence of transaction costs is here examined in the four momentum strategies with formation and holding periods of identical length\textsuperscript{197}, using the entire sample period from 1996 through 2009.

When calculating the effect of transaction costs, it is important to recognise that the cost of trading has been continuously decreasing during the sample period. In other words, one must account with significantly higher transaction costs in the beginning of the period. Furthermore, short-selling the loser portfolio is considerably more expensive than buying the winner portfolio. To account for the differences in transaction costs, several rates are selected for the analysis. It is, in this connection, decided to use the rates available to private investors, since these rates exceed the rates available to institutional investors. In general, it is believed that the rates for the analysis are set at a rather conservative level.\textsuperscript{198}

\textsuperscript{197} That is the 3-month/3-month, 6-month/6-month, 9-month/9-month, and 12-month/12-month strategies.

\textsuperscript{198} The rate used for the winner portfolio 2005 through 2009 is an average of the current market rates from www.danskebank.dk, www.nordea.dk and www.nordnet.dk. The rate used for the winner portfolio 1996 through 1999 is the one way rate reported for small firms by Chan and Lakonishok (1995); Geist and Lifson (1999) p. 143. The remaining rates are estimated from these two rates.
The rates are as follows:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner Portfolios</td>
<td>1,50%</td>
<td>1,00%</td>
<td>0,20%</td>
</tr>
<tr>
<td>Loser Portfolios</td>
<td>3,00%</td>
<td>2,00%</td>
<td>0,40%</td>
</tr>
</tbody>
</table>

The relevant rates above are used twice in each holding period to account for the roundtrip cost of first buying (short-selling) then selling (buying back) the stocks in the portfolios. Again, this way of accounting for transaction costs is rather conservative, since it is unlikely that the portfolios are 100% rebalanced at the beginning of each holding period.

The following table shows the previously calculated momentum returns, excluding transaction costs, and the momentum returns when transaction costs are incorporated:

<table>
<thead>
<tr>
<th>Momentum Strategies excl. and incl. Transaction Costs</th>
<th>3-month/3-month</th>
<th>6-month/6-month</th>
<th>9-month/9-month</th>
<th>12-month/12-month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-Cost (excl. TC)</td>
<td>1,18%***</td>
<td>0,91%**</td>
<td>0,80%**</td>
<td>0,84%*</td>
</tr>
<tr>
<td></td>
<td>(2,640)</td>
<td>(2,165)</td>
<td>(1,780)</td>
<td>(1,410)</td>
</tr>
<tr>
<td>Zero-Cost (incl. TC)</td>
<td>1,04%**</td>
<td>0,80%**</td>
<td>0,71%*</td>
<td>0,77%</td>
</tr>
<tr>
<td></td>
<td>(2,334)</td>
<td>(1,941)</td>
<td>(1,594)</td>
<td>(1,297)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

As expected, the transaction costs have a negative effect on the momentum returns, which are both slightly reduced and, in most cases, less significant than before. However, the returns are still positive, and they still exceed the index return of 0.66%, being statistically significant at the 5% level.

Also the momentum strategies continue to significantly outperform the winner portfolios, as illustrated below:

<table>
<thead>
<tr>
<th>Winner and Zero-Cost Portfolios incl. Transaction Costs</th>
<th>3-month/3-month</th>
<th>6-month/6-month</th>
<th>9-month/9-month</th>
<th>12-month/12-month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner (incl. TC)</td>
<td>0,68%*</td>
<td>0,61%</td>
<td>0,25%</td>
<td>0,42%</td>
</tr>
<tr>
<td></td>
<td>(1,367)</td>
<td>(1,095)</td>
<td>(0,370)</td>
<td>(0,566)</td>
</tr>
<tr>
<td>Zero-Cost (incl. TC)</td>
<td>1,04%**</td>
<td>0,80%**</td>
<td>0,71%*</td>
<td>0,77%</td>
</tr>
<tr>
<td></td>
<td>(2,334)</td>
<td>(1,941)</td>
<td>(1,594)</td>
<td>(1,297)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

That the momentum strategies outperform the winner portfolios even after accounting for transaction costs is noteworthy in that the main driver for the declining after-cost momentum profits is the short-selling of the loser portfolios.

The fact that the momentum strategies show profitable even after accounting for transaction costs makes the momentum phenomenon appear even stronger, and even more at stake with

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199 The annualised returns can be found in Appendix 5G.
200 The annualised returns can be found in Appendix 5H.
the traditional finance theory, according to which no trading strategy should be able to provide investors with a continuous after-cost profit.\textsuperscript{201}

### 5.4.2. Short-Selling

The momentum strategies investigated above all require the investor to buy the winner portfolio and simultaneously sell short the loser portfolio. Naturally, it would be possible merely to buy the winner portfolio; however, as the above analysis shows, the winner portfolio on its own generates a significantly lower return than the zero-cost portfolio in almost all cases. Thus, restrictions on short-selling could have a significant influence on the profitability of the momentum strategies in practice.

In general, rules prohibiting short-selling have not been common on the Danish stock market. However, in an attempt to stop the huge fall in financial stock prices in the second half of 2008, Denmark, or more precisely the Danish FSA, decides to follow the United States and the United Kingdom and introduces a prohibition against short-sale of financial stocks, which comes into force the 13\textsuperscript{th} of October 2008.\textsuperscript{202} The sample for the empirical analysis contains 25 financial stocks, which amounts to 23\% of the entire sample. Nevertheless, since the prohibition only exists throughout the last 14 months of the selected sample period, it seems unlikely that it should have a significantly negative effect on the observed profitability.\textsuperscript{203}

Apart from legal restrictions, one should also look at the actual possibilities for short-selling. For example, private investors typically have to use online brokers such as Nordnet or SAXO-ETRADE to engage in short-selling of stocks. These brokers offer attractive short-selling possibilities in the mid cap and large cap segments. However, due to limited lending possibilities, short-selling in the small cap segment can be difficult to execute in practice.\textsuperscript{204}

In terms of institutional investors short-selling is possible in all three size segments. Yet, because of low liquidity in the small cap and mid cap segments, institutional investors often choose to go short in large cap stocks only.\textsuperscript{205} Thus, although short-selling is legally allowed in all types of stocks, except the before-mentioned financial stocks, presumably only the large cap, and to some extend the mid cap, segment has an active market for short-selling. Since the

\textsuperscript{201} Notice that the conclusion from including transaction costs could have turned out differently if the method of partial rebalancing had been used. As previously mentioned, using partial rebalancing increases the number of rebalancings and thus the transaction costs.

\textsuperscript{202} Finansiel Stabilitet 2008 2. halvår, www.nationalbanken.dk.

\textsuperscript{203} The prohibition will not have any effect looking forward either, as it expires on the 30\textsuperscript{th} of September 2010 along with the Danish Bank Package I; Tine Choi Ladefoed, Senior Strategist, Strategic Investment Advice, Nordea Savings & Asset Management.

\textsuperscript{204} Michael Højer Jørgensen, Senior Sales Manager, Equity Sales DK, Nordea Markets.

\textsuperscript{205} Michael Højer Jørgensen, Senior Sales Manager, Equity Sales DK, Nordea Markets.
strongest momentum is found in the mid cap, followed by the small cap, segment, this suggests that investors, in practice, are unlikely to obtain the full benefits from the investigated momentum strategies.

5.4.3. Summary
The above results show that the momentum strategies remain profitable even after accounting for transaction costs. Also, they are still able to outperform both the index portfolio and the winner portfolios on their own\textsuperscript{206}. In terms of short-sale restrictions, the one rule prohibiting short-sale of financial stocks is not assumed to have any severe consequences for momentum strategies during the sample period in question. The fact that short-sale possibilities in practice appear to be limited to the large cap, and to some extent the mid cap, segment is, however, likely to reduce the observed profitability of the strategies, as momentum is found to be strongest in the mid cap and small cap subsamples. Nevertheless, since the momentum strategies prove profitable in all size subsamples, and since all types of stocks can be included in the winner portfolios, the success of the strategies, even after accounting for transaction costs, still questions the validity of the traditional finance theory in explaining the financial market.

The next chapter investigates possible explanations for the observed momentum phenomenon.

\textsuperscript{206} In fact, if the momentum effect continues to exist on the market, the after-cost profit can only be expected to increase, since transaction costs, looking forward, will either be equal to or lower than the most recent rates in the above analysis.
6. Momentum Explanations

Evidently, a large number of researchers, and portfolio managers, subscribe to the view that momentum strategies yield significant profits in the intermediate horizon. The source of the profits is, however, widely debated.\(^{207}\)

The following chapter looks at different explanations of the observed momentum effect. The explanations are broadly divided into risk-related explanations, data snooping and flawed methodology, and explanations based on behavioural finance.

6.1. Risk-Related Explanations

The significant profits from momentum strategies have provided the drive for a large number of researchers to try to explain the empirical findings, with investment risk being the most obvious candidate. As stated earlier, fundamental risk factors should, according to the traditional finance theory, be able to explain all differences in stock returns. What is expected to be found from a traditional viewpoint is therefore that the profitability of the momentum strategies is simply caused by winner portfolios containing more risky stocks than loser portfolios. The risk factors most commonly referred to are beta, size (measured as the firms’ market capitalisations), and book-to-market values, as these are identified as being the most important determinants of stocks returns by Fama and French (1993) in the development of their Three-Factor Model. Specifically, it is expected that the winner portfolios consist of stocks with high beta values, small market capitalisations, and high book-to-market values.

Among the researchers trying to clarify whether the momentum effect can be explained in terms of common risk factors are Jegadeesh and Titman (1993). They investigate their 6-month/6-month strategy in detail to determine what characterises the winner and the loser portfolios. From this analysis, they find that the beta of the portfolio with past losers is higher than the beta of the portfolio with past winners; with beta values of 1.38 and 1.28, respectively.\(^{208}\) As a consequence, the beta of the zero-cost portfolio is negative, and Jegadeesh and Titman therefore conclude that the momentum effect cannot be explained in terms of markets risk.\(^{209}\)

Also Rouwenhorst (1998) examines whether the observed momentum return can be explained by beta. Rouwenhorst first calculates the sample average excess return of the market, which

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\(^{207}\) Jegadeesh and Titman (2001) p. 699
\(^{208}\) Jegadeesh and Titman (1993) p. 73
\(^{209}\) Jegadeesh and Titman (1993) p. 72
he finds to be around 0.6% per month. It follows that in order for the zero-cost portfolio return of 1.2% per month\textsuperscript{210} to be explained by market risk, the beta of the winner portfolio must exceed the beta of the loser portfolio by about two. However, what is found is that the beta of the zero-cost portfolio is insignificantly different from zero, meaning that the beta values of the winner and loser portfolios are virtually the same\textsuperscript{211}.\textsuperscript{212} In addition, Rouwenhorst notes that, for the momentum effect to be consistent with market-dependent beta, losers must have higher beta in down markets and lower beta in up markets relative to winners. The exact opposite is, however, found to be true. Although the betas do vary with market conditions, losers consistently have a higher beta in up markets and a lower beta in down markets than winners. Hence, the beta of the zero-cost portfolio’s return is significantly negative in up markets and positive in down markets.\textsuperscript{213} Like Jegadeesh and Titman, Rouwenhorst concludes that market risk seems to have no explanatory power in relation to the momentum returns.

Besides looking at beta values, Jegadeesh and Titman (1993) investigate the average market capitalisations of the stocks in the different portfolios. They find the stocks in the winner portfolio to be larger than the stocks in the loser portfolio, with the average market capitalisation of the winners being twice as large as the average market capitalisation of the losers\textsuperscript{214}, thus suggesting that the momentum return cannot be explained by the stocks in the winner portfolio being smaller than stocks in the loser portfolio. This finding is supported by Jegadeesh and Titman (2001), who find the losers to load more heavily on Fama and French’s SMB factor; with loadings of 0.55 and 0.41 for losers and winners, respectively.\textsuperscript{215} Rouwenhorst (1998) also investigates whether size can be a determinant in explaining the observed momentum profits but finds, like Jegadeesh and Titman, that the average size of the stocks in the winner portfolio is larger than the average size of the stocks in the loser portfolio. Thus, allowing for exposure to size, as measured by an international version of Fama and French’s (1996) SMB factor, actually increases the momentum return, as the losers, on average, load more on the SMB factor than do winners. The momentum return in Rouwenhorst’s study is increased from 1.14% (t=3.94) to 1.46% (t=5.05) per month when

\begin{itemize}
\item \textsuperscript{210}1.16% (t=4.02) to be exact; Rouwenhorst (1998) p. 270, table I, panel A
\item \textsuperscript{211}1.02 and 1 for the winner and loser portfolios, respectively.
\item \textsuperscript{212}Rouwenhorst (1998) p. 271
\item \textsuperscript{213}Rouwenhorst (1998) p. 278
\item \textsuperscript{214}Jegadeesh and Titman (1993) pp. 72-73
\item \textsuperscript{215}Jegadeesh and Titman (2001) p. 706
\end{itemize}
adjusting for risk, and it is therefore, also by Rouwenhorst, concluded that size as a risk measure cannot explain the momentum effect.\textsuperscript{216}

In addition to the above, numerous researchers have studied size-based subsamples as part of their analysis. As explained in the empirical analysis, the effect of these subsamples is that stocks within each size-group become size-neutral. Thus, if the profitability of the momentum strategies can be explained by winners being smaller than losers, the return from the individual size-based subsamples should be close to zero. However, the majority of studies find the momentum returns to be significantly positive in each of the subsamples, and some even find the returns from the subsamples to be greater than the return from the overall sample.\textsuperscript{217}

The last risk measure identified by Fama and French (1993) is the book-to-market value of stocks. According to Fama and French’s theory, the winner portfolios should concentrate on the more risky value stocks, while the loser portfolios should concentrate on growth stocks. Complete opposite to this, Chan, Jegadeesh and Lakonishok (1996) find that the portfolio of winners tend to include growth stocks with low book-to-market values, whereas the portfolio of losers tend to include value stocks with high book-to-market values. In other words, the winner portfolio loads negatively on the HML factor, whereas the loser portfolio loads positively on the HML factor, indicating that the book-to-market value as a risk measure is unable to account for the momentum effect.\textsuperscript{218} A similar conclusion is reached by Jegadeesh and Titman (2001). Although they find both the winner and the loser portfolios to load negatively on the HML factor, the HML loadings are -0.245 and -0.02 for winners and losers, respectively, meaning that losers are more sensitive to the HML factor and thus more risky.\textsuperscript{219}

A slightly different method is used by Dijk and Huibers (2002). They initially put forward the hypothesis that the momentum effect equals the book-to-market effect, in which stocks with high book-to-market values outperform stocks with low book-to-market values. To test the hypothesis, Dijk and Huibers calculate the average book-to-market values for the winner and the loser portfolios and find an almost perfectly linear negative relationship between price momentum and book-to-market values in the month of portfolio construction. Also after the formation month, the data suggests a negative relationship between the two\textsuperscript{220}, meaning that when momentum returns are high (winners), book-to-market values are low. Dijk and Huibers

\textsuperscript{216} Rouwenhorst (1998) p. 277
\textsuperscript{217} See for example Jegadeesh and Titman (1993) or the empirical results for the Danish stock market.
\textsuperscript{218} Chan et al. (1996) p. 1707
\textsuperscript{219} Jegadeesh and Titman (2001) p. 707
\textsuperscript{220} Dijk and Huibers (2002) p. 102
thus reject the hypothesis that price momentum can be considered equivalent to the book-to-market effect and conclude that the momentum effect cannot be explained in terms of book-to-market values.

Apart from the separate findings on beta, size and value, Grundy and Martin (2001) show that the profitability of their 6-month/1-month momentum strategy cannot be explained as a reward for bearing the dynamic exposure to the three factors of the Three-Factor Model.\footnote{Grundy and Martin (2001) p. 29} The raw average monthly return of Grundy and Martin’s 6-month/1-month strategy amounts to 0.78\% (t=2.45) in the period from 1966 to 1995. However, when risk-adjusted with respect to Fama and French’s Three-Factor Model, the average monthly return increases to 1.48\% (t=7.83).\footnote{Grundy and Martin (2001) p. 38, table I}

The inability of the combined model to explain the momentum effect is also found by Moskowitz and Grinblatt (1999).\footnote{Grundy and Martin (2001) p. 31} Most noteworthy, however, is that Fama and French, in an article from 1996, try to explain various asset pricing anomalies in terms of their Three-Factor Model, but fail to account for the profitability of momentum strategies in particular.\footnote{Fama and French (1996) p. 55} They call it “the main embarrassment of the Three-Factor Model”, but argue that since the continuation of medium term returns is so far from the contrarian spirit of other anomalies\footnote{For example the size, BE/ME, E/P, C/P, sales-growth, and long term reversal effects.\footnote{Fama and French (1996) p. 81} Even though the APT seems replaced by the Three-Factor Model, it should be mentioned that also the macroeconomic risk variables proposed by Chen, Roll, and Ross (1986) have been used as risk measures in an attempt to explain momentum profits, but without success; Griffin et al. (2003) p. 2529. The factors proposed by Chen et al. are unexpected inflation, changes in expected inflation, term spread, changes in industrial production, and default risk premium; Griffin et al. (2003) p. 2525.\footnote{Geist and Lifson (1999) p. 102} data snooping appears to be a likely explanation for the observed momentum effect.\footnote{Geist and Lifson (1999) p. 102} 

\section*{6.2. Data Snooping and Flawed Methodology}

In the absence of a risk-related explanation, the evidence on momentum strategies stands out for many researchers as a major unsolved puzzle. Due to lack of better explanations some researchers have reached the conclusion that the documented momentum effect is merely a statistical fluke, which is unlikely to work out-of-sample.\footnote{Fama (1998) argues that adjusting methodology and performing out-of-sample testing, in general, tend to work.} For example, Fama (1998) argues that adjusting methodology and performing out-of-sample testing, in general, tend to
eliminate observed anomalies.\textsuperscript{229} The many studies across different markets and time periods documenting the momentum effect (referring to the above literature review), however, make it unlikely that the observed phenomenon is merely attributable to data snooping and flawed methodology. Even the empirical study of the Danish stock market, which investigates the most recently available time period, seems to document the momentum effect. The explanations related to data snooping and flawed methodology thus appear unfounded.

Where some researchers seem to have left the profitability of momentum strategies as an unsolved puzzle and others, despite the above, have decided on the explanation with data snooping and flawed methodology, others again have looked for alternative explanations. These researchers are those who, in general, believe the traditional finance theory to be too simple to explain the behaviour of the financial market. Instead they look for explanations within the theories from behavioural finance, which are considered next.

### 6.3. Explanations Based on Behavioural Finance

Indeed, the outperformance of simple price momentum strategies remains so much a mystery that Fama (1998) has identified this as the one outstanding anomaly in market behaviour.\textsuperscript{230} Using the theories from behavioural finance, there are, however, several possible explanations for the observed momentum effect.

The models from behavioural finance are, as expected, essentially based on the way people behave. In particular, most of them require that investors are prone to one or two psychological biases, whereby investors make systematic errors in forming their beliefs and preferences.\textsuperscript{231} Others, however, simply build on the interaction between different investor types.

The models to be considered are roughly divided into one of two groups, as the momentum effect, in general, is thought to arise as a consequence of either underreaction or overreaction to new information. Where underreaction causes the stock price reaction to be less than it should be in relation to a given piece of information, overreaction causes the stock price reaction to be stronger than it should be. Hence, underreaction leads to a gradual correction phase, in which the stock price continues in the same direction until equilibrium has been

\textsuperscript{229} Fama (1998) p. 288; it should be noticed, however, that the focus in this article is mainly on long term return anomalies.

\textsuperscript{230} Bird and Whitaker (2003) p. 224

\textsuperscript{231} Definitions of some of the most often used psychological biases and decision-making errors in behavioural finance can be found in Appendix 2. In addition, the psychological biases used to explain the momentum effect are shortly described under the relevant models.
reached, whereas overreaction causes an initial price movement too far in one direction and, as a consequence, leads to eventual price reversal in order for the stock price to return to equilibrium.

6.3.1. Momentum Caused by Underreaction

6.3.1.1. Underreaction to Earnings Announcements

As mentioned, one possible explanation for the momentum effect is that the market underreacts, and thus only gradually responds, to new information. Since earnings provide an ongoing source of information about a company’s prospects, many studies focus on the market’s reaction to earnings announcements, when investigating the underreaction hypothesis.

Some of the first to examine returns around earnings announcements are Jones, Latane, and Rendleman (1982), who investigate the return response of stocks to unexpected quarterly earnings; measured as the difference between actual and expected earnings.\textsuperscript{232} In their study\textsuperscript{233}, stocks are initially categorised into one of ten groups based on their unexpected earnings.\textsuperscript{234} The stocks’ excess returns over the market are then calculated on a daily basis for days -20 to +90 around earnings announcements. Jones et al. find the average cumulative excess return to be 8% and -8.7% for the group of stocks with the highest and lowest unexpected earnings, respectively.\textsuperscript{235} More interestingly, however, they find that for the positive surprise stocks, 4.3% of the cumulative excess return occurs not on announcement days but over the 90 days following the announcements days. Similarly, for the negative surprise stocks, -4% of the cumulative excess return occurs during the post-announcement periods. Hence, it is found that price reactions to earnings announcements are gradual over time rather than instantaneous.\textsuperscript{236} Bernhard and Thomas (1989), and Bernhard, Thomas, and Wahlen (1995) likewise find that firms reporting unexpectedly high earnings outperform firms reporting unexpectedly poor earning, and that this superior performance lasts over a period of about 6 months after earnings announcements.\textsuperscript{237} Chan, Jegadeesh, and Lakonishok (1996) find that stocks with large favourable announcement returns subsequently outperform

\textsuperscript{232} Chaturvedi (1999) p. 81
\textsuperscript{233} The sample consists of a minimum of 618 companies in 1971 and a maximum of 1496 companies in 1980; Chaturvedi (1999) p. 82.
\textsuperscript{234} In fact, unexpected earnings are statistically deflated for standardisation purposes and called Standardised Unexpected Earnings (SUE); Chaturvedi (1999) p. 82.
\textsuperscript{235} Chaturvedi (1999) p. 84
\textsuperscript{236} Chaturvedi (1999) p. 85
\textsuperscript{237} Chan et al. (1996) p. 1682
stocks with large unfavourable announcement returns by 5.9% in the first 6 months, and by 8.3% in the first year following the announcement day.\footnote{Chan et al. (1996) p. 1693} The substantial amount of evidence documenting a post-announcement drift indeed indicates that the market underreacts to earnings-related information.\footnote{Bird and Whitaker (2003) p. 224}

To evaluate whether price momentum can be explained by the market’s underreaction to earnings announcements, Jegadeesh and Titman examine the returns of past winners and losers around their quarterly earnings announcement days within the 36 months following the portfolio formation date. If the market underreacts to information about future earnings, it is expected that past winners, which presumably had favourable information revealed in the past, should realise positive returns around the time when their actual earnings are announced, whereas past losers should realise negative returns at the time of announcement. Jegadeesh and Titman find that for the first 6 months, the announcement date returns of past winners exceed the announcement date returns of past losers by more than 0.7% on average.\footnote{Jegadeesh and Titman (1993) p. 88} The general pattern of winner minus loser announcement date returns appears to be consistent with that of the momentum portfolio, and Jegadeesh and Titman conclude that the returns around the earnings announcement days represent about 25% of the observed momentum return during the first 6 months following the formation date.\footnote{Chan, Jegadeesh, and Lakonishok (1996) p. 1690} Chan, Jegadeesh, and Lakonishok (1996) find an even more striking result and conclude that, for the first 6 months, the returns around the earnings announcement days are able to account for 41% of the spread between winners and losers in the momentum portfolio.\footnote{Jegadeesh and Titman (1993) p. 88} Both Jegadeesh and Titman (1993) and Chan et al. (1996, 1999) thus conclude that momentum profits seem to be, at least partly, explained by delayed stock price reactions to firm-specific information.\footnote{Chan et al. (1996) p. 1690} This conclusion is later supported by Grundy and Martin (2001).\footnote{Jegadeesh and Titman (1993) p. 89}

Apart from finding that underreaction to earnings announcements could play a vital role in explaining the momentum effect it seems interesting to investigate what causes the underreaction in the first place. Here a number of researchers point towards analyst behaviour, in that many investment decisions are presumably based on analysts’ forecasts and recommendations. Thus, if analysts, on average, are found to respond only gradually to new information, this could be driving the market’s overall underreaction.

\footnote{Grundy and Martin (2001) p. 31}
By looking at different studies, a general finding appears to be that analysts’ forecasts are overly optimistic at the outset, but are then adjusted downward over time. One reason for the initial optimism could be that analysts try to encourage investors to buy stocks, thereby generating brokerage income. Another explanation could be that unfavourable forecasts may damage relations between the analysts and company managements, thus jeopardising future relations. In 1996, Chan, Jegadeesh, and Lakonishok investigate analysts’ revisions in earnings forecasts based on a decile momentum strategy. Consistent with the downward adjustments above, they find the revisions across the 10 portfolios to be mostly negative. When looking at the winner and the loser portfolios alone, they find a slightly positive average monthly revision of 0.004% for the winner portfolio during the first 6 months and a considerably larger negative average monthly revision of -2.138% for the loser portfolio. Furthermore, from month 7 to month 12 the average monthly revisions for the winner portfolio reverse and become negative (-0.180%), whereas the average monthly revisions for the loser portfolio continue to be negative (-1.843%). The fact that revisions continue to be negative for firms that have experienced poor stock price performance is supported by Klein (1990).

Similar to the above, Dijk and Huibers (2002) investigate the underreaction hypothesis on the European market, using data from 15 different countries, and conclude that the most likely explanation for the observed drift in stock prices seem to be the existence of a pessimism bias for winner portfolios and an optimism bias for loser portfolios among analysts. In accordance with previous studies, they find the optimism bias, i.e. the overestimation of earnings for past losers, to be more substantial than the pessimism bias. The above findings seem to support the suggestion that the market’s underreaction is caused, or at least influenced, by analysts’ underreaction to earnings announcements, which for logical reasons are found to be especially pronounced for companies with poor announcements. Thus, the overall section suggests that momentum in stock prices, especially momentum in losing stocks, is partly caused by the analysts’, and in turn the market’s, underreaction to new firm specific information.

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245 Chan et al. (1996) p. 1690
246 Chan et al. (1996) p. 1689, table II
247 Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.
248 Dijk and Huibers (2002) p. 103
249 Dijk and Huibers (2002) p. 103
6.3.1.2. A Model of Investor Sentiment

As opposed to the above, which merely seeks to explain the medium term momentum effect, Barberis, Shleifer, and Vishny (1998) develop a model which seeks to explain the medium term momentum as well as the long term reversal effect observed in the market. The model is called a Model of Investor Sentiment; referring to the idea that the market is influenced by the way investors form their beliefs. In particular, the model relies on the two psychological biases conservatism and representativeness. In short, the conservatism bias suggests that individuals are too slow to change their beliefs when confronted with new information; in other words, new information is underweighted. Hence, one important implication of the conservatism bias, in a financial context, is that prices only gradually adjust to new information. The representativeness heuristic refers to judgement based on stereotypes. In a financial context, one possible manifestation of the representativeness heuristic is that people often seem to find patterns in sequences that are in fact random so that, for example, a small increase in stock prices is likely to resemble previous bull markets. The representativeness heuristic can also be explained in terms of size neglect, whereby people infer too much on the basis of too little information. Consequently, representativeness may lead investors in the financial market to overweight the significance of recent company performance without taking long term average performance into account. The Model of Investor Sentiment includes only one risk-neutral investor, where the investor is viewed as one whose beliefs reflect consensus forecasts. It is the forecasted future earnings by this investor alone that affect prices and returns. In reality, earnings streams follow a random walk; however, the investor does not know that. Rather the investor believes that the behaviour of earnings move between two states; in the first state, earnings are mean-reverting, whereas in the second state, they trend. The investor uses two different models to determine future earnings in the two different states; neither of which is random walk. Model 1 generates effects identical to those predicted by conservatism; thus, when the investor uses model 1 to forecast earnings, the investor reacts too little to a given earnings announcement.

250 In addition to the below, definitions of the conservatism bias and the representativeness heuristic can be found in Appendix 9A and 9D, respectively.
251 Barberis and Thaler (2003) p. 1065
253 Tvede (2007) p. 94
255 Ritter (2003) p. 4
256 This is consistent with the notion of herding, whereby investors imitate each other and thus act as one.
257 Barberis et al. (1998) p. 308
258 Barberis et al. (1998) p. 309
In contrast, model 2 generates effects identical to those predicted by the representativeness heuristic, meaning that the earnings forecasts made by the investor extrapolate past performance too far into the future.\textsuperscript{259} It is assumed that the investor more often believes the market to be mean-reverting, and thus more often uses model 1 to forecast future earnings.\textsuperscript{260} Since the investor on average believes in model 1, the investor expects a positive earnings shock to be partly reversed in the next period. Hence, a negative shock in the next period will cause an insignificant stock return, since this was exactly what the investor expected. If, however, the shock is positive, the stock return will be large and positive, since the investor is taken by surprise.\textsuperscript{261} The average return after a positive earnings shock is therefore positive; just as the average return after a negative earnings shock is negative; both consistent with the empirically observed post-earnings drift and the medium term momentum effect.\textsuperscript{262}

As stated, the Model of Investor Sentiment is developed to account for long term mean reversion as well. This requires the investor to use model 2 to forecast future earnings, which happens after a series of earnings shocks with the same sign; either positive or negative. Thus, in addition to the above, the model shows that after a series of positive earnings shocks the average return is negative, whereas after a series of negative earnings shocks the average return is positive; consistent with the long term reversal effect.\textsuperscript{263}

### 6.3.1.3. The Gradual Information Diffusion Model

In 1999, Hong and Stein propose a model which, in contrast to the model by Barberis, Shleifer, and Vishny (1998), does not rely on any cognitive biases on part of the investors, but instead emphasises the interaction between different investor types.

The model, most often referred to as the Gradual Information Diffusion Model, includes two groups of boundedly rational investors; news watchers and momentum traders. The investors are boundedly rational, since each type of investor is only able to process some subset of the available public information. Specifically, the news-watchers make forecasts solitarily based on signals which they privately observe about future fundamentals, whereas momentum traders base their trading decisions on past price changes only.\textsuperscript{264}

\textsuperscript{259} Barberis et al. (1998) p. 320
\textsuperscript{260} The parameters $\lambda_1$ and $\lambda_2$ determine the probabilities of transition from one state to another. Since transition is believed to take place rarely, it is assumed that $\lambda_1 + \lambda_2 < 1$. Also it is assumed that $\lambda_1 < \lambda_2$. Since the unconditional probability of being in state 1 is $\lambda_2/(\lambda_1 + \lambda_2)$, this implies that the investor, on average, thinks of model 1 as being more likely than model 2; Barberis et al. (1998) p. 324.
\textsuperscript{261} Barberis et al. (1998) p. 322
\textsuperscript{262} Barberis et al. (1998) p. 322
\textsuperscript{263} Barberis et al. (1998) pp. 321-322
\textsuperscript{264} Hong and Stein (1999) p. 2145
One essential assumption in the model is that the private information diffuses gradually across the news-watcher population, making prices adjust only slowly. The slow adjustment means that prices initially underreact to new information and that momentum traders as a consequence can profit from subsequent trend-chasing.\textsuperscript{265} It is this trend-chasing, caused by the initial underreaction, which is thought to explain the momentum in stock prices. It follows that the first momentum traders entering the market will have a correcting effect on stock prices, as they push prices in the direction of equilibrium. However, since the momentum traders only observe past price movements, but not fundamental news, new momentum traders entering the market are likely to respond, not to the initial, and insufficient, price movement created by the news-watchers, but to price movements created by the early momentum traders. Thus, the effect of the momentum traders will eventually be to create an overreaction in stock prices\textsuperscript{266}, why both the medium term momentum effect and the long term reversal effect are explained by the model.

### 6.3.1.4. The Disposition Model

Grinblatt and Han (2002) suggest a model, which explains the momentum effect based on what Shefrin and Statman (1985) have termed the disposition effect; in short stating that investors are predisposed to selling winning stocks too early, while holding on to losing stocks for too long.\textsuperscript{267} The disposition effect is closely related to the previously described prospect theory, where investors are thought to possess concave risk-averse utility functions in the region of gains, but convex risk-seeking utility functions in the region of losses; graphically illustrated as the s-shaped value function.\textsuperscript{268} The model, which is here referred to as the Disposition Model, includes two types of investors; rational investors and disposition investors. What Grinblatt and Han argue is that if too many investors fall prey to the disposition bias, this will eventually lead to momentum in stock prices.

The model sets out by assuming that the fundamental value of a stock either increases or decreases due to some good or bad news about the company. If the stock price rises, based on good news, the disposition investors sell the stock quickly to capture the gain before the price may fall. If the stock price falls, based on bad news, the disposition investors hold on to the

\textsuperscript{265} Hong and Stein (1999) p. 2143
\textsuperscript{266} Hong and Stein (1999) p. 2145
\textsuperscript{267} Shefrin (2000) p. 8
\textsuperscript{268} Kahneman and Tversky (1979) p. 279
losing stock, hoping that the price may rise at a later point.\textsuperscript{269} Consequently, the price never rises or falls enough to account for the fundamental good or bad news about the company; there is an underreaction in the stock price.\textsuperscript{270} This underreaction on its own does, however, not explain the momentum effect. The momentum effect arises as the rational investors realise that the stock has not risen or fallen as much as it should, meaning that there is a gap between the stock’s fundamental value (i.e. the stock price that would exist in the absence of the disposition effect) and its current market price.\textsuperscript{271} If the gap is positive (fundamental value > market price), the rational investors find the stock to be undervalued and start buying the stock, thereby creating an upward momentum in the stock price. Similarly, if the gap is negative (fundamental value < market price), the rational investors find the stock to be overvalued and start short-selling the stock (expecting to buy it back later at a lower price), thereby creating a downward momentum in the stock price.\textsuperscript{272} It follows that stocks with past price run-ups and stocks on which most investors have experienced capital gains will have higher expected returns than those that have experienced large declines and capital losses.\textsuperscript{273} As illustrated, the model by Grinblatt and Han explains the momentum effect in terms of underreaction caused by disposition investors and following gap convergence initiated by rational investors. The model does not account for long term reversals in stock prices.

\textbf{6.3.2. Momentum Caused by Overreaction}

Instead of explaining the momentum effect in terms of underreaction and a following adjustment of prices, some have suggested that the momentum effect should be explained by overreaction.

Originally, overreaction is used to account for long term mean reversion in markets. As previously stated, De Bondt and Thaler (1985) document the existence of a long term reversal effect, whereby past losers tend to outperform past winners over horizons of 3 to 5 years. According to De Bondt and Thaler, the explanation for the observed mean reversion is that investors tend to overreact to information about company performance causing stocks to temporarily depart from their fundamental values. More precisely, De Bondt and Thaler apply Tversky and Kahneman’s (1972) notion of representativeness\textsuperscript{274} to market pricing and argue

\textsuperscript{269} Grinblatt and Han (2002) p.4
\textsuperscript{270} Grinblatt and Han (2002) p. 6
\textsuperscript{271} Grinblatt and Han (2002) p. 2
\textsuperscript{272} In general, it can be said that the sign of the current period’s spread between the fundamental value and the market price is the same as the sign of the expected future price change; Grinblatt and Han (2002) p. 10.
\textsuperscript{273} Grinblatt and Han (2002) p. 10
\textsuperscript{274} Apart from what has already been stated, a definition of the representativeness heuristic can be found in Appendix 9A.
that investors who rely on the representativeness heuristic become overly pessimistic about past losers and overly optimistic about past winners. As a consequence, losers become undervalued and winners become overvalued.\footnote{According to De Bondt and Thaler (1990), this extrapolation bias, caused by the representativeness heuristic, applies not only to investors but also to security analysts; De Bondt et al. (1999) p. 112.} The mispricings are, however, not permanent and will start correcting themselves so that eventually past losers outperform past winners.\footnote{Shefrin (2000) p. 34} Despite the fact that overreaction is originally used in connection with the long term reversal effect, a number of researchers have subsequently developed models in which overreaction explains medium term momentum as well. Two of these models are presented below.

### 6.3.2.1. The Positive Feedback Trader Model

In general, the presence of rational investors is thought to have a stabilising effect on prices. For example, proponents of traditional finance theory argue that rational investors immediately explore possible mispricings in the market, thereby ensuring that securities always carry their fundamental values. In the light of noise trader risk, proponents of behavioural finance, however, argue that rational traders might be reluctant to exploit such mispricings in case they are risk-averse and have short investment horizons. De Long, Shleifer, Summers, and Waldmann (1990) take it one step further. They argue that in case positive feedback traders (i.e. investors that buy securities when prices rise and sell when prices fall) are prevalent in the market, rational investors might choose to take advantage of these traders’ actions, thereby worsening the mispricing created by the positive feedback traders in the first place. De Long et al. thus refer to rational speculators, as opposed to rational investors, and argue that in the presence of positive feedback traders, rational speculation can be destabilising.

The model by De Long et al., known as the Positive Feedback Trader Model, includes four periods: 0, 1, 2, and 3, where period 0 merely provides a benchmark against which the positive feedback traders can measure the appreciation or depreciation of stock prices from period 0 to periods 1 and 2.\footnote{De Long et al. (1990a) p. 387}

In period 1, the rational speculators receive a signal about period 2 fundamental news. If the fundamental news is expected to be positive they buy, if it is expected to be negative they sell. In addition to trading for fundamental reasons, the rational speculators realise that the price increase or decrease from period 0 to 1, caused by their initial trading, will stimulate the positive feedback traders to, respectively, buy or sell in period 2. In anticipation of these
trades, the rational speculators trade more in period 1 than they otherwise would have, and so drive prices up or down more than the fundamental news justifies. Positive feedback traders do not trade in period 1 since they react to past price movements only.\textsuperscript{278}

In period 2, the positive feedback traders’ demand responds to the price change between period 0 and 1; if the price has risen they buy, if the price has fallen they sell.\textsuperscript{279} Hence, the positive feedback traders create a drift in stock prices; that is either upward or downward momentum. Since the rational speculators at this point have received the fundamental news and therefore know the expected period 3 value of the stock, no rational investor would follow a positive feedback trader strategy. They realise that the stock in period 2 is either overvalued or undervalued, and thus start betting on reversion to fundamentals. If they have bought in period 1, they sell, if they have sold in period 1, they buy.\textsuperscript{280}

In period 3 no trading occurs. Investors pay each other according to the positions they hold.\textsuperscript{281}

According to De Long et al. the Positive Feedback Trader Model, explaining both medium term momentum and long term reversal in stock prices, is partly influenced by George Soros’ description of his own investment strategy, in which he states that his success comes from betting not on fundamentals but on future herd behaviour.\textsuperscript{282} De Long et al., however, argue that the observed pattern of positive autocorrelation at medium horizons and negative autocorrelation at long horizons can also be obtained without anticipatory trading by rational speculators.\textsuperscript{283} In this case, it is herd behaviour and psychological biases, such as the representativeness heuristic, among the positive feedback traders alone that cause prices to overreact and eventually revert back to fundamentals.\textsuperscript{284}

6.3.2.2. The Overconfidence Hypothesis

In an article from 1998, Daniel, Hirshleifer and Subrahmanyam suggest that the momentum effect, as well as the long term reversal effect, can be explained in terms of market under- and overreactions caused by the two psychological biases; investor overconfidence and self-attribution.\textsuperscript{285} In short, overconfidence refers to the tendency of individuals to overestimate their own abilities in various contexts; so, for example, an overconfident investor will tend to

\textsuperscript{278} De Long et al. (1990a) p. 387
\textsuperscript{279} De Long et al. (1990a) p. 385
\textsuperscript{280} De Long et al. (1990a) p. 391
\textsuperscript{281} De Long et al. (1990a) p. 384
\textsuperscript{282} De Long et al. (1990a) p. 380
\textsuperscript{283} De Long et al. (1990a) p. 391
\textsuperscript{284} Apart from what has already been stated, definitions of herd behaviour and the representativeness heuristic can be found in Appendix 9I and 9A, respectively.
\textsuperscript{285} In addition to the below, definitions of overconfidence and the self-attribution bias can be found in Appendix 9E and 9F, respectively.
overestimate the precision of own value estimates of companies.\textsuperscript{286} According to Daniel et al., investors are especially likely to be overconfident about signals or assessments with which they have greater personal involvement. Thus, Daniel et al. define an overconfident investor as one who overestimates the precision of private information signals, but not of information signals publicly received by all. This, in turn, leads to overreaction on private signals but underreaction on public signals.\textsuperscript{287} The evidence regarding the self-attribution bias suggests that people tend to credit themselves for past success, while blaming external factors for past failure.\textsuperscript{288} As a consequence, the self-attribution bias has a tendency to reinforce overconfidence.\textsuperscript{289}

The model proposed by Daniel et al., here referred to as the Overconfidence Hypothesis, is most easily explained by a graphic illustration:

![Average Price as a Function of Time with Overconfident Investors](image)

The illustration shows the average price as a function of time with (dashed lines) and without (solid lines) self-attribution bias. The black lines represent the fully rational price level.

Focusing on the solid blue lines, the figure illustrates the average price path following a positive (upper blue line) or negative (lower blue line) private signal to the investors at date 1. In short, overconfidence in the date 1 private signal causes the stock price to overreact to the new information, at date 2, when public information signals arrive, the inefficient deviation of the price is partially corrected, and at date 3, when conclusive public information arrives, the

\textsuperscript{286} Daniel et al. (1998) p. 1841
\textsuperscript{287} Daniel et al. (1998) p. 1841
\textsuperscript{288} Daniel et al. (1998) p. 1845
\textsuperscript{289} Daniel et al. (1998) p. 1856
price move to the security’s fundamental value. The solid blue lines thus illustrate how overconfident investors generate long term mean reversion in stock prices. To see how the model explains medium term momentum, the self-attribution bias must be included.

With the inclusion of the self-attribution bias, the confidence level is no longer fixed but dependent on outcomes and subsequent public signals. More precisely, the self-attribution bias has the effect that the confidence level of an investor rises if subsequent public information confirms the previous private signal, and thereby the trade made by the investor, but falls only modestly if public information disconfirms the private signal. This implies that, with the inclusion of the self-attribution bias, on average, public information increases investor overconfidence, thereby intensifying overreaction. This intensified overreaction leads to positive autocorrelation during the initial overreaction phase (the blue dashed line between date 1 and 2). The model by Daniel et al. thus suggests that momentum in stock prices occurs since investors initially overreact to private signals, and since subsequent public information triggers further overreaction to the initial private signal. As without the self-attribution bias, the continuous arrival of further public information gradually moves prices back toward fundamentals (the blue dashed line between date 2 and 3).

6.4. Evaluation of Momentum Explanations

As illustrated above, there are many different opinions as to what causes the empirically observed momentum effect. The explanations based on data snooping and flawed methodology overall appear unfounded due to the many empirical studies across different markets and time periods documenting the momentum effect. These explanations are therefore disregarded in the below. Also the risk-based explanations seem unable to account for the momentum effect. Nevertheless, whether or not risk can be a possible explanation is once again evaluated. Last, the models from behavioural finance seem to provide the most valid explanations; however, the behavioural models are many, and at a first glance no one model appear to be superior.

In order to distinguish between some of the above explanations, Jegadeesh and Titman (2001) investigate the returns of a 6-month/6-month momentum portfolio in the period from 1965 to 1998. In particular, they investigate the returns in the 60 months following the portfolio formation date, as the post-holding period returns are able to indicate which type of

290 Daniel et al. (1998) p. 1847
291 Daniel et al. (1998) p. 1856
292 Daniel et al. (1998) p. 1856
explanation seems most likely. It is argued that if risk is the correct explanation, what is expected to be found is that the momentum strategy continues to be profitable in the post-holding period.\textsuperscript{293} This is the case since, if the momentum effect can be explained by winners being more risky than losers, the momentum return is not abnormal but merely a compensation for risk, which is not assumed to decrease or disappear.\textsuperscript{294} Contrary, if momentum is caused by underreaction to new information (here referring to the models where no subsequent overreaction is predicted\textsuperscript{295}) it is expected that as soon as the stocks, winners and losers, have incorporated all information and reached their fundamental values, there will be no further predictability in stock returns. Thus, the return of the momentum portfolio in the post-holding period will be zero.\textsuperscript{296} Last, in order to find support for the models suggesting the momentum effect to be caused by overreaction\textsuperscript{297} (or the underreaction models which predict eventual overreaction\textsuperscript{298}), the momentum return in the post-holding period must be negative.\textsuperscript{299} This is so since overreaction, as previously stated, leads to long term reversal in stock prices, why the returns of losers must eventually exceed the returns of winners.

The implications of risk, underreaction and overreaction (or underreaction followed by overreaction) can be illustrated graphically as follows:

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{long_horizon_momentum_profits.png}
\caption{Long Horizon Momentum Profits under Different Hypotheses}
\end{figure}

\textsuperscript{293} Jegadeesh and Titman (2001) p. 701

\textsuperscript{294} The risk-based explanation tested by Jegadeesh and Titman (2001) is adopted from Conrad and Kaul (1998), who suggest that momentum profits are simply generated due to cross-sectional differences in expected returns. This explanation is consistent with an efficient market in which stocks have different expected rates of return because of different risk exposures; Chui et al. (2000) p. 12.

\textsuperscript{295} This is predicted by the researchers who suggest that price momentum is, at least partly, explained by earnings momentum and by Grinblatt and Han (\textit{The Disposition Model}).

\textsuperscript{296} Jegadeesh and Titman (2001) p. 708

\textsuperscript{297} This is predicted by De Long et al. (\textit{The Positive Feedback Trader Model}) and by Daniel et al. (\textit{The Overconfidence Hypothesis}).

\textsuperscript{298} This is predicted by Barberis et al. (\textit{A Model of Investor Sentiment}) and by Hong and Stein (\textit{The Gradual Information Diffusion Model}).

\textsuperscript{299} Jegadeesh and Titman (2001) p. 700
As can be seen from the graph, all the hypotheses imply momentum profits in the holding period. However, the post-holding performance of the momentum portfolios differs sharply, as explained above.

Consistent with their previous study from 1993, Jegadeesh and Titman (2001) find the momentum portfolio to yield significantly positive returns in the first 12 months following the formation date, leading to a cumulative return of 12.7% at the end of month 12. In addition, they find that the momentum returns in months 13 to 60 are, on average, negative, why the cumulative momentum return starts to decrease from month 13. In month 60, the cumulative return has declined to -0.44%.\footnote{Jegadeesh and Titman (2001) p. 711} That momentum returns are positive during the first 10 to 12 months but reverse and become negative over longer horizons are also found by Lee and Swaminathan (2000)\footnote{Lee and Swaminathan (2000) p. 2026} on the American market\footnote{Lee and Swaminathan (2000) find that the negative momentum returns are especially large and statistically significant in years 4 and 5 after portfolio formation.}, Rouwenhorst (1998)\footnote{Rouwenhorst (1998) p. 280} and Bird and Whitaker (2003)\footnote{Bird and Whitaker (2003) p. 237} on the European market, and Chui, Titman, and Wei (2000)\footnote{Chui et al. (2000) p. 13} on the Asian market. Furthermore, the eventual mean reversion is compatible with the long term reversal effect documented by De Bondt and Thaler (1985).

The negative post-holding period returns of the momentum portfolio once and for all seem to invalidate the risk-based explanations, which would require the momentum strategy to be continuously profitable. In addition, the negative returns lend less support to the behavioural models that do not predict eventual reversal in stock prices, while favouring the models that do. When investigating the two sub-periods 1965 to 1981 and 1982 to 1998, Jegadeesh and Titman, however, find that the reversal is much weaker in the second period, whereas the momentum returns appear to be of both equal magnitude and statistical significance.\footnote{Jegadeesh and Titman (2001) p. 701} This suggests that perhaps none of the behavioural models can be disregarded after all.

Looking at the behavioural models, they appear very different and seem extremely difficult to combine. Nonetheless, all the models have been documented and supported by subsequent evidence. One possible explanation for the difficulty in selecting one superior model could be that in fact all the models contribute to explaining the observed momentum effect, but that different models are superior in different situations.
As one might recall, the models incorporating one or two psychological biases incorporate biases that are indeed very different. Yet, all the biases appear to be very well documented. Instead of assuming that different investors suffer from different psychological biases, one could assume that investors suffer from different biases under different types of market conditions. For example, say that investors are, on average, more sceptical and conservative in nature throughout a bear market, but more overconfident or prone at following the market trend throughout a bull market. As seen from the behavioural models, conservatism tends to cause underreaction, whereas overconfidence and herding are more likely to cause overreaction. Thus, one possibility could be that models explaining the momentum effect in terms of underreaction are superior during bear markets, whereas models explaining the momentum effect in terms of overreaction are superior in bull markets.

An alternative suggestion might be that underreaction models are better at explaining momentum in losing stocks, whereas overreaction models are better at explaining momentum in winning stocks. For example, it is found that analysts especially underreact when it comes to making forecasts for losing stocks, why underreaction to earnings announcements appears to be a better explanation for the momentum effect for this type of stocks. Also, evidence suggests that the *Gradual Information Diffusion Model*, again using underreaction to account for the momentum effect, is a better model for losing stocks. To see this, one must look at the alternative prediction of the model, namely that momentum should be more pronounced in stocks with slow information diffusion. In 2000, Hong, Lim, and Stein use firm size and analyst coverage as proxies for the rate of information diffusion, where information is expected to diffuse more slowly in small stocks and stocks with low analyst coverage. Consistent with the model by Hong and Stein (1999), they do find momentum to be stronger in small stocks and stocks with low analyst coverage, and in addition, they find the effect of analyst coverage to be greater for past losers than for past winners. More generally, the idea that bad news diffuses more slowly seems like a reasonable assumption as companies themselves must be expected to contribute more to the spreading of good news. In the *Model of Investor Sentiment* the momentum effect is thought to be caused by the representative investor making forecasts that are too conservative. Since it is empirically documented that analysts mainly suffer from the conservatism bias when making forecasts for companies with poor performance, it does not seem like a preposterous assumption that this is also the case for investors. As a consequence, also this model appears to be a better explanation for

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307 Chui et al. (2000) p. 17
momentum in losing stocks. The last model to explain the momentum effect in terms of underreaction is the *Disposition Model.* This model is based on the disposition effect stating that investors are predisposed to holding on to losing stocks for too long, while selling winning stocks too early. Although both behaviours have been documented, the latter tendency seems very much at stake with the almost greedy behaviour investors often appear to have in winning situations. It is therefore tempting to assume that at least this tendency must be less pronounced than the prior, why this model too could seem more attractive for losers than for winners.

In contrast to the underreaction models, the *Overconfidence Hypothesis* is presumably better at explaining momentum in winning stocks. For example, Darke and Freedman (1997) find that lucky events lead to overconfidence\(^{308}\), and Chuang and Lee (2006) find that market gains make overconfident investors trade more aggressively in the subsequent periods. Hence, it seems sensible to assume that a model explaining the momentum effect in terms of overconfidence and the self-attribution bias best explains momentum in winners. In general, it is found that winning situations make people trade more.\(^{309}\) Since the *Positive Feedback Trader Model* requires trading activity by many investors, also this model appears more likely to explain momentum in winning stocks. This assumption is supported by Jegadeesh and Titman (2001), who find their evidence to be inconsistent with the idea that the momentum in losers is generated by positive feedback trading.\(^{310}\)

The suggestion that different models are superior in different markets or different types of stocks is not empirically proven. However, as already stated, the behavioural models are all documented and subsequently supported, and disagreement as to which model is superior does exist. Thus, the intention with the suggestion is to at least bring forward the possibility, perhaps for further investigation in the future. Looking forward, the true goal of behavioural finance should, however, not be to clarify which of the above models best explains the momentum effect. Rather it should be to develop a pricing model, which is able to price all types of stocks and to account for all the observed anomalies in the market. Only when such a model is developed, behavioural finance can be expected to fully replace the traditional finance theory in practice. In the meantime, behavioural finance should be viewed as a useful tool to increase the understanding of the financial market and the various phenomena with it.

\(^{308}\) Sornette (2003) p. 107

\(^{309}\) Ritter (2003) p. 5

\(^{310}\) Jegadeesh and Titman (2001) p. 716
7. Conclusion

At the outset the purpose of the thesis was divided into three main areas. In particular, the purpose was to clarify what has already been documented on momentum strategies, to test whether the momentum effect has existed on the Danish stock market in more recent times, and to present and evaluate possible explanations for the momentum phenomenon.

The momentum effect is first documented by Jegadeesh and Titman (1993) on the American market during the period from 1965 to 1989, but has subsequently been documented by numerous other researchers across different geographical markets and time periods. The momentum return appears to be around 1% per month, and the momentum strategies show profitable even after accounting for risk and transaction costs. In general, strategies with long formation periods of 9 to 12 months and short holding periods of 3 to 6 months are found to generate the largest momentum returns. Nevertheless, all strategies, regardless of the formation and the holding periods show able to provide significantly positive returns.

The momentum effect does not seem to be confined to any particular types of stocks or any sub-periods. However, the returns are, on average, found to be somewhat larger in small cap stocks, low book-to-market value stocks and high volume stocks. In terms of markets, the profitability of the strategies is found to be more pronounced in developed markets, than in emerging and Asian markets. Still, the momentum effect is present across all markets and is therefore considered a worldwide phenomenon.

Finally, different researchers have investigated the persistence of the momentum effect and find the positive momentum returns to last for about 12 months. In years 2 and 3, the returns become slightly negative and in years 4 and 5 a significant pattern of mean reversion appears. In fact, the cumulative momentum return after year 5 is found to be just slightly above zero; consistent with the studies documenting long term mean reversion in stock prices.

Having clarified what has so far been found concerning price momentum strategies, the thesis turns to the empirical analysis of the Danish stock market.

The sample period for the empirical analysis runs from 1996 through 2009, and the sample consists of 108 stocks from the KAX Index. The methodology used to test the momentum effect is the equally-weighted quintile strategy with full rebalancing.

The results from the overall test of momentum, testing 16 different momentum strategies, suggest that the momentum effect has indeed existed on the Danish stock market over the period from 1996 through 2009. The returns from all 16 strategies are found to be positive
and statistically significant at least the 10% level. The average monthly momentum returns range from 0.61% to 1.55%, where the 12-month/3-month strategy is found to be the most profitable. As in previously conducted studies, strategies with long formation periods and short holding periods generally turn out to be the most successful. The momentum strategies show able to outperform the winner portfolios on their own, indicating that both winner and loser portfolios contribute to the momentum returns, and the index portfolio.

The two-dimensional robustness tests show that the momentum strategies are, in general, robust across different types of stocks, when examined within size-based and value-based subsamples. The magnitude of the returns, however, varies from 0.97% to 1.46% in the size-based samples and from 0.58% to 1.07% in the value-based samples. In particular, momentum is found to be strongest in mid cap stocks followed by small cap and large cap stocks, and to be monotonically increasing with the book-to-market values of stocks. This latter finding, however, contradicts previous studies, which, in general, find low book-to-market value stocks to generate the largest momentum returns. From investigating the volume-based subsamples it is found that momentum is by far strongest in high volume stocks; with returns ranging from 0.23% to 1.95%. This result is consistent with most other studies of the momentum effect, but at stake with the conventional theory stating that the most actively traded stocks should be better arbitrated and thus more rationally priced. In general, the returns from all subsamples are found to be positive, and in most cases statistically significant, why the momentum effect does not seem to be confined to particular types of stocks. In addition, the results from the two-dimensional tests indicate that neither size nor book-to-market values, being the two most important risk measures identified by Fama and French (1993), are able to account for the observed return pattern.

The results from the sub-period analysis suggest that the profitability of the momentum strategies is, at least somewhat, influenced by the selected sample period. In particular, it is found that the strategies tend to perform better under more stable, as opposed to more volatile, market conditions. The performance of the strategies is found to be especially weak during market reversals, whereas the strategies seem able to provide significantly positive returns during both strong bull and bear markets.

Finally, the empirical results show that the momentum strategies are able to generate significantly positive returns even after accounting for transaction costs. The fact that short-selling in practice appears to be limited to the large cap, and to some extent the mid cap, segment, however, suggests that investors are unlikely to obtain the full benefits from the investigated momentum strategies, as the strongest momentum is found in the mid cap,
followed by the small cap, sample. Nevertheless, since significantly positive returns are found in all size subsamples, and since all types of stocks can be included in the winner portfolios, the short-selling limitation is assumed to decrease but not erase the documented profitability.

Evidently, a significant number of researchers subscribe to the view that momentum strategies yield significant profits in the intermediate horizon. However, the source of the profits is widely debated. It appears that most researchers initially try to explain the momentum effect in terms of the three risk measures identified by Fama and French (1993), but fail to do so. In fact, correcting for beta, size, and book-to-market values is often found to increase the momentum returns. In the absence of a risk-related explanation, it is suggested that the momentum effect could simply be a result of data snooping and flawed methodology. However, the many studies documenting the momentum effect across different geographical markets and time periods seem to render this explanation invalid. Last, some researchers have turned to behavioural finance to explain the momentum effect. According to these researchers the phenomenon is essentially caused by various psychological biases or by interaction between different investor types. For example, researchers have explained the momentum effect in terms of: a) underreaction to earnings announcements, possibly due to a conservatism bias on part of investors and analysts, b) slow information diffusion and subsequent trend-chasing, c) a disposition bias leading to underreaction and following correction, d) speculation in trends created by less informed investors, and e) overconfidence together with a reinforcing self-attribution bias leading to sustained overreaction in stock prices. The models from behavioural finance seem to provide the best explanations of the momentum phenomenon, but the models are many and no single model appears to be superior. In fact, all the models are very well documented and subsequently supported by other studies. One explanation for the difficulties in finding one superior model could be that all the models individually contribute to explaining the momentum effect, but that different models are better at explaining momentum in different markets or different types of stocks. This latter suggestion is, however, not empirically documented, why further research is needed to clarify the matter.
8. References

8.1. Articles

8.2. Books


8.3. Web Pages

- www.danskebank.dk
- www.nordea.dk
- www.nordnet.dk
- www.nationalbanken.dk
- www.valueline.com

8.4. Contact Persons

- Tine Choi Ladefoed, Senior Strategist, Strategic Investment Advice, Nordea Savings & Asset Management.
- Michael Højer Jørgensen, Senior Sales Manager, Equity Sales DK, Nordea Markets.
9. Appendices

9.1. Appendix 1 – CAPM Assumptions

The assumptions behind the standard Capital Asset Pricing Model are as follows:311:

1. No transaction costs.
2. Assets are infinitely divisible.
3. No personal income tax.
4. An individual cannot affect the price of a stock by his/her buying or selling action. This is analogous to the assumption of perfect competition.
5. Investors are expected to make decisions solely in terms of expected values and standard deviations of the returns of their portfolios.
6. Unlimited short sales possibilities.
7. Unlimited lending and borrowing at the riskless rate.
8. Investors are concerned with the mean and variance of returns over a single period, and all investors define the relevant period in exactly the same manner.
9. All investors have identical expectations with respect to the necessary inputs to the portfolio decision. The inputs are expected returns, the variance of returns, and the correlation matrix representing the correlation structure between all pairs of stocks.
10. All assets are marketable.

9.2. Appendix 2 – Psychological Biases and Decision-Making Errors

The following defines some of the most often used psychological biases and decision-making errors in behavioural finance. It is these biases and errors, which, according to behavioural finance, lead to the irrational behaviour of investors.

A: Representativeness Heuristic

The representativeness heuristic, proposed by Kahneman and Tversky (1974), refers to judgement based on stereotypes.312 For example, in assessing the probability that object A belongs to class B, people tend to rely on the degree to which A resembles, or is representative of, B. In a financial context, one possible manifestation of the representativeness heuristic is that people often seem to find patterns in sequences that are in

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312 Shefrin (2000) p. 14
fact random\textsuperscript{313}, so that, for example, a small increase in stock prices is likely to be compared with previous bull markets. Prior probabilities have no effect on the representativeness heuristic, which moreover fails to understand the statistical element of regression towards the mean.\textsuperscript{314} The representativeness heuristic can also be explained in terms of size neglect, whereby people infer too much on the basis of too little information.\textsuperscript{315} Thus, representativeness may lead security analysts and investors to over weight the significance of recent company performance without taking long term average performance into account.\textsuperscript{316}

\textbf{B: Availability Heuristic}

The availability heuristic is used for estimating the probability of an event, where people often seem to make the decision based on the degree to which information is readily available.\textsuperscript{317} Naturally, if not all relevant information is included in the decision-making process, suboptimal decisions are likely to be made.

\textbf{C: Anchoring and Adjustment Heuristic}

The anchoring and adjustment heuristic sets out to explain how first impressions affect the decision-making of individuals. For example, a common way for investors to make estimates is to start from an initial value and then make adjustments to yield a final conclusion. Making adjustments to an initial value will, however, result in an estimate that is biased towards the initial value.\textsuperscript{318}

\textbf{D: Conservatism}

Several psychologists, including Edwards (1968), have identified the phenomenon known as conservatism. The conservatism bias is strongly related to the anchoring and adjustment heuristic above, as it suggests that individuals underweight new information in updating their priors. Conservatism thus describes the situation where individuals are slow to change their beliefs in the face of new information.\textsuperscript{319} On the financial market, the conservatism bias will cause prices to react only gradually to new information.

\textsuperscript{313} Barberis et al. (1998) p. 316
\textsuperscript{314} Shefrin (2000) p. 16
\textsuperscript{315} Barberis and Thaler (2003) p. 1065
\textsuperscript{316} Shefrin (2000) p. 16
\textsuperscript{317} Shefrin (2000) p. 14
\textsuperscript{318} Barberis and Thaler (2003) p. 1066
\textsuperscript{319} Barberis et al. (1998) p. 315
E: Overconfidence

The idea of investor overconfidence is derived from a large body of evidence from cognitive psychological experiments, showing that individuals overestimate their own abilities in various contexts.\footnote{Daniel et al. (1998) p. 1841} Einhorn (1980) finds people to be especially overconfident in relation to diffuse problems with moderate to extreme difficulty, tasks which require a large degree of judgement, and situations where the final result has low predictability and where feedback of a given action is slow and unclear.\footnote{Daniel et al. (1998) p. 1844} In a financial context, overconfident investors will tend to overestimate the precision of their own value estimates of companies and will, as a consequence, make insufficient analyses and suboptimal decisions.\footnote{Tvede (2007) p. 129} It is, furthermore, found that overconfident investors tend to trade more frequently than is prudent, leading to excessive trading volume.\footnote{Shefrin (2000) p. 41} In 1997, Dark and Freedman find that especially lucky events leads to overconfidence, and so overconfidence is likely to be more severe in bull markets.\footnote{Sornette (2003) p. 107}

F: Self-Attribution Bias

The self-attribution bias refers to the psychological evidence indicating that people tend to credit themselves for past success, while blaming external factors for past failure.\footnote{Daniel et al. (1998) p. 1842} For example, Bem (1965) finds that individuals too strongly attribute events that confirm the validity of their actions to high ability, and events that disconfirm the actions to external noise or sabotage.\footnote{Sornette (2003) p. 107} The self-attribution bias relates to the notion of cognitive dissonance, and has a tendency to reinforce the above overconfidence bias.\footnote{Tvede (2007) p. 130}

G: Cognitive Dissonance Theory

According to the cognitive dissonance theory, first presented by Festiger in 1957, people tend to disregard new information that contradicts actions already made. The cognitive dissonance theory is closely linked to the notion of selective exposure, whereby people try to expose themselves only to information that confirms existing beliefs.\footnote{Tvede (2007) p. 130} In the financial market, cognitive dissonance theory and selective exposure can lead to trending stock prices in that
investors are found to pay more attention to analysts and economists speaking in favour of the existing market trend and thereby the most commonly held beliefs.\textsuperscript{329}

**II: Frame Dependence**

Frame dependence, documented by Kahneman and Tversky (1979), refers to the tendency of people to evaluate things according to how they are framed, instead of making independent and objective analyses from scratch.\textsuperscript{330} In general, peoples’ frames tend to be based on information about what other people think\textsuperscript{331}, and hence investors’ frames tend to be based in large part on analysts’ opinions and existing market trends.\textsuperscript{332}

**III: Herd Behaviour**

Herd behaviour is the concept whereby people imitate the behaviour of others and thus act as a group as opposed to independent individuals. The herd behaviour is found to be especially strong when information is limited and when complexity is high.\textsuperscript{333} This is in accordance with the concept of social comparison, stating that people use the behaviour of others as a source of information about issues they find difficult to understand.\textsuperscript{334} Shiller (2000) is one of the many researchers having documented herding in the financial market. He finds that herd behaviour among investors often arises from an information cascade; a situation where individuals, based on observations of others, make the same decision regardless of their own private signal in the believe that others know better.\textsuperscript{335} Herd behaviour in the financial market will often take form of investors trading according to the current market trend, since asset prices are the best indicators of what other people think.
9.3. Appendix 3 - Bloomberg Definitions

The following provides the Bloomberg definitions of the four different variables used in the empirical analysis. Since data is collected on a monthly basis, closing prices, market capitalisations, and price-to-book ratios are obtained based on values from the last day of the month. Withdrawing the volume on a monthly basis, however, returns the sum of all shares traded in a given month.

**Historical Last Price (PX_LAST)**

PX_LAST returns the last price provided by the exchange.

**Historical Current Market Cap (CUR_MKT_CAP)**

CUR_MKT_CAP is the current monetary value of all outstanding shares. The market capitalisation is a measure of corporate size, and will be returned in the pricing currency of the security. The current market capitalisation is calculated as:

\[
\text{Current Market Capitalisation} = \text{Current Shares Outstanding} \times \text{Last Price}
\]

**Historical Price to Book Ratio (PX_TO_BOOK_RATIO)**

PX_TO_BOOK_RATIO is the ratio of the stock price to the book value per share. The price-to-book ratio is calculated as:

\[
\text{Price-to-Book Ratio} = \frac{\text{Last Price}}{\text{Book Value per Share}}
\]

Data from the most recent reporting period (quarterly, semi-annual or annual) is used in the calculation.

**Historical Volume (PX_VOLUME)**

PX_VOLUME returns the total number of shares traded on a security on the current day. If the security has not traded, then it is the total number of shares from the last day the security traded.
9.4. Appendix 4 – Selected Companies

The below table shows the 108 companies selected for the empirical analysis of the Danish stock market:

<table>
<thead>
<tr>
<th>Company List</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Aalborg Boldspilklub</td>
</tr>
<tr>
<td>2 Affitech</td>
</tr>
<tr>
<td>3 Alm. Brand</td>
</tr>
<tr>
<td>4 Amagerbanken</td>
</tr>
<tr>
<td>5 Ambu B</td>
</tr>
<tr>
<td>6 Andersen &amp; Martini B</td>
</tr>
<tr>
<td>7 A.P. Møller - Mærsk B</td>
</tr>
<tr>
<td>8 Arkil Holding B</td>
</tr>
<tr>
<td>9 Auriga Industries B</td>
</tr>
<tr>
<td>10 Bang &amp; Olufsen B</td>
</tr>
<tr>
<td>11 Bavarian Nordic</td>
</tr>
<tr>
<td>12 BioPorto</td>
</tr>
<tr>
<td>13 Brdr. Klee B</td>
</tr>
<tr>
<td>14 Brdr. Hartmann B</td>
</tr>
<tr>
<td>15 Capinordic</td>
</tr>
<tr>
<td>16 Carlsberg B</td>
</tr>
<tr>
<td>17 Coloplast B</td>
</tr>
<tr>
<td>18 Columbus IT Partner</td>
</tr>
<tr>
<td>19 Dan-Ejendomme Holding</td>
</tr>
<tr>
<td>20 Danionics</td>
</tr>
<tr>
<td>21 Danisco</td>
</tr>
<tr>
<td>22 Danske Bank</td>
</tr>
<tr>
<td>23 Dantherm</td>
</tr>
<tr>
<td>24 DanTruck</td>
</tr>
<tr>
<td>25 DFDS</td>
</tr>
<tr>
<td>26 DiBa Bank</td>
</tr>
<tr>
<td>27 Djurslands Bank</td>
</tr>
<tr>
<td>28 DLH B</td>
</tr>
<tr>
<td>29 D/S Norden</td>
</tr>
<tr>
<td>30 DSV</td>
</tr>
<tr>
<td>31 East Asiatic Co Ltd</td>
</tr>
<tr>
<td>32 Egetæpper B</td>
</tr>
<tr>
<td>33 Eitzen Bulk Shipping</td>
</tr>
<tr>
<td>34 F.E. Bording B</td>
</tr>
<tr>
<td>35 FLSmith &amp; Co.</td>
</tr>
<tr>
<td>36 Flügger B</td>
</tr>
<tr>
<td>73 PARKEN Sport &amp; Entertainment</td>
</tr>
<tr>
<td>75 Rias B</td>
</tr>
<tr>
<td>77 Roblon B</td>
</tr>
<tr>
<td>79 Royal UNIBREW</td>
</tr>
<tr>
<td>81 Sanistål B</td>
</tr>
<tr>
<td>83 SimCorp</td>
</tr>
<tr>
<td>85 Skjern Bank</td>
</tr>
<tr>
<td>87 Solar B</td>
</tr>
<tr>
<td>89 Sparbank</td>
</tr>
<tr>
<td>91 Sydbank</td>
</tr>
<tr>
<td>93 TDC</td>
</tr>
<tr>
<td>95 Topdanmark</td>
</tr>
<tr>
<td>97 Torm</td>
</tr>
<tr>
<td>99 Tender Bank</td>
</tr>
<tr>
<td>101 Vestas Wind Systems</td>
</tr>
<tr>
<td>103 Vestjysk Bank</td>
</tr>
<tr>
<td>105 Vordingborg Bank</td>
</tr>
<tr>
<td>107 Østjylland Bank</td>
</tr>
</tbody>
</table>
9.5. Appendix 5 – Annualised Momentum Returns

The following tables show the annualised momentum returns from various tests in the empirical part of the thesis. The annualised returns are calculated in Excel as:

\[ \text{Annualised Return} = \text{POWER} \left( 1 + \text{Average Monthly Momentum Return} ; \frac{12}{1} \right) - 1 \]

### A: Overall Tests of Momentum

<table>
<thead>
<tr>
<th>Holding Period</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Zero-Cost</strong></td>
<td>15.12%***</td>
<td>13.76%**</td>
<td>14.84%**</td>
<td>14.03%**</td>
</tr>
<tr>
<td></td>
<td>(2.640)</td>
<td>(2.213)</td>
<td>(2.381)</td>
<td>(1.840)</td>
</tr>
<tr>
<td><strong>Zero-Cost</strong></td>
<td>13.89%**</td>
<td>11.48%**</td>
<td>10.82%**</td>
<td>9.77%*</td>
</tr>
<tr>
<td></td>
<td>(2.266)</td>
<td>(2.165)</td>
<td>(2.157)</td>
<td>(1.674)</td>
</tr>
<tr>
<td><strong>Zero-Cost</strong></td>
<td>13.62%**</td>
<td>18.30%***</td>
<td>10.03%**</td>
<td>7.57%*</td>
</tr>
<tr>
<td></td>
<td>(1.950)</td>
<td>(3.092)</td>
<td>(1.780)</td>
<td>(1.379)</td>
</tr>
<tr>
<td><strong>Zero-Cost</strong></td>
<td>20.27%***</td>
<td>20.13%***</td>
<td>11.22%**</td>
<td>10.56%*</td>
</tr>
<tr>
<td></td>
<td>(2.768)</td>
<td>(3.113)</td>
<td>(1.825)</td>
<td>(1.410)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

### B: Size-Based Subsamples

<table>
<thead>
<tr>
<th>Size-Based Subsamples (Annualised)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small Cap</td>
</tr>
<tr>
<td>Zero-Cost</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

### C: Value-Based Subsamples

<table>
<thead>
<tr>
<th>Value-Based Subsamples (Annualised)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Book-to-Market</td>
</tr>
<tr>
<td>Zero-Cost</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

### D: Volume-Based Subsamples

<table>
<thead>
<tr>
<th>Volume-Based Subsamples (Annualised)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Volume</td>
</tr>
<tr>
<td>Zero-Cost</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.
### E: Sub-Period Analysis – Two Periods

**Sub-Period Analysis (Annualised)**

<table>
<thead>
<tr>
<th>Zero-Cost</th>
<th>1/7-96 to 31/12-02</th>
<th>1/1-03 to 31/12-09</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>15,94%**</td>
<td>7,31%</td>
</tr>
<tr>
<td></td>
<td>(2,636)</td>
<td>(0,884)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

### F: Sub-Period Analysis – Bull Market, Bear Market, and Mean Reversion

**Sub-Period Analysis (Annualised)**

<table>
<thead>
<tr>
<th>Bull Market</th>
<th>Bear Market</th>
<th>Mean Reversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-Cost</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>20,41%*</td>
<td>24,02%*</td>
</tr>
<tr>
<td></td>
<td>(1,827)</td>
<td>(2,368)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

### G: Momentum Strategies excluding and Including Transaction Costs

**Momentum Strategies excl. and incl. Transaction Costs (Annualised)**

<table>
<thead>
<tr>
<th>3-month/3-month</th>
<th>6-month/6-month</th>
<th>9-month/9-month</th>
<th>12-month/12-month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-Cost (excl. TC)</td>
<td>15,12%***</td>
<td>11,48%**</td>
<td>10,03%**</td>
</tr>
<tr>
<td>(2,640)</td>
<td>(2,165)</td>
<td>(1,780)</td>
<td>(1,410)</td>
</tr>
<tr>
<td>Zero-Cost (incl. TC)</td>
<td>13,22%**</td>
<td>10,03%**</td>
<td>8,86%*</td>
</tr>
<tr>
<td>(2,334)</td>
<td>(1,941)</td>
<td>(1,594)</td>
<td>(1,297)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

### H: Winner and Momentum Returns Including Transaction Costs

**Winner and Zero-Cost Portfolios incl. Transaction Costs (Annualised)**

<table>
<thead>
<tr>
<th>3-month/3-month</th>
<th>6-month/6-month</th>
<th>9-month/9-month</th>
<th>12-month/12-month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner (incl. TC)</td>
<td>8,47%*</td>
<td>7,57%</td>
<td>3,04%</td>
</tr>
<tr>
<td>(1,367)</td>
<td>(1,095)</td>
<td>(0,370)</td>
<td>(0,566)</td>
</tr>
<tr>
<td>Zero-Cost (incl. TC)</td>
<td>13,22%**</td>
<td>10,03%**</td>
<td>8,86%*</td>
</tr>
<tr>
<td>(2,334)</td>
<td>(1,941)</td>
<td>(1,594)</td>
<td>(1,297)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.
9.6. Appendix 6 – Critical Values

The tables below show the critical values used to evaluate the statistical significance of various test results:

**A: Overall Test of Momentum**

<table>
<thead>
<tr>
<th>Degrees of freedom (n-1)</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>α = 0.10</strong></td>
<td>1,297</td>
<td>1,315</td>
<td>1,333</td>
<td>1,356</td>
</tr>
<tr>
<td><strong>α = 0.05</strong></td>
<td>1,674</td>
<td>1,706</td>
<td>1,740</td>
<td>1,782</td>
</tr>
<tr>
<td><strong>α = 0.01</strong></td>
<td>2,397</td>
<td>2,479</td>
<td>2,567</td>
<td>2,681</td>
</tr>
</tbody>
</table>

Positive critical values obtained from a Student's t-distribution.

**B: Two-Dimensional Robustness Tests**

<table>
<thead>
<tr>
<th>Degrees of freedom (n-1)</th>
<th>17</th>
<th>13</th>
<th>26</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>α = 0.10</strong></td>
<td>1,333</td>
<td>1,350</td>
<td>1,315</td>
</tr>
<tr>
<td><strong>α = 0.05</strong></td>
<td>1,740</td>
<td>1,771</td>
<td>1,706</td>
</tr>
<tr>
<td><strong>α = 0.01</strong></td>
<td>2,567</td>
<td>2,650</td>
<td>2,479</td>
</tr>
</tbody>
</table>

Positive critical values obtained from a Student's t-distribution.

**C: Sub-Period Analysis – Two Periods**

<table>
<thead>
<tr>
<th>Degrees of freedom (n-1)</th>
<th>1/7-96 to 31/12-02</th>
<th>1/1-03 to 31/12-09</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>α = 0.10</strong></td>
<td>1,356</td>
<td>1,350</td>
</tr>
<tr>
<td><strong>α = 0.05</strong></td>
<td>1,782</td>
<td>1,771</td>
</tr>
<tr>
<td><strong>α = 0.01</strong></td>
<td>2,681</td>
<td>2,650</td>
</tr>
</tbody>
</table>

Positive critical values obtained from a Student's t-distribution.
D: Sub-Period Analysis – Bull Market, Bear Market, and Mean Reversion

<table>
<thead>
<tr>
<th>Degrees of freedom (n-1)</th>
<th>Bull Market</th>
<th>Bear Market</th>
<th>Mean Reversion</th>
</tr>
</thead>
<tbody>
<tr>
<td>α = 0.10</td>
<td>1,476</td>
<td>1,886</td>
<td>1,397</td>
</tr>
<tr>
<td>α = 0.05</td>
<td>2,015</td>
<td>2,920</td>
<td>1,860</td>
</tr>
<tr>
<td>α = 0.01</td>
<td>3,365</td>
<td>6,965</td>
<td>2,896</td>
</tr>
</tbody>
</table>

Positive critical values obtained from a Student’s t-distribution.

9.7. Appendix 7 – KAX Index

The graph shows the price movement of the KAX Index during the sample period from 1996 through 2009. The graph is based on the 201 stocks currently existing in the index.336

336 Ultimo December 2009.
9.8. Appendix 8 – Sub-Period Analysis with Four Periods

Below are the graph, the results, and the critical values from the four-period analysis.

A: Graphic Illustration of the Four Equally-Sized Sub-Periods

![Graph showing average sample price with sub-period intervals]

B: Momentum Returns for the 6-month/6-month Strategy

<table>
<thead>
<tr>
<th>Sub-Period Analysis</th>
<th>1/7-96 to 30/6-99</th>
<th>1/7-99 to 31/12-02</th>
<th>1/1-03 to 30/6-06</th>
<th>1/7-06 to 31/12-09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner (1)</td>
<td>0,63%</td>
<td>0,49%</td>
<td>2,68%***</td>
<td>-1,22%</td>
</tr>
<tr>
<td></td>
<td>(0,731)</td>
<td>(0,559)</td>
<td>(3,680)</td>
<td>(-0,678)</td>
</tr>
<tr>
<td>2</td>
<td>0,59%</td>
<td>-0,03%</td>
<td>3,13%</td>
<td>-0,88%</td>
</tr>
<tr>
<td>3</td>
<td>0,14%</td>
<td>-0,55%</td>
<td>2,57%</td>
<td>-1,62%</td>
</tr>
<tr>
<td>4</td>
<td>0,25%</td>
<td>-0,56%</td>
<td>1,96%</td>
<td>-1,94%</td>
</tr>
<tr>
<td>Loser (5)</td>
<td>0,15%</td>
<td>-1,40%</td>
<td>1,74%</td>
<td>-1,48%</td>
</tr>
<tr>
<td></td>
<td>(0,143)</td>
<td>(-1,331)</td>
<td>(3,080)</td>
<td>(-0,616)</td>
</tr>
<tr>
<td>Zero-Cost</td>
<td>0,48%</td>
<td>1,89%***</td>
<td>0,93%</td>
<td>0,26%</td>
</tr>
<tr>
<td></td>
<td>(0,667)</td>
<td>(3,377)</td>
<td>(0,997)</td>
<td>(0,203)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

C: Annualised Momentum Returns

<table>
<thead>
<tr>
<th>Sub-Period Analysis (Annualised)</th>
<th>1/7-96 to 30/6-99</th>
<th>1/7-99 to 31/12-02</th>
<th>1/1-03 to 30/6-06</th>
<th>1/7-06 to 31/12-09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero-Cost</td>
<td>5,91%</td>
<td>25,19%***</td>
<td>11,75%</td>
<td>3,17%</td>
</tr>
<tr>
<td></td>
<td>(0,667)</td>
<td>(3,377)</td>
<td>(0,997)</td>
<td>(0,203)</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the result is significant at the 10%, 5%, and 1% level respectively.

D: Critical Values

<table>
<thead>
<tr>
<th>Critical Values for Sub-Period Analysis</th>
<th>1/7-96 to 30/6-99</th>
<th>1/7-99 to 31/12-02</th>
<th>1/1-03 to 30/6-06</th>
<th>1/7-06 to 31/12-09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degrees of freedom (n-1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>α = 0,10</td>
<td>1,476</td>
<td>1,440</td>
<td>1,440</td>
<td>1,440</td>
</tr>
<tr>
<td>α = 0,05</td>
<td>2,015</td>
<td>1,943</td>
<td>1,943</td>
<td>1,943</td>
</tr>
<tr>
<td>α = 0,01</td>
<td>3,365</td>
<td>3,143</td>
<td>3,143</td>
<td>3,143</td>
</tr>
</tbody>
</table>

Positive critical values obtained from a Student's t-distribution.