# Returns to Buying Winners and Selling Losers

**Abstract**

The argument put forward in this paper is that stocks listed on the Stockholm Stock Exchange, from 1993 to 2016, exhibits return continuation over an intermediate-horizon. The best performing strategy, which selects stocks based on the previous six months' returns and holds the portfolio for three subsequent months, yields an average monthly return of 2.33%. Moreover, results are robust after risk-adjustment. The Capital Asset Pricing Model, as well as the Fama and French three-factor model, produce qualitatively incorrect predictions that losers are riskier, which consequently increases the risk-adjusted return rather than decreasing it.

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# 1. Introduction

One of the most fiercely debated areas in finance the last couple of decades has been whether, or to what extent, future stock prices are predictable. The well-known Efficient Market Hypothesis proposed by Fama (1970), states that asset prices efficiently incorporate all relevant information, with the implication that technical analysis, consistently on a risk-adjusted basis, is incapable of acquiring abnormal returns. In disparity to the conclusions drawn from the Efficient Market Hypothesis, are Jegadeesh and Titman's (1993) empirical findings that stocks with high historical return outperform stocks with low historical return. They conclude that a strategy of buying (selling) stocks that have performed well (poorly) over the past three to twelve months, generates high abnormal return the following three to twelve months. The uncovered anomaly of continuation in stock returns is often referred to as cross-sectional momentum. The concept that some stocks outperform its peers is by proponents of traditional finance attributed to cross-sectional differences in expected returns rather than to any time-series dependence in returns. However, Jegadeesh and Titman (1993; 2001) successfully demonstrate that conventional risk factors are inadequate in explaining the observed phenomenon. Fama and French (1996) find that among the CAPM anomalies, momentum is the only one unexplained by the three-factor model. Consequently, the existence of momentum has become central to the market efficiency debate, and according to Bodie, Kane and Marcus (2017) the focal point of asset pricing studies, with researchers widely debating over its determinants. The potential explanations of the origin of the momentum premium are broadly divided into risk-related explanations, data snooping and alternative explanations based on behavioural finance.

Since 1993, a considerable amount of research has documented the momentum effect across different markets and data periods. In an extensive study of developed markets in 12 European countries, Rouwenhorst (1998) finds statistically significant evidence of return continuation in all examined countries, except for Sweden. The absence of momentum returns in Sweden is later supported by Griffin, Ji and Martin (2003) in a worldwide study of price momentum. Motivated by the above, this paper sets out to investigate whether there is evidence of cross-sectional momentum on the Swedish stock market in more recent times, and subsequently document what has already been reported concerning the anomaly.

## 1.1 Problem Statement

This paper aims to examine whether there is evidence of price momentum on the Swedish stock market between the period 1993 to 2016**.** Along with the central research question, the following sub-questions will be answered; Which are the empirically uncovered explanations for the momentum effect? Can conventional asset pricing models explain the momentum return in Sweden?

## 1.2 Scope

Several types of momentum have been documented throughout the years following 1993; including earnings momentum, industry momentum, and price momentum. In short, earnings momentum is the phenomenon of return continuation following favourable or adverse earnings announcements, meaning that positive announcement stocks outperform negative announcement stocks in the post-announcement period. Industry momentum concentrates on the aggregate of companies by industry, whereby industries with strong past performance continue to outperform industries with poor past performance. Lastly, price momentum refers to the phenomenon were stocks with high historical returns continue to outperform stocks with low historical returns. To limit the scope of the empirical study, it solely covers price momentum. However, concerning the literature review, earnings momentum will be explored as a potential explanation for the observed return continuation in stocks. Furthermore, even though there is substantial evidence of price momentum across different asset classes including equity, debt, currency, and commodities, it has been determined to focus on equities exclusively.

The specific methodology used to conduct the empirical analysis is in line with the methodology used by Jegadeesh and Titman (1993). Their methodology is by far the most applied one in the momentum literature, which makes the results of the paper comparable to previous conducted empirical research. Finally, although both institutional investors and private investors can implement momentum strategies, it has been determined to first and foremost discuss the results from an institutional investor point of view. The reason for this is that the impact of short-selling restrictions is hard to quantify and measure, thus, throughout the paper, the reader should bear this in mind. Moreover, the market is assumed to be frictionless, in the sense that transactions costs will be disregarded.

## 1.3 Criticism of Sources

It is important to state that much of the publications, which this thesis is based upon, is authored by researchers who generally question the validity of the traditional finance theory. Therefore, it should at least be noted, that an equally significant amount of studies could have been found in support of the Efficient Market Hypothesis. Concerning the empirical study, one downside to be highlighted is that the general problem of unavailable data could lead to biased results. The occurrence of missing data in the sample is discussed in further detail in the empirical part of the study in Chapter 4.

## 1.4 Structure

The paper is organized as follows:

**Chapter 2 - Financial Theory**
An overview of the most important theories in the field of traditional finance is contrasted with contradictions proposed by the field of behavioural finance. The chapter serves as a theoretical background in the sense that it enables the reader to comprehend the hypothesized nature of price momentum.

**Chapter 3 - Literature Review of Price Momentum Strategies**
The concept of momentum is defined, described and followed by a review that clarifies what has already been observed and documented within the area of price momentum strategies. The chapter is divided into studies of the American market and studies of other international markets.

**Chapter 4 - Empirical study of the Swedish Stock Market**
Monthly stock prices dating back to 1993 is analysed to investigate the possible occurrence of price momentum on the stock market in Sweden. The results are examined and compared to previous studies. The study ends with a regression analysis based on risk-related explanations for price momentum.

**Chapter 5 - Conclusion**
Summarises the entire paper and answers the initial problem statements.

# 2. Financial Theory

Stock price predictability is an economic hardliner that has divided researchers into two schools of thought. Consequently, the answer to whether stock prices move randomly or follow some predictable pattern is mainly dependent on what is considered to influence and determine these prices. This chapter intends to give the reader a coherent understanding of the differences and implications of traditional and behavioural finance theory, as well as a brief discussion of possible explanations for price momentum.

## 2.1 Traditional Finance Theory

In its attempts to capture the financial market in models, traditional finance theory focuses on how individuals should behave. The cornerstone of the capital market theory is the assumptions regarding investors rational behaviour, and the conditions under which trades are executed in the market. Specifically, investors are presumed to consider all available information in the decision-making process, resulting in security prices reflecting all available information (Bodie et al. 2017). Additionally, it is assumed that an effective arbitrage mechanism continuously preserves the concept of market efficiency (Bodie et al. 2017). It is these assumptions that have enabled researchers to build a mathematical framework for asset pricing under uncertainty.

### 2.1.1 Equilibrium Asset Pricing Models

Based on the pioneering work of Markowitz (1952) for risky assets in a portfolio, Sharpe (1964), Lintner (1965) and Mossin (1966) derived a general equilibrium single factor model for the pricing of assets under uncertainty, labelled the Capital Asset Pricing Model (CAPM). The model gives a precise prediction of the relationship between the risk of an asset and its expected return, resulting in its central conclusion, that only systematic risk will be rewarded with a risk premium (Bodie et al. 2017). The CAPM is based on two sets of assumptions.[1] The first set pertains to investors rational behaviour, specifically that they are mean-variance optimizers with homogeneous expectations regarding expected return and risk of all stocks in the market (Bodie et al. 2017). The second set pertains to market structure, asserting that they are well-functioning and friction-free. Build upon these assumptions, the theory states that all investors will invest in a combination of a riskless security and the same well-diversified and efficient

[1] The full list of CAPM-assumptions can be found in Appendix 1.

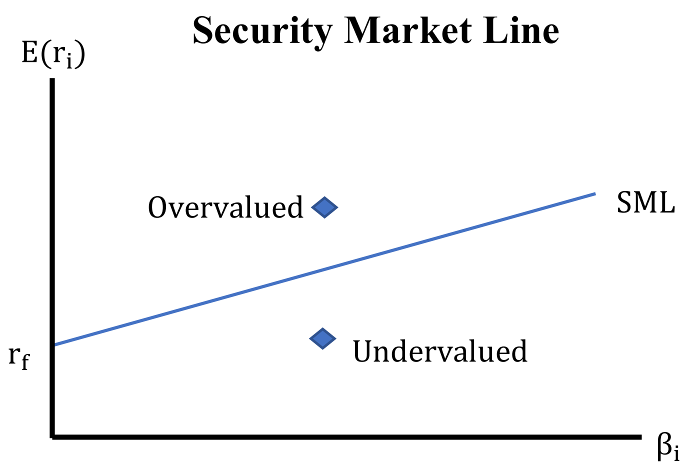
portfolio of risky stocks (Bodie et al. 2017).[2] In terms of asset pricing, Sharpe (1964), Lintner (1965) and Mossin (1966) suggest that if all investors hold a well-diversified portfolio, thereby eliminating all idiosyncratic risk, and at the same time requiring higher expected return for bearing higher undiversifiable risk, there must be a linearly increasing relationship between the expected return of any given stock and its systematic risk, beta.[3] The linear relationship is given by the following equation:

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f] \qquad \text{Eq. (1)}$$

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.

As shortly explained by Bodie et al. (2017), this expected return-beta relationship utilize the fact that the total expected rate of return is the sum of the risk-free rate (time value of money) plus a risk premium (compensation for undiversifiable risk), measured by the asset's contribution to the variance of the market portfolio. Graphically, the relationship is illustrated as the Security Market Line (SML):

Fig. (1)




According to the theory, all assets must lie somewhere along the SML, that is, their expected returns are commensurate with their risk (Bodie et al. 2017). If any security or portfolio were to plot above or below the line, they would be considered either over- or undervalued, which would offset the arbitrage mechanism, forcing the security prices back to their long-term equilibrium (Bodie et al. 2017). Consequently, securities always carry their correct fundamental

[2] In other words, the market portfolio. That is, a portfolio in which the fraction invested in all possible asset's is equal to the market value of that asset divided by the market value of all risky assets (Bodie et al. 2017, p. 279).
[3] Systematic risk is measured by beta, which is stock i's co-variation with the market; $\beta_i = cov\,(r_i, r_m)/\sigma_m^2$. The market portfolio has beta of 1 (Bodie et al. 2017)

value, with the implication that differences in expected returns are only due to differences in stock betas.

### 2.1.2 Arbitrage Pricing Theory and Multifactor Models of Risk and Return

To improve the discrepancy of the CAPM's unrealistic assumptions, Ross (1976) proposed the Arbitrage Pricing Theory (APT) as a general theory of asset pricing. Like the CAPM, the APT predicts a security market line linking expected returns to risk, with the difference that its central assumption is that well-functioning security markets do not allow for the persistence of arbitrage opportunities (Bodie et al. 2017).[4] Recall that the CAPM requires all investors to be mean-variance optimizers. In contrast, the APT's primary requirement is that a sufficient number of sophisticated arbitrageurs scour the market for arbitrage opportunities (Bodie et al. 2017). The theory states that the expected return of any given stock is related to one or more factors, constructed as portfolios tracking the evolution of one particular source of macroeconomic risk (Bodie et al. 2017). The value of the factors is thought to be identical for all securities, whereas the sensitivity to each of the factors is unique to the individual security (Bodie et al. 2017). Consequently, given the effective arbitrage mechanism, securities that plot above or below their fair-value will almost immediately converge to their fundamental value.

The disadvantage with the APT is, however, that neither the relevant factors nor the size or the sign of these factors is defined by the theory, making it less practical in comparison with the CAPM (Bodie et al. 2017). Various researchers have attempted to classify these factors, most notably are Sharpe (1982), Chen, Roll and Ross (1986), and Fama and French (1993). Using firm characteristics, that seem on empirical grounds to proxy for exposure to systematic risk, Fama and French (1993) found 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, and a book-to-market equity factor. The three-factor model is given by the following equation:

$$E(r_i) = r_f + \beta_{iM}\left[E(r_m) - r_f\right] + \beta_{iSMB}E(SMB) + \beta_{iHML}E(HML) \qquad \text{Eq. (2)}$$

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 return of a portfolio of small stocks in excess of the return on a portfolio of large stocks; E(HML) = the expected return of a portfolio of stocks with a high book-to-market ratio in excess of the return on a portfolio of stocks with a low book-to-market ratio; $\beta_{iM}$, $\beta_{iSMB}$ and $\beta_{iHML}$= the sensitivity of stock i's return to the excess return of the market portfolio, the size factor and the book-to-market factor, respectively.

[4] The full list of APT-assumptions can be found in Appendix 1.

Notably, the first factor is expected to capture systematic risk originating from macroeconomic factors, as in the CAPM (Bodie et al. 2017). The two other factors are, however, not apparent candidates for relevant risk factors; nevertheless, Fama and French (1993) argues that these variables proxy for hard-to-measure fundamental risk. On empirical grounds, they argue that small capitalization stocks and stocks with high book-to-market ratios (i.e. value stocks) are riskier than large capitalization stocks and stocks with low book-to-market ratios (i.e. growth stocks). Much of the three-factor model's success can be attributed to the fact that Fama and French (1996) proved that most of the CAPM anomalies could be explained in their model.

### 2.1.3 The Efficient Market Hypothesis

In 1953 Maurice Kendall published his work, "The Analysis of Economic Time Series". He found, to his surprise, that there was no predictable pattern in stock prices (Bodie et al. 2017).[5] Kendall (1953) concluded that stock prices were as likely to go up as down regardless of past performance. With its origin in Kendall's work, the Efficient Market Hypothesis (EMH) first appears in the 1960's and is, among others, developed by Fama (1970). On the contrary to the equilibrium models, the EMH is not a pricing tool, but merely a hypothesis stating that security prices reflect all currently available information (Bodie et al. 2017). Consequently, only new information will move stock prices, and this information is equally likely to be good news as bad news, which is equivalent to stock prices following a random walk (Bodie et al. 2017).[6] On the other hand, the requirement for a market to be fully efficient, the cost of obtaining information and trading securities must be zero (Bodie et al. 2017). Realising that these are positive, Fama (1970) proposed three degrees of market efficiency; weak-form efficiency, semistrong-form efficiency, and strong-form efficiency. In short, the weak-form hypothesis asserts that all historical information is incorporated in stock prices, in case of the semistrong-form all publicly available information, including all historical information, is incorporated, and lastly in the case of the strong-form, both historical, public and insider information is incorporated in stock prices (Bodie et al. 2017). Consequently, studying past price movements, i.e. technical analysis, will not enable investors to earn abnormal returns under any degree of market efficiency as historical information is publicly available at minimal cost. So, to what extent are markets considered efficient? Bodie et al. (2017, p. 364) declare "We conclude that

[5] Prior to 1953 the common belief was that stock prices followed specific patterns (Bodie et al. 2017 p. 333).
[6] The random walk model assumes that successive returns are independent and identically distributed over time (Bodie et al. 2017 p. 334).

markets are generally very efficient, but that rewards to the especially diligent, intelligent, or creative may, in fact, be waiting".

According to Bodie et al. (2017), the most essential characteristics of an efficient market is that: (1) Prices respond quickly and accurately to new information. (2) Changes in expected return are only due to changes in the level of the risk-free rate and risk premiums. Consequently, at any given time, there is a linear relationship between expected return and risk. (3) Distinguishing between profitable and unprofitable investments is improbable. In other words, it is impossible to identify consistently profitable trading strategies. (4) Differences in investment performance of investors are solely a result of chance. These four characteristics are assumed to hold due to the well-informed and rational investors continually analysing and trading in the market (Bodie et al. 2017). However, the EMH does not assume all investors to be rational, instead it assumes the market to be rational (Bodie et al. 2017). Fame (1970) argues that the irrational actions made by investors are thought to be random, and consequently the actions will, on average, cancel out each other. Furthermore, in the case of price deviations, arbitrageurs are assumed to adequately correct the mispricing, resulting in the main conclusion that security prices never exhibit systematic deviations from their fundamental value (Bodie et al. 2017).

### 2.1.4 Implications of Traditional Finance Theory

A common thread in the traditional finance theory is that stocks are entirely priced according to some fundamental risk factors. Implying, that any deviations from its fair-value are corrected by well-informed and rational arbitrageurs immediately (Bodie et al. 2017). Proponents of the EMH often advocate passive as opposed to active investment strategies, that is, buy and hold a broad-based index fund (Bodie et al. 2017). After all, both the equilibrium models and the EMH imply that it is close to impossible to identify over- or undervalued stocks, and certainly impossible to consistently generate abnormal returns (Bodie et al. 2017). It appears that the existence of profitable momentum strategies indicate that the Efficient Market Hypothesis is insufficient in explaining how the financial market functions.

## 2.2 Behavioural Finance

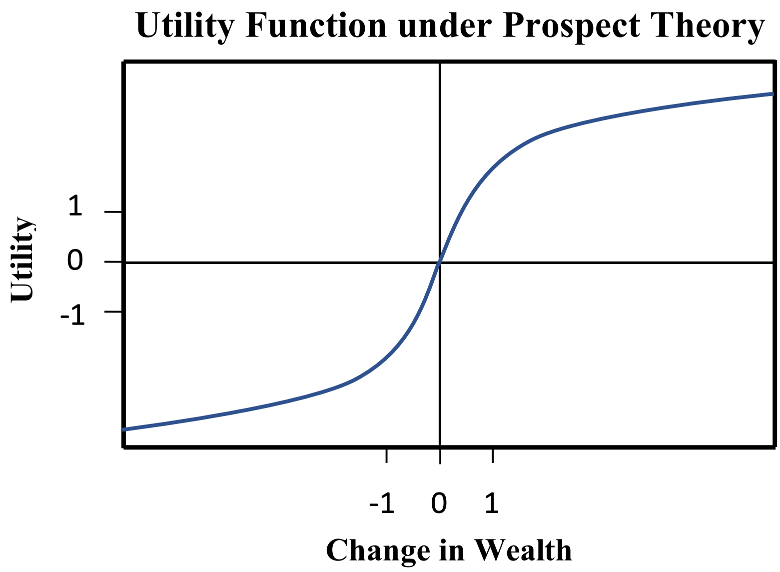
In the 1980's, researchers discover a range of empirical results inconsistent with the belief that prices are determined according to the traditional equilibrium models, among these anomalies are the momentum effect, the size effect, the January effect and the reversal effect (Bodie et al. 2017). Due to the insufficiency of traditional theory to explain these phenomena, a field known as behavioural finance emerges. Whereas conventional theories presume that investors are rational, behavioural finance starts with the assumption that they are not (Bodie et al. 2017). Resting on two pillars, namely irrationalities and limits to arbitrage, the field of behavioural finance attempts to explain the observed anomalies (Bodie et al. 2017).

### 2.2.1 Irrationalities

Behavioural finance main critique of the traditional finance theory is that it neglects how real people make decisions, by focusing on how idealised economic investors should behave. Instead, in contrast to what is assumed by conventional theories, theories from behavioural finance are built on the assumption that investors act irrational (Bodie et al. 2017). These irrationalities fall into two different categories; the first category pertains to investor information processing and the second to suboptimal decisions (Bodie et al. 2017).

If investors process information incorrect, due to the inability to interpret the vast amount of information available, and consequently misestimate the exact probability about future events and rates of return, several biases arise (Bodie et al. 2017). Among the information processing errors uncovered in the psychology literature are forecasting errors, overconfidence, conservatism, and representativeness, which are heuristics, that is, simple rules used when making judgments (Bodie et al. 2017). However, even if information processing were assumed to be faultless, proponents of behavioural finance claim individuals would tend to make less-than-fully-rational choices (Bodie et al. 2017). These suboptimal decisions are characterized by how investors irrationally frame risk versus return, thus, causing errors in their risk-aversion preferences (Bodie et al. 2017). The prospect theory, proposed by Kahneman and Tversky (1979), states that investors are risk-averse over gains, but risk-seeking in relation to losses. The idea is that people presented with a choice between alternatives that involves risk, where the probabilities of outcomes are unknown, tend to make decisions based on the potential value of losses and gains rather than the outcome (Bodie et al. 2017). Contrary to what is assumed by conventional theory, Kahneman and Tversky (1979) found that gains and losses have a different impact on investor decision-making, and thus, advocate a utility function defined in terms of losses relative to current wealth. The result is an S-shaped function that is concave in the region of gains, but convex in the region of losses.

Fig. (2)




Contrary to conventional utility functions, the prospect theory does not imply that investors become less risk-averse as their wealth increases, instead, the focus is always on current wealth, where zero denotes no change (Kahneman & Tversky 1979). The most important implication of this is that investors value gains and losses differently and as such, base their decisions on perceived gains rather than perceived losses, which contradicts the underlying assumptions of rationality (Bodie et al. 2017). Nevertheless, recall that according to the Efficient Market Hypothesis, irrational actions are assumed to be random and cancel out each other. More precisely, for actions to be random, investors are required to form expectations and make decisions independently of each other (Bodie et al. 2017). Proponents of behavioural finance disagree with this proposition, and argue that people, instead of following their private signals, are prone to imitate the behaviour of others; most commonly referred to as herding behaviour (Bodie et al 2017). Thus, in a market where investors, consciously or unconsciously, make irrational decisions dependent on the actions of other investors, or suffer from the same biases and have the same irrational risk preferences, the total impact on the market could lead to mispricing of financial assets (Bodie et al. 2017). The concept of mispricing is, however, not unique to behavioural finance, proponents of traditional finance rely on the fact that it is sufficient with a few sophisticated arbitrageurs taking advantage of any mispricing, for prices to never exhibit systematic deviations from their efficient means (Bodie et al. 2017).

### 2.2.2 Limits to Arbitrage

The idea that any mispricing is short-lived and insignificant for the overall market has been questioned by several researchers, most notably by Delong, Shleifer, Summers, and Waldmann (1990a). In order to understand the limits to arbitrage, it is crucial to recognize that one of the central assumptions concerning arbitrage is that arbitrage-trading is risk-free (Bodie et al. 2017). Delong et al. (1990a) disagree with this proposition, arguing that there is in fact risk associated with arbitrage-trading. They claim that some investors, known as noise traders, trade based on noise which they, wrongly, interpret as valid information. More precisely, if noise traders have been bearish on a stock, pushing its price below its fundamental value, rational well-informed investors should buy the stock expecting it to return to its fundamental value (Bodie et al. 2017). However, Delong et al. (1990a) propose, what they call noise trader risk, as the risk that noise traders push the stock price even further away from its fundamental value. Consequently, given that rational investors are risk-averse and have a short investments horizon, they will be reluctant to exploit the mispricing, resulting in the mispricing lasting over more extended periods (Delong et al. 1990a).

### 2.2.3 Implications of Behavioural Finance

Opposite to the conventional theory, behavioural finance does not attempt to capture the financial markets in asset pricing models. Instead, it aims to explain the documented shortcomings of traditional asset pricing theory, by emphasizing, that psychological biases and non-rational risk preferences can influence the overall behaviour of the market (Bodie et al. 2017). In short, it is believed, that investors irrationality causes mispricing, whereas limits to arbitrage allow the mispricing to persist (Bodie et al. 2017). The most essential implication of this, concerning the purpose of the paper, is that prices are, at least somewhat, predictable in the short-run.

## 2.3 Momentum Explanations

Following Jegadeesh and Titman's findings in 1993, researchers have presented a long list of possible explanations for the observed phenomenon. The following will present and discuss some of the most common explanations, which are broadly divided into risk-related explanations, data snooping and alternative explanations based on behavioural finance.

### 2.3.1 Risk-Related Explanations

According to the traditional finance theory, fundamental risk factors should be able to explain all differences in portfolio returns (Bodie et al. 2017). Specifically, when examining the profitability of momentum strategies, it is expected that the portfolio of stocks which outperforms its peers, contains riskier stocks. The prevailing models of risk-adjustment are the Capital Asset Pricing Model and Fama and French's three-factor model, with risk factors most commonly referred to as beta, SMB, and HML. These risk factors, have on empirical grounds been identified as being the most significant determinants of differences in stock returns by Fama and French (1993). It is expected that the portfolio of stocks which outperforms its peers, loads heavily on high beta values, SMB and HML. However, it should be noted that fundamental risk assessments methods are subtle. As proponents of risk-related explanations often point out, the factor models mentioned above may not account for all relevant risk factors.

### 2.3.2 Data snooping

Others, as a critique of Jegadeesh and Titman, have argued that momentum profits are the result of data snooping. Indeed, if one processes a significant amount of data and searches over many different alternatives, it is likely that a profitable trading strategy will occur. The documented returns could be the result of historical circumstances that are not likely to exist again. For example, Fama (1998) argues that out-of-sample testing, in general, tend to eliminate observed anomalies. The issue of data snooping is illustrated by Leinweber (2009), who demonstrates how the utterly meaningless and accidental correlations between butter production in Bangladesh and the U.S. stock market return over a twelve-year period, can lead to spurious conclusions.

### 2.3.3 Explanations Based on Behavioural Finance

The fact that simple momentum strategies consistently proves to be profitable remains an unsolved puzzle, for example, Fama (1998) identified the momentum effect as the one outstanding anomaly in market behaviour. In the absence of satisfying explanations, proponents of behavioural finance have attributed the return of momentum strategies to investors behavioural biases (Bodie et al. 2017). More precisely, they propose that the consequences of over- and underreaction to firm-specific information can cause stock prices to exhibit momentum (Bodie et al. 2017). In short, overreaction is the tendency of stock prices to react too strongly to new information, and likewise, underreaction is the tendency of stock prices to react too little to the given piece of information. The following figure illustrates under- and overreaction to positive news in relation to the Efficient Market Hypothesis:

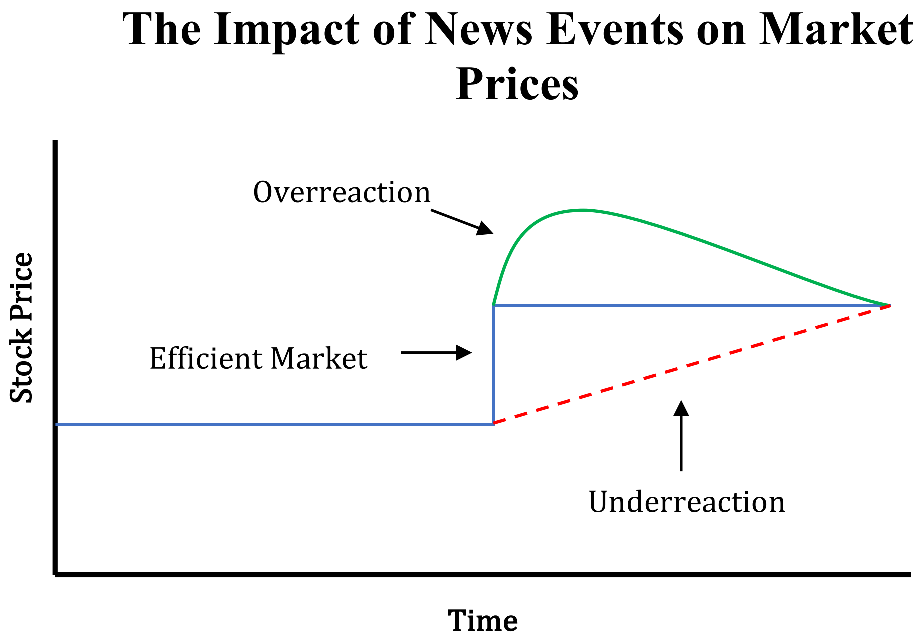



Fig. (3)

The blue line is the efficient markets' reactions to favorable news and is therefore also assumed to be the fundamental value of the stock. It follows, that overreaction leads to an initial price movement too far in one direction and, consequently, a later price reversal back to its fundamental value. Underreaction, on the other hand, leads to a gradual correction phase, in which the stock price continues in the same direction until its fundamental value has been reached. The following presents some of the potential reasons for under- and overreaction, respectively.

### 2.3.3.1 Momentum caused by Underreaction

Since earnings serve as an ongoing source of information about a company, researchers have studied the return pattern of stocks around earnings announcements dates (Bodie et al. 2017). Jones, Latane, and Rendleman (1982) are some of the first to study the response of stocks to unexpected quarterly earnings, measured as the difference between actual and expected earnings.[7] Jones et al. (1982) find that the average excess return over the market is -8.7% for stocks with the lowest unexpected earnings and 8.0% for stocks with the highest unexpected earnings. They further document that approximately half of the excess return occurs, not on the announcement dates, but in the following 90 days. Consequently, they conclude that prices react

[7] The return of the stocks in their sample is calculated from -20 up until +90 days from the earnings announcement date (Jones et al. 1982)

gradually over time rather than instantaneous to earnings announcements, which is in accordance with the hypothesis of underreaction. This has prompted some researchers to develop models based on limited rationality and investor mis-reaction, to explain the observed post-news drift in stocks (Bodie et al. 2017). In short, it is believed that the underreaction to stock-specific news is caused by anchoring bias, slow information diffusion, and the disposition effect; i.e. holding on to losers to avoid admitting mistakes while quickly selling winners to show success (Bodie et al. 2017). The interested reader is referred to Barberis, Shleifer and Vishny (1998) model of Investor Sentiment, Hong and Stein (1999) model of Gradual Information Diffusion and Grinblatt and Hans' (2002) Disposition Model.

#### 2.3.3.2 Momentum caused by Overreaction

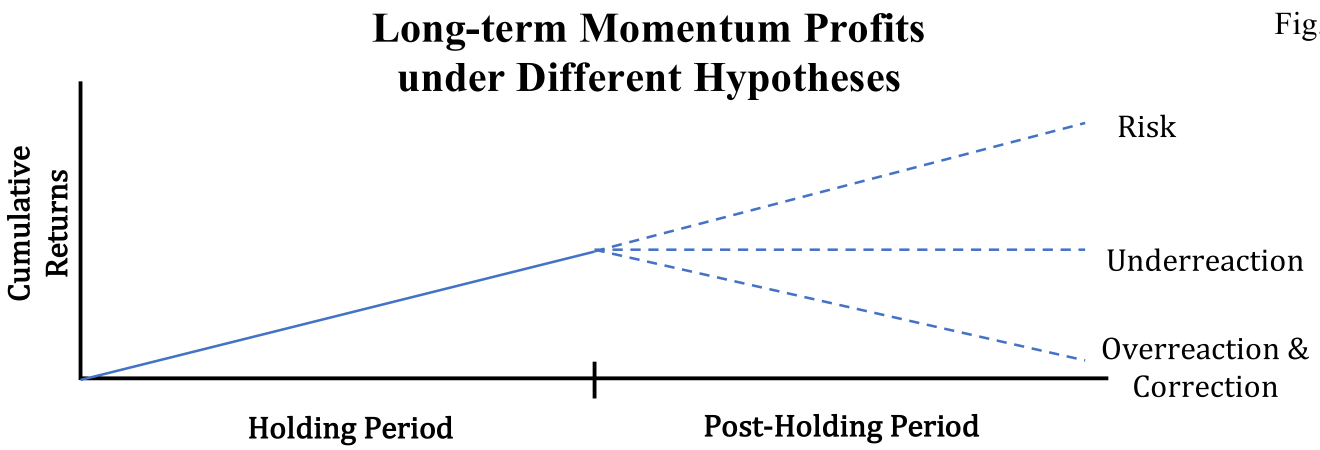
Others have argued that the observed momentum effect can be explained in terms of an initial overreaction followed by mean reversion (Bodie et al. 2017). De Bondt and Thaler (1985) are the first to document the existence of a long-term reversal in stock returns, whereby a portfolio of the worst performing stocks in the past 3 to 5 years tend to outperform a portfolio of the best performing stocks in the following 3 to 5 years.[8] De Bondt and Thaler (1985) attribute this long-term return reversal to investor overreaction, caused by the psychological bias representativeness. The representativeness heuristic, proposed by Kahneman and Tversky (1974), refers to the tendency of investors to interfere patterns too quickly based on small samples and extrapolate trends too far into the future. For example, a short-lived run of high stock returns would cause investors who suffer from the representativeness heuristic to revise their assessments of likely future performance and thus generate buying pressure that exaggerates the price run-up. However, eventually the gap between the stock price and its fundamental value becomes conspicuous and the market corrects its initial error. Although overreaction originally was used to explain long-term reversal effects, several researchers have proposed models in which overreaction explains medium-term momentum as well (Bodie et al. 2017). The interested reader is referred to DeLong, Shleifer, Summers, and Waldmann (1990b) Positive Feedback Trader model and Daniel, Hirshleifer and Subrahmanyam (1998) Overconfidence Hypothesis.

[8] The strategy of buying past losers and short-sell past winners are referred to as contrarian strategies.

### 2.3.4 Implications of Momentum Explanations

As emphasized above, researchers have not reached consensus regarding precisely what causes the empirically observed momentum effect. Explanations based on data snooping implies that the observed phenomenon should be contained to Jegadeesh and Titman's original sample, and thus, not hold in an out-of-sample test. On the other hand, if risk is the correct explanation, Jegadeesh and Titman (2001) argue that it is expected that the profitability of momentum strategies continues in the post-holding period. That is, if the portfolio of stocks which outperforms its peers contains riskier stocks, the return is not abnormal but merely compensation for risk, which according to the models should not decrease nor disappear (Jegadeesh & Titman, 2001). On the contrary, they argue, if overreaction causes momentum, the return in the post-holding period must be negative, due to the long-term reversal effect in stocks. This is since the return of past losers eventually exceeds the returns of past winners, as documented by De Bondt and Thaler (1985). Lastly, the authors argue, if underreaction causes momentum, it is expected that as soon as all the information has been incorporated and the stock has reached its fundamental value, the post-holding period return will be zero. Jegadeesh and Titman (2001, p. 712) illustrate the implications of risk, underreaction and overreaction as follows:

Fig. (4)



# 3. Literature Review of Momentum Strategies

Momentum investing is a strategy that aims to capitalize on the continuance of trends in the market. The basic idea is to short-sell a "loser portfolio" of the poorest performing stocks and use the proceeds to buy a "winner portfolio" consisting of stocks with the strongest performance. The result of the long-short strategy is a self-financed portfolio when disregarding transactions costs. It follows that the momentum strategy is profitable whenever the winner portfolio outperforms the loser portfolio.

The most frequently used test methodology, when examining the profitability of momentum strategies, is as follows.[9] At the beginning of each month, all stocks are ranked in ascending order based on their returns in the past *J* months, where *J* (the formation period) is set to 3, 6, 9 or 12 months. The stocks are then divided into ten equally weighted decile portfolios based on their historical returns, with the portfolio containing the stocks with the highest (lowest) past returns referred to as the winner (loser) portfolio. The winner- and loser portfolio are then held for *K* months, where *K* (the holding period) is set to 3, 6, 9 or 12 months. To increase the statistical significance of the results, overlapping portfolios are commonly used, thus, in any given month, the zero-cost portfolio consists of a series of portfolios selected in the current month as well as in the previous *K*-1 months. The return from the abovementioned *J*/*K*-strategy, which yields a total of 16 zero-cost portfolios, is calculated as the average monthly return of the winner portfolio minus the average monthly return of the loser portfolio, henceforth referred to as the WL-portfolio. Additionally, it is common to skip a week, or in some cases a month, between the formation and holding period, to mitigate the problems with bid-ask spread, price pressure and short-term reversal in stocks as documented by Jegadeesh (1990).

This chapter intends to present and summarize the most important empirical findings, by dividing the empirical studies into two subsections; the American market and the international markets. The literature review is limited to equity markets, with emphasis on the robustness of price momentum, risk-related explanations and whether the hypothesis of under- or overreaction can account for the observed findings. The reader should, however, bear in mind that the literature review is exemplary rather than exhaustive, in the sense that only empirical findings in relation to the purpose of the paper will be presented. That is, for example, that the impact of transaction costs and short-sell restrictions will be disregarded.

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[9] The description of the methodology is based on the pioneering work of Jegadeesh and Titman (1993).

## 3.1 Empirical Studies of the American Stock Market

Jegadeesh and Titman (1993) are the first to document that momentum strategies, implemented on stocks listed at the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX), yields positive returns over an intermediate-horizon. During the sample period 1965 to 1989, they find statistically significant returns to all the examined WL-portfolios, except for the J3/K3 strategy, which does not skip a week between the formation and holding period. The most successful WL-portfolio turns out to be the J12/K3 strategy, providing an average return of 1.31% per month with no time-lag and 1.49% average return per month if there is a one-week lag between the formation and holding period. More precisely, J12/K3 refers to the strategy that selects stocks based on the previous 12 months' returns and holds the portfolio for three subsequent months. In summary, Jegadeesh and Titman (1993) conclude that strategies with long formation periods of 9 or 12 months and short holding periods of 3 or 6 months, perform considerably better than the remaining strategies. These results are later verified by Lee and Swaminathan (2000), who examine all firms listed on the NYSE and AMEX, over the sample period 1965 to 1995. They find all 16 examined strategies to yield statistically significant positive returns. In agreement with Jegadeesh and Titman, they conclude the J12/K3 strategy to be most successful with an average monthly return of 1.54% and the J3/K3 strategy to be the worst performing strategy with an average monthly return of 0.66%.

To test for the robustness of the results, Jegadeesh and Titman (1993) examine the J6/K6 strategy in greater detail, which they consider the most representative strategy of the remaining 15. Specifically, they implement the J6/K6 strategy on subsamples stratified on market capitalization (small, medium and large cap) and ex-ante estimates of beta (low, medium and high beta). Jegadeesh and Titman (1993) thereafter examine whether the observed returns from the J6/K6 strategy is confined to a specific type of stocks. In comparison with the overall return of 0.95% when implemented on the total sample, Jegadeesh and Titman (1993) finds that the returns of the size- and beta-based subsamples are 0.99% (small cap), 1.26% (medium cap), 0.75% (large cap), 0.62% (low beta), 0.79% (medium beta), and 1.08% (high beta). Consequently, their results appear to be somewhat related to firm size and beta, with large firms generating the lowest abnormal return compared to medium- and small firms, and the returns being monotonically increasing with beta. However, when Jegadeesh and Titman (1993) examines whether the Capital Asset Pricing Model can explain the momentum effect, they find that the beta of the loser portfolio is higher than the beta of the winner portfolio; with beta values of 1.38 and 1.28, respectively. Consequently, the beta of the zero-cost portfolio is negative, and they conclude that the momentum effect cannot be explained in terms of systematic risk. To further test for robustness, Jegadeesh and Titman (1993) divide the total sample period into sub-periods of 5 years. They find the J6/K6 strategy to produce positive returns in all but one sub-period (1975 - 1979), which indicate that the momentum effect is not confined to any sub-periods. When further investigating the negative returns in 1975 to 1979, Jegadeesh and Titman (1993) conclude that the observed result is primarily due to the January effect.[10] That is, by examining the returns on a monthly basis, they discover that the J6/K6 strategy on average loses 6.86% in January, but achieves average returns of 1.66% in the remaining 11 months. Corresponding results are found by Grundy and Martin (2001), who examine stocks listed at NYSE and AMEX from 1926 up until 1995. They conclude that the J6/K1 strategy yields an average monthly return of -5.85% in January, and an average monthly return of 1.01% in the remaining months.

Lastly, to assess whether the returns are persistent over more extended time periods, Jegadeesh and Titman (1993) track the average portfolio returns in each of the 36 months following the portfolio formation date. They find that the average return of the WL-portfolio is positive in each month during the first year, excluding January. In the second year, however not statistically significant, the returns are negative in every month and stays negative until halfway through year three were they again turn slightly positive. More precisely, the cumulative return reaches a maximum of 9.51% at the end of year one and declines to 4.06% at the end of year three. This result, Jegadeesh and Titman (1993) interpret as evidence that the observed return pattern is not permanent over longer time periods, which further contradicts the hypothesis that the observed returns are due to systematic risk. Similar results are found by Chan, Jegadeesh, and Lakonishok (1996), who in addition to NYSE and AMEX also examine NASDAQ listed stocks over a sample period from 1977 to 1993. They find the J6/K6 strategy to yield an average return of 15.4% over the first year, -0.6% the second year and 1.2% the third year. Also, Lee and Swaminathan (2000) investigate the 5-year return of the portfolios following the portfolio formation date. During the first year, the WL-portfolios yields significant returns between 10.62% (J3) and 12.70% (J9). In year two and three, the returns are slightly negative, however not enough to account for the abnormal gains in the first 12 months. In year four and five, Lee and Swaminathan (2000) document a pattern of price reversal, where the total return of the

[10] Some researchers suggest that the January effect is due to tax-loss selling of stocks, that is, investors selling losing stocks at the end of the year to realise the losses for tax purposes (Bodie et al. 2017). It follows, that the selling pressure pushes stock prices below their fundamental values in December, after which the prices rebound strongly in January.

portfolio with the longest formation period (J12), is almost entirely offset at the end of year five. Lee and Swaminathan (2000) therefore conclude that momentum in stock prices reverse over longer horizons, which is in accordance with the hypothesis of overreaction and the findings of long-term reversal documented by De Bondt and Thaler (1985).

Due to the insufficiency of the conventional theory to explain the observed returns, Jegadeesh and Titman (1993) turn to earnings announcements to examine whether price momentum can be explained in terms of underreaction to firm-specific information. More precisely, they examine the returns of past winners and past losers around their quarterly earnings announcements days. Jegadeesh and Titman (1993) argue that, if the market underreacts to information about future earnings, it is expected that past winners, which reasonably had beneficial information revealed in the past, should realise positive returns around the time when their actual earnings are announced. Likewise, past losers, which reasonably had adverse information revealed in the past, should realise negative returns at the time of the announcement. Jegadeesh and Titman (1993) find that for the first six months following the announcement date, past winners outperforms past losers by 0.7% on average. In other words, Jegadeesh and Titman (1993) find the returns to be consistent with that of the momentum portfolios, and thus, conclude that the post-earnings drift represents about 25% of the observed momentum return the first six months following the formation date. Similar results are found by Chan et al. (1996), who conclude that the returns around the earnings announcements days' account for approximately 40% of the difference in return between the winner and loser portfolio the first six months following the formation date. However, Jegadeesh and Titman (1993) also find the post-earning returns in the 8 to 20 months following the formation date, to be significantly higher for stocks in the loser portfolio than for the stocks in the winner portfolio. It follows that this long-term reversal favours the hypothesis of overreaction, which predicts a negative return in the post-holding period.

In 2001, Jegadeesh and Titman refute accusations of data snooping, and extend the J6/K6 strategy from their original study with eight additional years, to include data from 1990 to 1998. The out-of-sample test, documents that the momentum strategy continues to be profitable with an average monthly return of 1.39%. Consistent with their original study, they find the momentum portfolio to yield a cumulative return of 12.7% during the first 12 months, following the formation date, and an average negative return in the consecutive 13 to 60 months. Consequently, after five years, the cumulative return has declined to -0.44%. Moreover, after allegations that small and illiquid stocks primarily drive the momentum return, Jegadeesh and Titman (2001) exclude stocks priced under 5 USD and the lowest decile in terms of market capitalization, and still find significant returns to all examined strategies. They furthermore conclude that the winner- and loser portfolios contribution to the observed momentum profits is about equal. At the time of Jegadeesh and Titman's (2001) study, Fama and French's three-factor model has risen to prominence. After its success in explaining other observed anomalies, with a size (SMB) and a book-to-market (HML) factor, Jegadeesh and Titman (2001) once again investigate if the observed returns are due to risk. They find the loser portfolio to load more heavily on the SMB factor than the winner portfolio, with loadings of 1.06 and 0.77, respectively. Moreover, both the loser portfolio and the winner portfolio exhibits negative sensitivity to the HML factor, with loadings of -0.02 and -0.245, respectively. Consequently, the loadings of the WL-portfolio are negative, resulting in an increased risk-adjusted return to 1.36% compared to the raw return of 1.23%. Jegadeesh and Titman (2001) therefore conclude that the Fama and French factors, as a measure of risk, is unable to account for the momentum effect. Chan, Jegadeesh and Lakonishok (1999) also extend their initial study to include five additional years from 1994 to 1998. Their results are similar to Jegadeesh and Titman's, in that they find the J6/K6 strategy to yield an average yearly return of 7.74% during the 5-year period. The conclusion reached by both studies are therefore that momentum strategies continue to be profitable throughout the 1990's.

## 3.2 Empirical Studies of International Stock Markets

Up until 1998, evidence of momentum has solely been documented by researchers using primarily the same database of U.S. stocks. To determine whether the observed phenomenon is caused by characteristics unique to the U.S. or simply due to data snooping, Rouwenhorst (1998) conduct a study covering 2,190 stocks from 12 European countries.[11] During the sample period, 1980 to 1995, Rouwenhorst (1998) find statistically significant returns to all examined strategies. In accordance with Jegadeesh and Titman, Rouwenhorst (1998) find the J12/K3 strategy to be most successful with an average monthly return of 1.35%, and the J3/K3 strategy to be the worst performing strategy with an average monthly return of 0.70%. Rouwenhorst (1998) conclude that international diversified momentum strategies, that invests in past medium-term winners, and short-sells past medium-term losers, yields a return of

[11] Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom

approximately 1% per month. The evidence of momentum in major developed European countries is later confirmed by Dijk and Huibers (2002), who find all examined momentum strategies to be profitable over the period 1987 to 1999. They further argue that the most likely explanation, for the observed price-drift in stocks, is analysts' underreaction to earnings announcements. Specifically, Dijk and Huibers (2002) find the overestimation of future earnings for past losers to be of substantial magnitude, and thus, conclude that analysts' underreaction to firm-specific information, partly causes momentum in losing stocks.

Moreover, to rule out that the results are not due to country-specific characteristics, Rouwenhorst (1998) examines a country-neutral portfolio based on the J6/K6 strategy. He finds, that controlling for country composition only slightly reduces the average monthly return from 1.16% to 0.93%, and thus, conclude that the observed returns are not due to country-specific market performance, but rather a general phenomenon. However, when implementing the momentum strategies on individual countries, Rouwenhorst (1998) find that the J6/K6 yields statistically significant result in all countries except for Sweden. In other words, with a modest insignificant return of 0.16%, Sweden is the only country in the study not to show conclusive signs of momentum. Rouwenhorst (1998) also examines whether exposure to size, as measured by an international version of Fama and French's (1996) SMB-factor, can account for the observed returns. Likewise, as Jegadeesh and Titman, Rouwenhorst (1998) find losers to load more heavily on the SMB-factor than winners, resulting in an increased risk-adjusted return. In summary, Rouwenhorst (1998) conclude that conventional risk-measurement is unable to account for the observed price momentum in Europe.

Five years later, Bird and Whitaker (2003) argue that most studies of momentum strategies have been conducted on periods with a consistent upward trend in stock prices. Bird and Whitaker (2003) therefore examine whether momentum strategies are robust over the sample period 1990 to 2002, a period characterized by a broad upward movement followed by a significant correction, caused by the burst of the dot-com bubble. Their study, conducted on seven of the major European markets, finds that past winners continue to outperform past losers with approximately 7%, during the sample period.[12] Thus, concluding that momentum investing seems to withstand sudden market corrections. Inspired by Rouwenhorst's study of momentum in an international context, Griffin, Ji and Martin (2003) conducts a worldwide study of momentum strategies. With data from a total of 40 countries from four regions: Africa,

[12] France, Germany, Italy, the Netherlands, Spain, Switzerland, and the United Kingdom

America, Asia and Europe, Griffin et al. (2003) find momentum strategies to be, on average, largely profitable all around the world.[13] They observe return continuation 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. More specifically, they find the J6/K6 strategy to yield an average monthly return of 1.63% in the combined region of Africa, 0.78% in America (excluding U.S.), 0.32% in Asia, and 0.77% in Europe, with insignificant result for Asia. Interestingly, when zooming in on Sweden, Griffin et al. (2003) findings support Rouwenhorsts. In other words, with an insignificant return of -0.01%, Sweden is one of only three countries in Europe not to exhibit return continuation. Griffin et al. (2003) furthermore find low intraregional and interregional correlations between momentum returns, and thus, conclude that momentum profits are most likely not driven by a global risk factor.

## 3.3 Summary

The above literature review seems to have established that equity markets around the world exhibit medium-term return continuation. All studies conclude that a strategy of buying stocks with positive price momentum, and short-sell stocks with negative price momentum, generates abnormal returns. The phenomenon is first discovered in the U.S. by Jegadeesh and Titman (1993), and later verified by numerous researchers across different time-periods and markets. The general pattern of profitability, is that strategies with relatively long formations periods and short holdings periods are preferable. More precisely, it is found that the most profitable J12/K3 strategy yields an average monthly return of approximately 1.3 to 1.5%. The various robustness test indicates that the momentum effect is present in all sub-samples of stocks, although, it is found to be strongest in smaller stocks. Furthermore, all studies confirm that the return of the strategies cannot be accounted for by a simple adjustment to systematic-risk, this is because the betas of the winner- and loser portfolios are found to be of equal magnitude. Likewise, it is found that allowing for exposure to Fama and French's size and book-to-market factors, increases the risk-adjusted return rather than decreasing it. Thus, the conclusion reached by all studies is that the payoffs are inconsistent with the joint hypotheses of market efficiency

[13] Africa: Egypt and South Africa. Americas: United States, 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. Their data sample includes monthly returns of NYSE-and AMEX stocks from 1926 to 2000. The time coverage of the non-U.S. countries starts from 1975 (10 markets covered) to 1995 (all countries, except Egypt covered).

and commonly used asset pricing models. Consequently, several researchers investigate whether momentum is caused by under- or overreaction to firm-specific information. At a first glance the findings are inconclusive, with studies reporting evidence of both hypotheses. Jegadeesh and Titman (1993) and Chan et al. (1996) find, respectively, that 25% and 45% of the observed momentum returns, the 6 months following the formation date, can be explained in terms of underreaction to earnings announcements. These findings are later supported by Dijk and Huibers (2002), who conclude that underreaction to firm-specific information in losing stocks is of substantial magnitude. On the other hand, there is also significant evidence suggesting that price momentum is caused by overreaction and long-term reversal in stocks. Several studies find the momentum returns to be positive the first 10 to 12 months, following the portfolio formation date, and later reverse over the following 4 years, resulting in a negative cumulative return at the end of year 5. The negative post-holding returns is compatible with the long-term reversal effect documented by De Bondt and Thaler (1985). It therefore appears that price momentum largely remains an unsolved puzzle in the world of finance. The only robust finding of the empirical studies seems to be the mere existence of price momentum.

Regarding return continuation on the Swedish stock market, both Rouwenhorst (1998) and Griffin et al. (2003) find the J6/K6 strategy to yield insignificant results, with returns of 0.16% and -0.01%, respectively. However, Rouwenhorst and Griffin et al. sample period end, respectively, two and seven years after the sample period used in this thesis starts. Thus, comparing their findings with the results of this thesis could highlight changes in the existence of the momentum effect on the Swedish stock market.

# 4. Empirical Study of the Swedish Stock Market

The following chapter is the empirical part of the paper, which examines the momentum effect on the Swedish stock market in recent times. The chapter is divided into three main sections; the first section contains information about the data, sample period and methodology. The second section presents the raw returns of the momentum strategies and lastly, the third section presents the results after risk-adjustment. Due to the time-limit of the thesis, no robustness test has been performed. Moreover, in line with the scope of the paper, exploration of under- and overreaction to earnings will be disregarded and left to future research. A description of the statistical diagnostics related to the tests can be found in Appendix 2.

## 4.1 Sample period

As previously discussed, the momentum effect on the Swedish stock market has already been tested and documented by Rouwenhorst (1998) and Griffin et al. (2003) as part of two larger studies. Both studies present evidence that return continuation is non-existent on the Swedish stock market between the periods 1980 to 1995 and 1975 to 2000, respectively. It is therefore found sensible to test a period that lies beyond this point, to shed light on whether the momentum effect has been present in Sweden in more recent times. Furthermore, the selected sample period, January 1993 to December 2016, was chosen mainly for three other reasons. Firstly, at the end of 1992, the Swedish Central Bank adopted a floating exchange rate, which caused a large depreciation of the Swedish Krona, which consequently can be viewed as a new era of the Swedish economy. Secondly, the sample period includes several business cycles, with the burst of the dot-com bubble in early 2000, the more recent financial crises and periods of steady increases of the general value of companies. Lastly, the Swedish version of the Fama and French's factors were only available up until December 2016.

## 4.2 Sample data

The dataset consists of monthly return data from 1993 up until 2016, for all stocks listed at the Stockholm Stock Exchange (SSE), thus also including delisted companies. Beyond SSE, several other smaller exchanges for trading stocks in Sweden exists, some are classified as a formal exchange, and some are not. What they all have in common is that they are made up of small volatile stocks. Thus, to avoid stocks with low or almost no liquidity, only stocks listed on SSE are included in the dataset. Furthermore, only companies that have its primary listing on SSE are considered, that is, no secondary listings or depositary receipts are allowed in the dataset. More precisely, prior to July 2000, the dataset consists of the A-, O-, and OTC-list, and after the merging of the O- and OTC-list, the A- and O-list. After 2006, when the current classification was introduced, the dataset consists of the Large-, Mid- and Small-cap. All data have been collected from the Swedish House of Finance's database Finbas.[14] In addition to the above, considering that the shortest momentum strategy is J3/K3, only stocks with a valid trading history of at least 6 months are included in the dataset. Moreover, when a company has listed more than one stock-class the most liquid class has been chosen. The final dataset consists of 356 different companies in total, and the average number of stocks traded any time is 197.

Analysing the data raises questions of further limitations in terms of size, liquidity, and short-sell constraints. Stock with relatively small size and trading volume can be found at the OTC- and small-cap list, which is often not possible to short-sell for a retail investor. Whether an institutional investor has had more extensive possibilities to short-sell these specific stocks is unclear. However, Jegadeesh and Titman (2001) concluded that, after excluding the lowest decile in terms of market capitalization and all stocks priced under 5 USD, the primary results is the same with or without restrictions. Based on their findings and for simplicity no restrictions in terms of stock price, market capitalization or trading volume will be used in this paper. Lastly, but perhaps most important, is the general problem of missing data. Approximately 17% of all stocks in the dataset have throughout the 24 year-long sample period missing price data in one or several months. Instead of worsening the problem by removing all stocks with missing data from the dataset, it has been determined to let all missing values be there, and instead exclude firms in a period when they have missing values, let it be the formation or the holding period. The bias from this procedure should be less than the bias inflicted on the dataset if all stocks with missing values had been removed. However, it should be noted that it could lead to some bias for strategies with long formation- and holding periods, although, there have been performed no robustness test to validate this.

Additional data collected from Swedish House of Finance is: **Risk-free rate**. Swedish 1-month Treasury Bill. **Market-index/benchmark-portfolio**. SIX Return Index, SIXRX is a broad value weighted index covering all companies listed at SSE. **Fama and French factors**. Equally weighted SMB and HML factors calculated over every Swedish stock, aggregated by month.

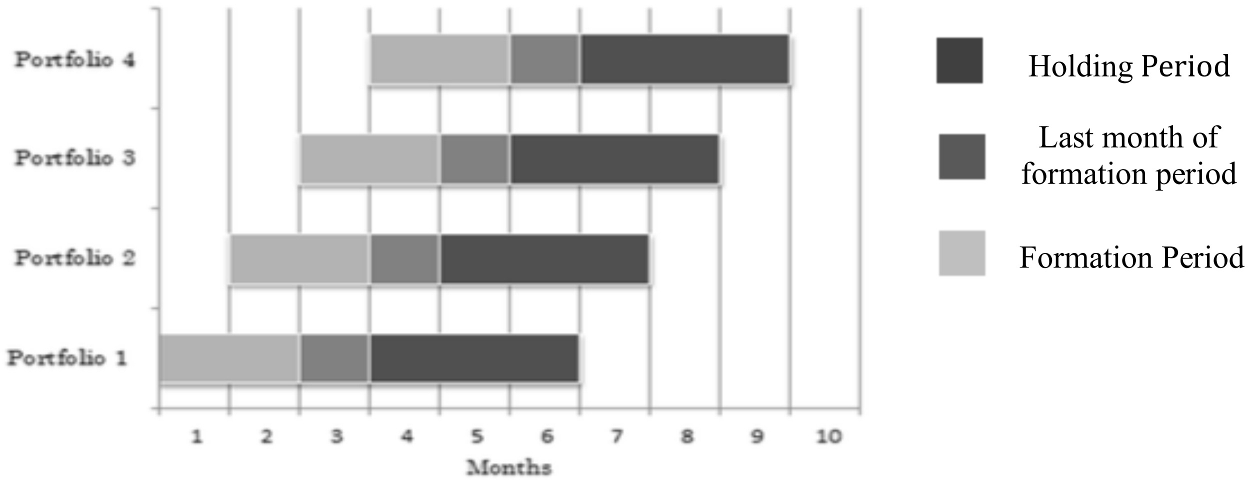
[14] Definition of data from ShoF; *Last*: is the last traded price of the stock at the end of the trade day. The last-price is adjusted for corporate actions making the prices in a time series comparable over time. *OAB*: Total amount traded in the stock in the currency of the market place.

## 4.3 Methodology

The portfolio formation process will follow Jegadeesh and Titman's (1993) methodology presented in the literature review. In total 16 different trading strategies will be evaluated. The procedure starts by calculating monthly returns for every company in the dataset over the entire sample period. At the beginning of each month, all stocks are ranked and organized into ten decile portfolios based on their cumulative past *J* months' return, where *J* is set to 3, 6, 9 or 12 months. The bottom decile portfolio (P1) consists of the 10% worst performing stocks, and the top decile portfolio (P10) of the 10% best-performing stocks. Henceforth referred to as the loser- and winner portfolio, respectively. Following Jegadeesh and Titman (1993) the portfolios will consist of equally weighted stocks, with monthly rebalancing. The momentum strategy is implemented by taking a long position in the winner portfolio and at the same time a short position in the loser portfolio. The Winner-minus-Loser portfolio is then held for *K* months, where *K* is set to 3, 6, 9 or 12 months. It follows, if the winner portfolio outperforms the loser portfolio, the WL-portfolio realises gains. Corresponding to Jegadeesh and Titman (1993), the returns from the abovementioned *J*/*K*-strategies is calculated as the arithmetic average monthly return of the winner portfolio minus the arithmetic average monthly return of the loser portfolio, throughout the sample period. Furthermore, to avoid the short-term reversal effect as documented by Jegadeesh (1990), all 16 strategies will also be implemented using a 1-month time-gap between the formation and holding period. Although Jegadeesh and Titman (1993) used a time-gap of 1 week, it is found by Jegadeesh (1990) that the reversal-effect is substantial up until one month. Thus, comparing the returns of strategies with time-gap versus non-gap will give insight to whether there is evidence of return reversal on a 1-month basis in Sweden.

Likewise, as with previous studies, overlapping holdings periods will be used. The advantage of using overlapping in relation to non-overlapping holding periods is that the statistical significance of the results will increase since considerably more observations are obtained. Illustration of the implications of non- and overlapping holding periods for the J3/K3-strategy can be found in figure 5. When the procedure of non-overlapping holding periods is used, the entire position in portfolio 1 is liquidated at the end of month 6, and reinvested in portfolio 4. On the other hand, when overlapping holding periods are used, the total position consists of several portfolios simultaneously. More precisely, at the beginning of month 4, one will be completely invested in portfolio 1, in month 5 one will be 50/50 invested in portfolio 1 and 2.

**Formation and Holding Periods of J3/K3** Fig. (5)




In month 6 the total position will consist of 1/3 in portfolio 1, 1/3 in portfolio 2 and 1/3 in portfolio 3. Thus, from month 6 and forward the total position will consist of three equally sized zero-cost portfolios. In general, at the end of each month 1/K of the total position is liquidated and invested in a new portfolio.

In addition to the overall test of momentum, a regression analysis for risk-adjustment using the Capital Asset Pricing Model as well as the Fama and French three-factor model will be performed.[15] Since the CAPM is a theory about expected returns rather than realized returns, equation (1) will need to be rearranged to be applicable. The result is a single-index model with the following regression equation:

$$r_{p,t} = \alpha_p + r_f + \beta_p[r_m - r_f] + \varepsilon_{p,t} \qquad \text{Eq. (3)}$$

Where $r_{p,t}$ = the return of portfolio p in period t; $\alpha_p$= the portfolio's alpha, or abnormal return; $r_f$ = the risk-free rate; $\beta_p$ = the sensitivity of portfolio p's return to the return of the market portfolio; $r_m$ = the return of the market portfolio in period t; $\varepsilon_{p,t}$= the error term.

It follows, that if the CAPM is successful in explaining the return in terms of systematic risk, the alpha will be zero. That is, the excess return of the momentum portfolio is entirely due to a high beta-value. On the other hand, if alpha is positively significant different from zero, the portfolio has provided a better return than what is expected given the portfolio's beta value. Likewise, if the observed returns are due to higher risk-bearing, it is expected that the zero-cost portfolio loads heavily on the two additional proxies of risk; SMB and HML in the Fama and

[15] All calculations concerning the portfolio formation, overall returns and regression analysis have been performed in Excel and Stata.

French three-factor model. Equation (2) has been rearranged to the following regression equation:

$$r_{p,t} = \alpha_p + r_f + \beta_{pM}[r_m - r_f] + \beta_{pSMB}SMB + \beta_{pHML}HML + \varepsilon_{p,t} \qquad \text{Eq. (4)}$$

Where $r_{p,t}$ = the return of portfolio p in period t; $\alpha_p$= the portfolio's alpha, or abnormal return; $r_f$ = the risk-free rate; $r_m$ = the return of the market portfolio in period t; *SMB* = the return of a portfolio of small stocks in excess of the return on a portfolio of large stocks; *HML* = the return of a portfolio of stocks with a high book-to-market ratio in excess of the return on a portfolio of stocks with a low book-to-market ratio; $\varepsilon_{p,t}$= the error term; $\beta_{pM}$, $\beta_{pSMB}$, $\beta_{pHML}$ = the sensitivity of portfolio p's return to the return of the market, the size factor and the book-to-market factor, respectively.

## 4.4 Momentum Results

The following section presents the results from the price momentum strategies implemented on the Swedish stock market during the period 1993 to 2016. An overview can be found in Table I. Panel A display strategies without time-lag, whereas Panel B display strategies with a one month lag between the formation and holding period. In accordance with previous studies, the strategies are evaluated based on average monthly returns.

All returns from the 16 zero-cost portfolios are, with or without time-lag, positive and statistically significant at the 1% level. The most profitable zero-cost portfolio selects stocks based on their returns over the previous six months and holds the portfolio for three months. This J6/K3 strategy yields an average monthly return of 2.19% and 2.33%, with and without time-lag, respectively. The strategy with the worst performance is the J12/K12 strategy with time-lag, yielding an average monthly return of 1.05%. The general finding seems to be that regardless of formation and holding period, the momentum strategy is able to generate highly profitable returns. Although, the returns are found to be higher for strategies with relative long formation periods compared to holding periods. That is, given a specific formation period, the returns are monotonically decreasing with holdings periods. Lastly, no matter the length of the holding period, a formation period of 6 months is preferable. When comparing the performance of the zero-cost portfolios in panels A with B, a pattern of return divergence appears over more extended periods. For a formation period of three months, the returns of portfolios with and without time-lag are indistinguishable. However, for longer formation periods, and especially for J12, the difference in returns are noticeable, with portfolios without time-lag outperforming portfolios with a one month gap between the formation and holding period.

**Table I**

# Returns of Momentum Portfolios

The following is an overview of the 16 different momentum strategies. The portfolios are formed based on *J*-months historical return and held for *K*-months. The values of *J* and *K* for the different strategies are indicated in the first row and column, respectively. The winner portfolio consists of an equally weighted portfolio of stocks in the highest past return decile. The loser portfolio consists of an equally weighted portfolio of stocks in the lowest past return decile. The W-L portfolio consists of a long- and short position in the winner- and loser portfolio, respectively. The raw average monthly returns of these portfolios are presented in this table. The portfolios in Panel A are without time-lag, whereas the portfolios in Panel B are formed one month after the end of the formation period. The t-statistics are reported in parentheses. The sample period is January 1993 to December 2016.

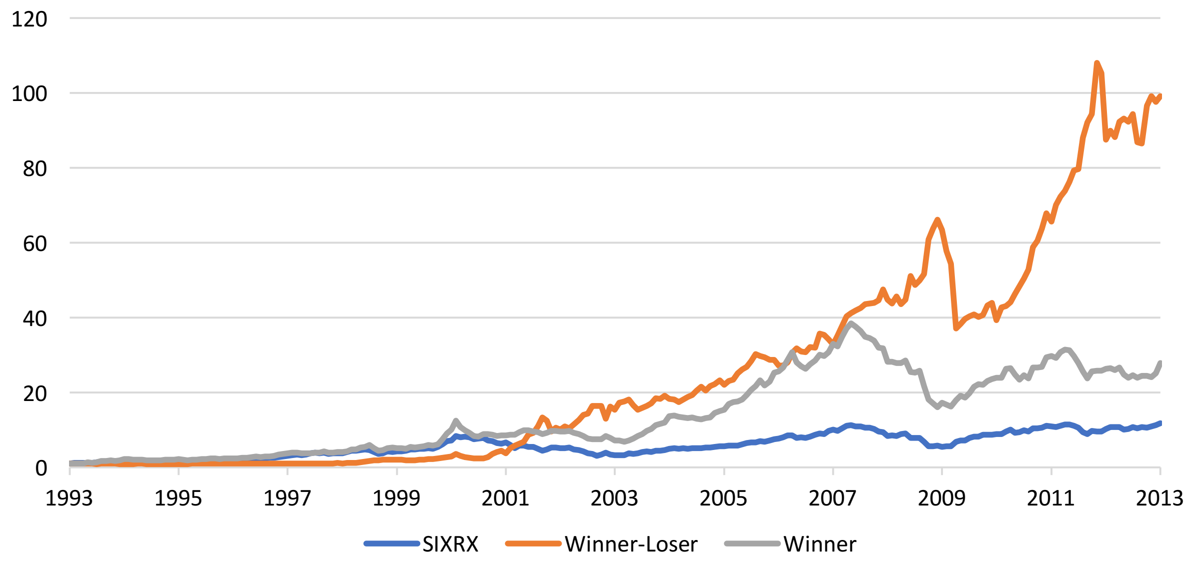
| | | Panel A | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | K=3 | 6 | 9 | 12 | K=3 | 6 | 9 | 12 |
| J=3 | Winner | 1,274 | 1,193 | 0,834 | 0,768 | 1,254 | 1,102 | 0,749 | 0,650 |
| | t | (3,42) | (3,32) | (2,26) | (2,12) | (3,30) | (3,06) | (2,07) | (1,77) |
| | Loser | -0,595 | -0,445 | -0,472 | -0,531 | -0,626 | -0,515 | -0,562 | -0,478 |
| | t | (-1,04) | (-0,83) | (-0,86) | (-1,03) | (-1,07) | (-0,94) | (-1,07) | (-0,93) |
| | W-L | 1,868 | 1,638 | 1,306 | 1,299 | 1,880 | 1,617 | 1,311 | 1,128 |
| | t | (4,56) | (4,65) | (3,99) | (4,77) | (4,45) | (4,55) | (4,45) | (4,21) |
| 6 | Winner | 1,651 | 1,347 | 1,030 | 0,701 | 1,263 | 1,151 | 0,983 | 0,710 |
| | t | (4,39) | (3,68) | (2,79) | (1,92) | (3,41) | (3,21) | (2,72) | (1,95) |
| | Loser | -0,675 | -0,613 | -0,686 | -0,683 | -0,925 | -0,587 | -0,462 | -0,478 |
| | t | (-1,17) | (-1,06) | (-1,26) | (-1,31) | (-1,58) | (-1,06) | (-0,87) | (-0,91) |
| | W-L | 2,326 | 1,961 | 1,716 | 1,384 | 2,188 | 1,739 | 1,445 | 1,188 |
| | t | (5,25) | (4,75) | (4,82) | (4,41) | (4,91) | (4,44) | (4,18) | (3,65) |
| 9 | Winner | 1,482 | 1,321 | 0,785 | 0,901 | 1,402 | 1,025 | 0,844 | 0,567 |
| | t | (3,99) | (3,59) | (2,14) | (2,40) | (3,74) | (2,78) | (2,24) | (1,53) |
| | Loser | -0,584 | -0,515 | -0,746 | -0,408 | -0,628 | -0,628 | -0,488 | -0,499 |
| | t | (-0,96) | (-0,89) | (-1,31) | (-0,74) | (-1,06) | (-1,12) | (-0,87) | (-0,95) |
| | W-L | 2,066 | 1,836 | 1,531 | 1,309 | 2,031 | 1,653 | 1,331 | 1,066 |
| | t | (4,44) | (4,38) | (3,89) | (3,60) | (4,53) | (4,09) | (3,54) | (3,19) |
| 12 | Winner | 1,407 | 1,116 | 0,998 | 0,837 | 1,301 | 1,075 | 0,440 | 0,701 |
| | t | (3,79) | (2,92) | (2,64) | (2,14) | (3,41) | (2,77) | (1,19) | (1,85) |
| | Loser | -0,700 | -0,701 | -0,552 | -0,368 | -0,561 | -0,433 | -0,719 | -0,349 |
| | t | (-1,17) | (-1,22) | (-0,98) | (-0,66) | (-0,95) | (-0,75) | (-1,31) | (-0,65) |
| | W-L | 2,107 | 1,816 | 1,550 | 1,205 | 1,862 | 1,508 | 1,160 | 1,050 |
| | t | (4,63) | (4,35) | (3,90) | (3,08) | (4,26) | (3,61) | (2,92) | (2,75) |

* Newey-West standard errors.

**Figure 6**

# Performance Overview

Cumulative return from January 1993 up until January 2013 for a 1 USD investment in the benchmark portfolio and the best performing zero-cost portfolio and winner portfolio. That is, the SIX Return Index, J6/K3 WL-portfolio, and J6/K3 Winner portfolio. In January 2013, the investment grew to 11.8, 99.1 and 27.8 USD, respectively. Between 2013 and 2016 the WL-portfolio massively outperforms the market. An overview of the performance throughout the full sample period can be found in Appendix 4.




Shifting focus towards the isolated portfolios, namely the winner- and loser portfolios, it becomes clear that all loser portfolios are insignificant at the 10% level, while nearly all winner portfolios are statistically significant at the same level.[16] At first glance, it appears that the success of the momentum strategies is mainly driven by the winner portfolios, although all winner (loser) portfolios yield positive (negative) returns. That is, for all 16 momentum strategies, the winner portfolio outperforms the loser portfolio in absolute terms. However, to accurately access which portfolio contributes the most to the momentum return, the isolated strategies must be compared to the benchmark-portfolio, SIX Return Index.[17] The average monthly return of the index over the sample period amounts to 1.20%, being statistically significant at the 5% level. Thus, the zero-cost portfolio outperforms the index in 12 out of 16

[16] Most winner portfolios are statistically significant at the 1% and 5% level, while winner portfolio: J9/K12 and J12/K9 in Panel B are statistically insignificant at the 10% level.
[17] The methodology of comparing the isolated returns to a benchmark-portfolio, to determine which portfolio contribute the most to the momentum return, is adapted from Jegadeesh and Titman (2001, p. 705).

cases.[18] When comparing the returns of the isolated portfolios to the index, it turns out it is the short-selling of the loser portfolios that contributes most to the momentum portfolios' outperformance. This is the case since the loser portfolios, in all 16 strategies, underperform the index to a greater extent than the winner portfolios outperform the index. In fact, the winner portfolios only outperform the index in 7 out of 16 cases, whereas the J6/K3 winner portfolio is the most profitable with an average monthly return of 0.45% in excess of the market.[19]

### 4.2.1 Implications of Results

There is conclusive evidence that price momentum has been present in Sweden during 1993 to 2016. It is found that momentum strategies, which invest in past medium-term winners, and short-sells past medium-term losers, yield a return of approximately 1.6% per month.[20] Likewise, as with previous studies, it is evident that strategies with relatively long formations periods and short holdings periods are preferable. However, unlike Jegadeesh and Titman (1993), Rouwenhorst (1998), and Lee and Swaminathan (2000) results, the most profitable strategy is not J12/K3, but J6/K3. Moreover, it is found that strategies that do not skip a month between the formation and holding period, perform better than strategies that do. Thus, it appears that there is no evidence of a short-term reversal in stocks, as documented by Jegadeesh (1990). This finding somewhat contradicts previous studies, as Jegadeesh and Titman (1993; 2001) conclude that strategies with a time-lag of one-week perform better than strategies without time-lag. Whether the returns had turned out differently if a one-week time-lag had been used instead, is unclear. Interestingly, previous studies have also pointed towards the J3/K3 as the worst performing strategy with a return well below 1%. Considering the J3/K3 strategy yields an average monthly return of 1.87%, the results suggest that this is not the case in Sweden. All in all, the results indicate that the momentum returns in Sweden are somewhat higher than in other international markets. This should, however, be interpreted with some caution since the studies in the literature review are from a different time-period.

In Jegadeesh and Titman's (2001) follow-up study they argue that the winner- and loser portfolios contribution to the observed momentum profits is about equal. The empirical findings do not support this proposition. In fact, it is found that it is the loser portfolio that is the main contributor to the observed returns for all 16 zero-cost portfolios. Nonetheless, the J6/K3 winner

[18] Strategies that have a holding period of 12 months with time-lag underperforms the Index.
[19] The same figure for portfolios that skip a month between the formation and holding period is 4 out of 16.
[20] The average return of all zero-cost portfolios in Panel A and B in Table I.

portfolio manages to single-handedly outperform the market, implying that an investor who faces short-sell restrictions can earn excess return over the market by following a simple long-only momentum strategy. Comparison of the returns in Figure 6 further manifests this. Moreover, it gives insight to why Rouwenhorst (1998) and Griffin et al. (2003) find insignificant momentum returns in Sweden. That is, from 1993 until 2000 the WL-portfolio underperformed the market by an average of 0.29% per month. It is first at the turn of the millennium and in the aftermath of the dot-com bubble the momentum strategy commence its outperformance of the market. Consequently, the results support Rouwenhorst (1998) and Griffin et al. (2003) findings that the momentum return in Sweden was close to zero in the 1990's. Furthermore, in accordance with Bird and Whitaker (2003), it seems that the momentum strategy is able to withstand unexpected market corrections. In times of falling prices the loser portfolio offsets the losses from the winner portfolio, which is captured by the opposite movements of the winner portfolio and the zero-cost portfolio around times of stock market crashes. For example, between July 2008 and December 2008 the winner portfolio had a return of -55%, while the WL-portfolio realized a return of 49%. Consequently, the loser portfolio did not only absorb the losses from the winner portfolio, but it also single-handedly provided high returns for the WL-portfolio. On the other hand, when the market bounces back up, the zero-cost portfolio takes a beating. Many of the "worst" months for a given zero-cost portfolio are concentrated around market turnarounds.[21] For example, in 2009, in response to the fallout of the 2008 financial crisis, the Swedish stock market underwent a reversal that sparked the recovery from a severe downturn. In 2009, the SIX Return Index had an average monthly return of 3.77%. During the same period the J6/K3 WL-portfolio had an average monthly return of -4.23%. Returns in 2003, which is a recovery year after the burst of the dot-com bubble, show similar characteristics. That momentum strategies perform poorly during market reversals, is also found by Jegadeesh and Titman (1993) when they back-test the J6/K6 strategy on the period 1927 to 1930. Jegadeesh and Titman (1993) argue that since the loser portfolio, by nature, tend to select high beta stocks following market decreases the WL-portfolio suffers great losses when the market bounce back up again. The momentum strategy is therefore by no means a riskless investment. The above-discussion naturally move the question to return measurements that accounts for risk.

[21] Between January 2009 and April 2009, the J6/K3 WL-portfolio suffered a loss of 46%.

## 4.3 Regression Analysis

The results have so far proved that the momentum strategy is profitable. However, the fact that the WL-portfolio suffers considerable losses in certain months prompts an investigation of risk-based explanations of the observed return continuation. More precisely, the returns from all 16 WL-portfolios will be regressed against conventional asset pricing models. The following section is divided into two parts; with the first part examining if the Capital Asset Pricing Model can explain the observed returns in terms of high beta-values. The second part examines if the extended multifactor model, namely the French and Fama three-factor model, can account for the returns in terms of a size- and book-to-market factor.

### 4.3.1 CAPM Risk-Adjusted Returns

This subsection considers the possibility that momentum strategies systematically pick high-risk stocks, that is, high-beta stocks. An overview of the risk-adjusted returns of all WL-strategies without time-lag can be found in Table II. By definition, the market has a beta of one; thus, any value larger than one implies a higher risk compared to the market. The higher risk should, according to the CAPM, generate a higher raw return. On the other hand, if the beta is less than one, the portfolio should not realize as high return as the market. Alpha denotes the amount of abnormal return that cannot be explained in terms of beta. That is, when alpha is positive, the investment receives an excess return on top of the return associated with the level of systematic risk.

The regression analysis contradicts the CAPM with statistically significant alpha values at the 1% level, for all 16 WL-portfolios. Similar results are found for strategies that skip a month between the formation and holding period. In line with the raw returns, the J6/K3 strategy generates the highest alpha of 2.71. That is, an investment in the J6/K3 WL-portfolio over the sample period, yields a return that is on average 2.71% higher per month than the fair compensation for the risk taken. Furthermore, all zero-cost portfolios have negative beta values, suggesting that when the market increases in value, the value of the WL-portfolio should decrease. This is, however, not the case since all 16 strategies, as well as the market, generates positive returns over the sample period. Since the beta of the WL-portfolios is negative, it follows that the beta of the loser portfolio is higher than the beta of the winner portfolio. This result is in accordance with previous studies. Although, the betas are found to be more negative in this study compared to Jegadeesh and Titman (1993).

**Table II**

# CAPM Adjusted Momentum WL-Portfolio Returns

This table reports the risk-adjusted returns of all 16 WL momentum strategies. The portfolios are formed based on *J*-months historical return and held for *K*-months. The values of *J* and *K* for the different strategies are indicated in the first and second column, respectively. Beta measures the portfolios' sensitivity to the return of the market as whole. The market being the SIX Return Index. Alpha measures the excess return over the fair-return in relation to the portfolios risk. The level of significance is presented by *, **, and *** corresponding to a statistically significant level of 10%, 5%, and 1%, respectively.

| | | Beta | Alpha | t(Beta) | t(Alpha) |
|---|---|---|---|---|---|
| J = 3 | K = 3 | -0.451*** | 2.304*** | -3.563 | 5.725 |
| | 6 | -0.376*** | 2.007*** | -3.642 | 5.872 |
| | 9 | -0.362*** | 1.596*** | -3.771 | 5.321 |
| | 12 | -0.294*** | 1.528*** | -3.775 | 5.843 |
| J = 6 | K = 3 | -0.416*** | 2.710*** | -3.183 | 6.111 |
| | 6 | -0.444*** | 2.362*** | -3.689 | 6.095 |
| | 9 | -0.351*** | 1.983*** | -3.506 | 5.750 |
| | 12 | -0.274*** | 1.573*** | -3.097 | 5.152 |
| J = 9 | K = 3 | -0.486*** | 2.506*** | -3.586 | 5.855 |
| | 6 | -0.429*** | 2.250*** | -3.574 | 5.647 |
| | 9 | -0.387*** | 1.789*** | -3.425 | 4.774 |
| | 12 | -0.327*** | 1.622*** | -3.019 | 4.407 |
| J = 12 | K = 3 | -0.444*** | 2.512*** | -3.337 | 5.655 |
| | 6 | -0.371*** | 2.150*** | -2.995 | 5.017 |
| | 9 | -0.357*** | 1.879*** | -3.049 | 4.625 |
| | 12 | -0.292*** | 1.438*** | -2.401 | 3.544 |

* Newey-West standard errors.

In conclusion, the CAPM fails grossly in explaining the observed returns. Price momentum is, however, not the first anomaly the CAPM fails to explain. Other anomalies, including the long-term reversal effect, contradicts the predictions made by the CAPM. These anomalies have, on the other hand, been successfully explained in terms of  size and book-to-market ratio in Fama and French (1996) three-factor model.

### 4.3.2 Three-factor model Risk-Adjusted Returns

This subsection considers the possibility that momentum strategies systematically pick high-risk stocks, that is, small capitalization stocks and stocks with high book-to-market ratios. An overview of all WL-strategies without time-lag, after adjustment for the Fama and French SMB and HML factors, can be found in Table III. Monthly average return for the SMB- and HML-portfolios, over the sample period, is 0.083% and 0.25%, respectively. If the observed returns are due to higher risk-bearing, it is expected that the winner portfolio exhibits greater sensitivity to SMB and HML, than the loser portfolio. Thus, if the model exceeds in explaining the observed returns, the loadings of the WL-portfolio should be high and positive. On the other hand, if the model fails to explain the observed returns, the loading of the zero-cost portfolio should be contrary or insignificantly different from zero. Alpha denotes the amount of abnormal return the model fails to explain, that is, if alpha is lower than the raw return, but not equal to zero, the model succeeds in explaining only some of the return.

Likewise, as with the CAPM-adjusted returns, the three-factor model reports negative betas at the 1% significance level for all WL-portfolios. Furthermore, all WL-portfolios loads negatively on the SMB-factor. The loadings are, however, in most cases insignificantly different from zero. Nevertheless, the results indicate that the loser portfolio exhibits greater sensitivity to the SMB-factor than the winner portfolio. Consequently, the model implies that the loser portfolio contains riskier stocks than the winner portfolio. This result corresponds to the findings of Rouwenhorst (1998) as well as Jegadeesh and Titman (2001), who also find the WL-portfolio to load negatively on the SMB-factor. However, compared to Jegadeesh and Titman (2001), who find the WL-portfolio to load negatively on the HML-factor, the results show that the HML-loadings for all WL-portfolios are insignificantly different from zero. Thus, it appears that the sensitivity of the loser- and winner portfolio to the HML-factor are about equal. The result of the negative beta and insignificant loadings on the SMB- and HML-factor is an increased risk-adjusted return captured by alpha. The alpha for the best performing J6/K3 WL-portfolio is 2.45, which is higher than the raw return of 2.32%. The conclusion is thus, in accordance with previous studies, that the Fama and French factors, as a measure of risk, is unable to account for the momentum effect.

**Table III**

# FF-factor Adjusted Momentum WL-Portfolio Returns

This table reports the risk-adjusted returns of all 16 WL momentum strategies. The portfolios are formed based on *J*-months historical return and held for *K*-months. The values of *J* and *K* for the different strategies are indicated in the first and second column, respectively. Beta measures the respective portfolios sensitivity to the return of the market as whole. The market being the SIX Return Index. SMB measures the respective portfolios sensitivity to the return of a portfolio of small stocks in excess of the return on a portfolio of large stocks. HML measures the respective portfolios sensitivity to the return of a portfolio of stocks with high book-to-market ratio in excess of the return on a portfolio of stocks with a low book-to-market ratio. Alpha measures the excess return over the fair-return in relation to the portfolios risk. The level of significance is presented by *, **, and *** corresponding to a statistically significant level of 10%, 5%, and 1%, respectively.

| | | Beta | SMB | HML | Alpha | t(Beta) | t(SMB) | t(HML) | t(Alpha) |
|---|---|---|---|---|---|---|---|---|---|
| J= 3 | K = 3 | -0.461*** | -0.144 | 0.035 | 2.220*** | -4.276 | -1.119 | 0.189 | 5.194 |
| | 6 | -0.368*** | -0.113 | 0.134 | 1.863*** | -4.110 | -1.008 | 0.904 | 5.519 |
| | 9 | -0.342*** | -0.213*** | 0.068 | 1.487*** | -4.475 | -2.202 | 0.567 | 5.544 |
| | 12 | -0.272*** | -0.143* | 0.038 | 1.261*** | -3.707 | -1.772 | 0.372 | 4.960 |
| J= 6 | K = 3 | -0.459*** | -0.107 | 0.113 | 2.446*** | -3.920 | -0.839 | 0.649 | 5.813 |
| | 6 | -0.428*** | -0.158 | 0.079 | 2.017*** | -4.200 | -1.389 | 0.557 | 5.618 |
| | 9 | -0.365*** | -0.169* | 0.074 | 1.658*** | -3.868 | -1.810 | 0.614 | 5.113 |
| | 12 | -0.313*** | -0.159* | 0.058 | 1.343*** | -3.553 | -1.670 | 0.470 | 4.330 |
| J= 9 | K = 3 | -0.479*** | -0.220* | 0.013 | 2.367*** | -4.106 | -1.767 | 0.076 | 5.667 |
| | 6 | -0.401*** | -0.216* | 0.057 | 1.864*** | -3.721 | -1.865 | 0.381 | 4.922 |
| | 9 | -0.364*** | -0.187* | 0.068 | 1.536*** | -3.677 | -1.926 | 0.508 | 4.282 |
| | 12 | -0.270*** | -0.158 | 0.082 | 1.184*** | -2.844 | -1.538 | 0.582 | 3.522 |
| J= 12 | K = 3 | -0.435*** | -0.208* | 0.025 | 2.163*** | -3.607 | -1.658 | 0.155 | 5.008 |
| | 6 | -0.380*** | -0.187 | 0.079 | 1.749*** | -3.361 | -1.644 | 0.509 | 4.286 |
| | 9 | -0.373*** | -0.171 | 0.054 | 1.278*** | -3.416 | -1.493 | 0.354 | 3.268 |
| | 12 | -0.288*** | -0.203 | 0.053 | 1.222*** | -2.428 | -1.635 | 0.335 | 3.079 |

* Newey-West standard errors.

# 5. Conclusion

The argument put forward in this paper is that stocks listed at Stockholm Stock Exchange, during the period 1993 to 2016, exhibits return continuation over an intermediate-horizon. The main finding is that all 16 examined strategies yield statistically significant returns, and 12 out of them successfully outperforms the market. More precisely, it is found that the best performing strategy, which selects stocks based on the previous six months' returns and holds the portfolio for three subsequent months, yields an average monthly return of 2.33%. The exact combination of formation and holding period, that results in the best performing strategy is therefore J6/K3. Thus, as in previously conducted studies, the general pattern of profitability is that strategies with relatively long formation periods and short holdings periods are superior. However, the study finds no evidence that a time-lag of one month between the formation and holding period, enhances the performance of the strategies. Furthermore, in contrast to Jegadeesh and Titman (2001), the study finds that it is the loser portfolio that is the main contributor to the observed returns of all 16 strategies. In fact, the winner portfolio only outperforms the benchmark portfolio in 7 out of 16 strategies. Due to the time-limit of the thesis, there have been performed no sub-period analysis. However, the cumulative return of a 1 USD investment in best performing zero-cost portfolio, reveals that the momentum strategy performed poorly prior to 2000. Consequently, the study supports the findings of insignificant momentum returns during the 1990's in Sweden, as documented by Rouwenhorst (1998) and Griffin et al. (2003).

Moreover, the study finds that the return of the strategies cannot be accounted for by an adjustment to systematic risk. As in previous studies, both the CAPM and Fama and French three-factor model produce qualitatively incorrect predictions that losers are riskier, which consequently increases the risk-adjusted return rather than decreasing it. Thus, the conclusion is that conventional asset pricing models are unable to explain the momentum effect. Sceptics have suggested that price momentum is a product of data snooping. However, the large body of evidence of return continuation across different time periods and different stock markets makes such an explanation unlikely. Consequently, several researchers investigate whether momentum is caused by under- or overreaction to firm-specific information. Jegadeesh and Titman (1993) find evidence that the observed momentum returns can be explained in terms of underreaction to earnings announcements. On the other hand, there is also significant evidence suggesting that overreaction and long-term reversal in stocks cause price momentum. Several studies find the momentum returns to be positive the first 10 to 12 months, following the portfolio formation date, and later reverse over the following four years, resulting in a negative cumulative return at the end of year five. With evidence of both hypotheses, it appears that price momentum largely remains an unsolved puzzle in the world of finance.

Lastly, even though it is argued that momentum strategies are highly profitable, and it seems that the return is not due to systematic risk, the study found the momentum strategy to be highly sensitive to market turnarounds. After a severe price fall of the overall market, the loser portfolio consists in large parts of high beta stocks, which have suffered from great losses during the previous market decline. Simultaneously, the winner portfolio naturally consists of low beta stocks, which in general have better resistance to market declines. When the market bounces back up, the high beta stocks outperform the low beta stocks, and the WL-portfolio suffers losses. The momentum investment strategy is therefore by no means risk-free. One could imagine that the momentum strategy systematically picks stocks with high crash-risk, which would imply that the observed returns are due to a crash-premium. However, even though testing such models is outside the scope of this paper, I encourage others to pursue this venue.

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# 7. Appendices

## 7.1 Appendix 1 - Assumptions of Traditional Finance Theory

The assumptions behind the standard Capital Asset Pricing Models are as follows.[22]

1. Individual behavior
   a. Investors are rational, mean-variance optimizers.
   b. Their common planning horizon is a single period.
   c. Investors all use identical input lists, an assumption often termed homogeneous expectations. Homogeneous expectations are consistent with the assumption that all relevant information is publicly available.
2. Market Structure
   a. All assets are publicly held and trade on public exchanges.
   b. Investors can borrow or lend at a common risk-free rate, and they can take short positions on traded securities.
   c. No taxes.
   d. No transaction costs.

The assumptions behind the Arbitrage Pricing Theory are as follows.[23]

1. Security returns can be described by a factor model.
2. There are sufficient securities to diversify away firm-specific risk
3. Well-functioning security markets do not allow for the persistence of arbitrage opportunities.

[22] Bodie et al. (2017) p. 278
[23] Bodie et al. (2017) p. 312

## 7.2 Appendix 2 - Statistical Issues

To assess the accuracy of the results, in terms of statistical significance, a one-sample two-sided t-test with n-1 degrees of freedom is calculated, using the following formula:

$$t_{n-1} = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \qquad \text{Eq. (5)}$$

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

The t-statistics 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, that is, reject the hypothesis that the observed returns are insignificant different from zero, the absolute value of the t-statistic must be greater than its corresponding critical value. The t-values are reported in brackets below the raw returns of the winner, loser, and zero-cost portfolios. In the regression analysis, the level of significance is presented by *, **, and *** corresponding to the 10%, 5%, and 1% level, respectively.

Moreover, the following four data characteristics has been analysed: multicollinearity, heteroscedasticity, autocorrelation and normally distributed errors. The regression diagnostics are performed on the J6/K6-strategy, which is presumed to be representative of the overall sample. An overview of the diagnostic results can be found in Table IV. The Variance Inflation Factor (VIF) is used to detect multicollinearity. In short, multicollinearity is a state of high correlation among explanatory variables (Gujarati & Porter, 2010). The VIF estimates how much the variance of a regression coefficient is inflated due to multicollinearity in the model, that is, if VIF exceeds 10 the variable is said to be highly collinear (Gujarati & Porter, 2010). The diagnostic show no sign of multicollinearity, with VIF values of about 1. The Breusch-Pagan / Cook-Weisberg (BP/CW) test is used to detect any linear form of heteroscedasticity. The BP/CW test the null hypothesis that the errors variance is equal versus the alternative that they are not (Gujarati & Porter, 2010). The performed test is unable to reject the null hypothesis. The Durbin Watson (WT) test is used to detect the presence of autocorrelation at lag 1 in the residuals. In short, autocorrelation refers to the characteristic in which the values of the same variable are correlated over time (Gujarati & Porter, 2010). In the WT test, a d-statistic of 2 indicates that there is no autocorrelation in the sample, thus, the diagnostic show no sign of serial correlation (Gujarati & Porter, 2010).

**Table IV**

# Overview of Diagnostics

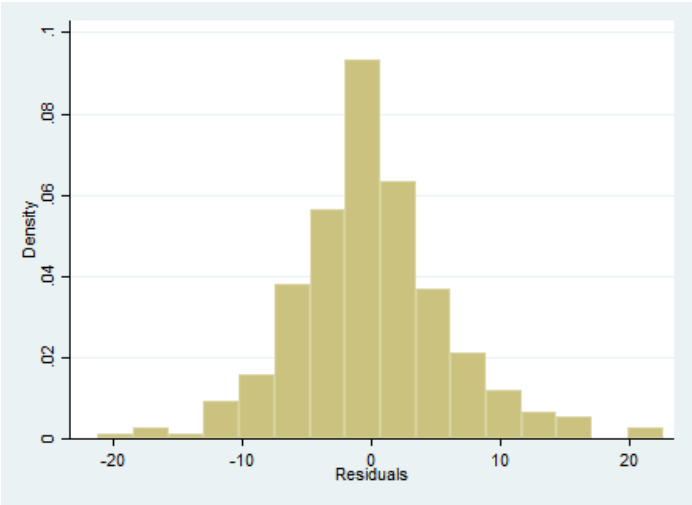
The following is an overview over performed regression diagnostic of the J6/K6 strategy without time-lag. To examine the presence of multicollinearity, heteroscedasticity, autocorrelation and normal distributed errors in the data, the following diagnostics have been performed; Variance Inflation Factor test, Breusch-Pagan / Cook-Weisberg test, Durbin-Watson test, and Shapiro-Wilk test. The reported values in column 2-4 are; mean VIF, P-value, d-statistic and P-value, respectively.

| Strategy | Multicollinearity | Heteroscedasticity | Autocorrelation | ND-errors |
|---|---|---|---|---|
| CAPM - Winner | 1 | 0.3663 | 1.775 | 0.06 |
| CAPM - Loser | 1 | 0.6314 | 2.141 | 0 |
| CAPM - WL | 1 | 0.57 | 1.992 | 0 |
| FF3 Model - Winner | 1.18 | 0.1046 | 1.841 | 0.008 |
| FF3 Model - Loser | 1.18 | 0.0797 | 2.06 | 0 |
| FF3 Model - WL | 1.18 | 0.1602 | 1.922 | 0 |

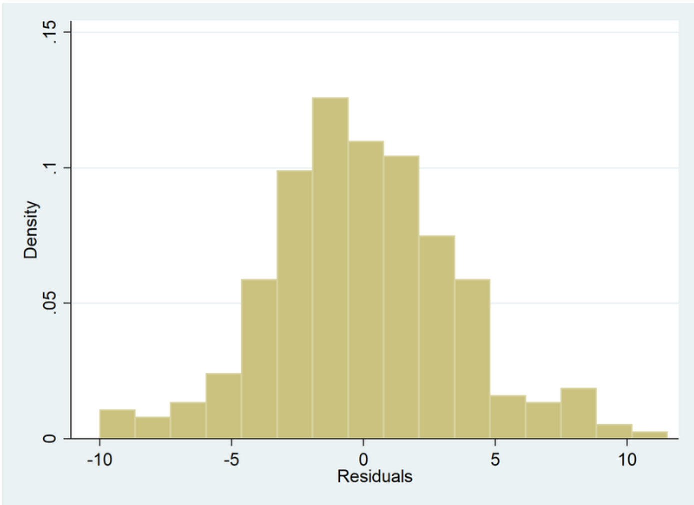
Lastly, the Shapiro-Wilk (SW) test is used to access the normality of the error terms. The SW test the null hypothesis that the population is normally distributed versus the alternative that they are not. The performed test rejects the null hypothesis in 5 out of 6 cases. However, the assumption of normally distributed errors is often relaxed when the sample size is sufficiently large, since the Central Limit Theorem ensures that the distribution of error terms will approximate normality (Gujarati & Porter, 2010). Although, the conclusion of the overall diagnostics is that there is no need to correct for any bias, it has been determined to carry out the tests with Newey-West standard errors. The procedure ensures that any undetected autocorrelation or heteroscedasticity do not affect the inference.

## 7.3 Appendix 3 - Histogram of Residuals

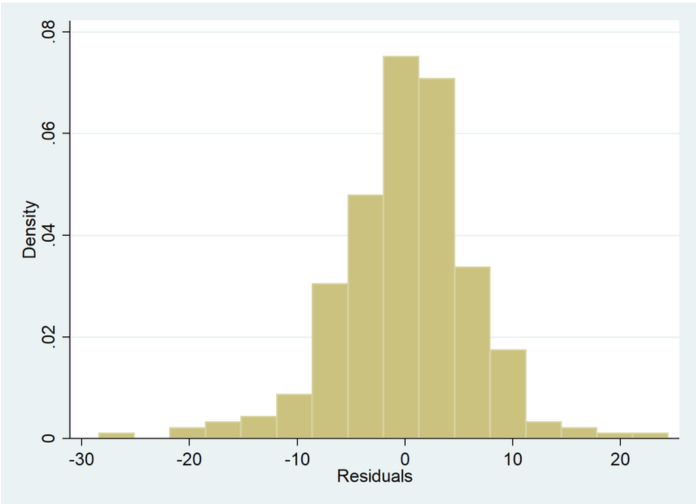
### CAPM – J6/K3 Winner Portfolio



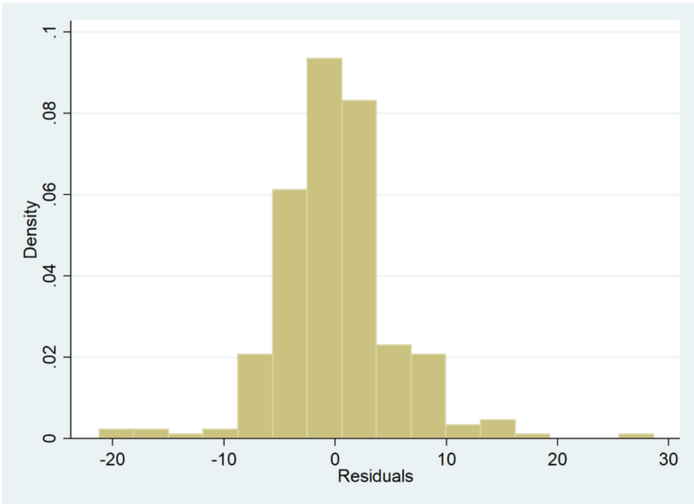

### CAPM – J6/K3 Loser Portfolio



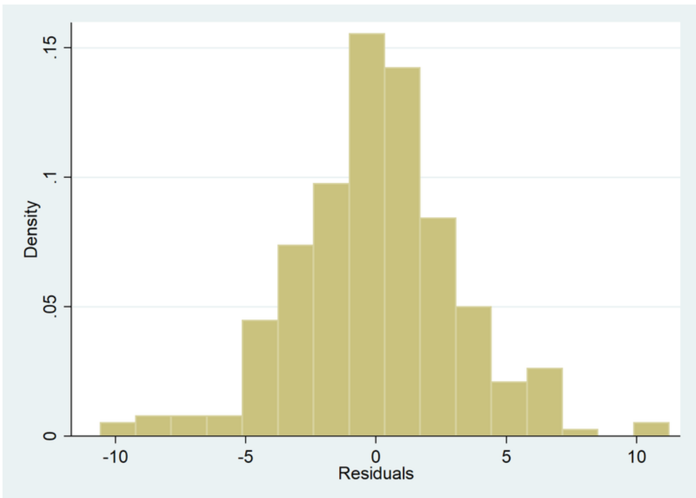

### CAPM – J6/K3 WL-Portfolio



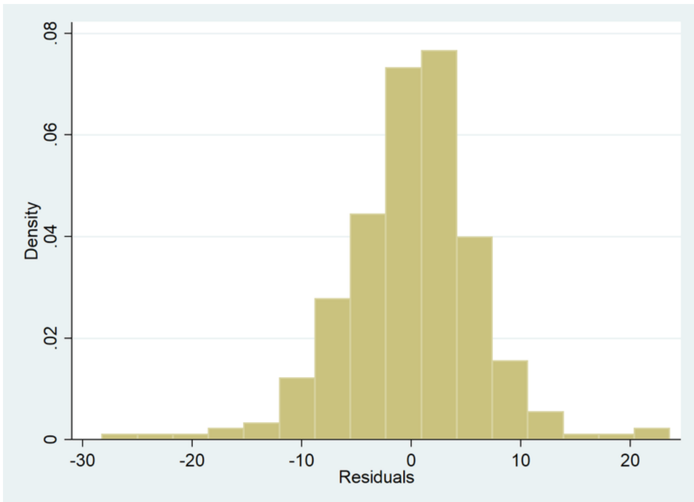

### FF – J6/K3 Winner Portfolio




### FF – J6/K3 Loser Portfolio




### FF – J6/K3 WL-Portfolio

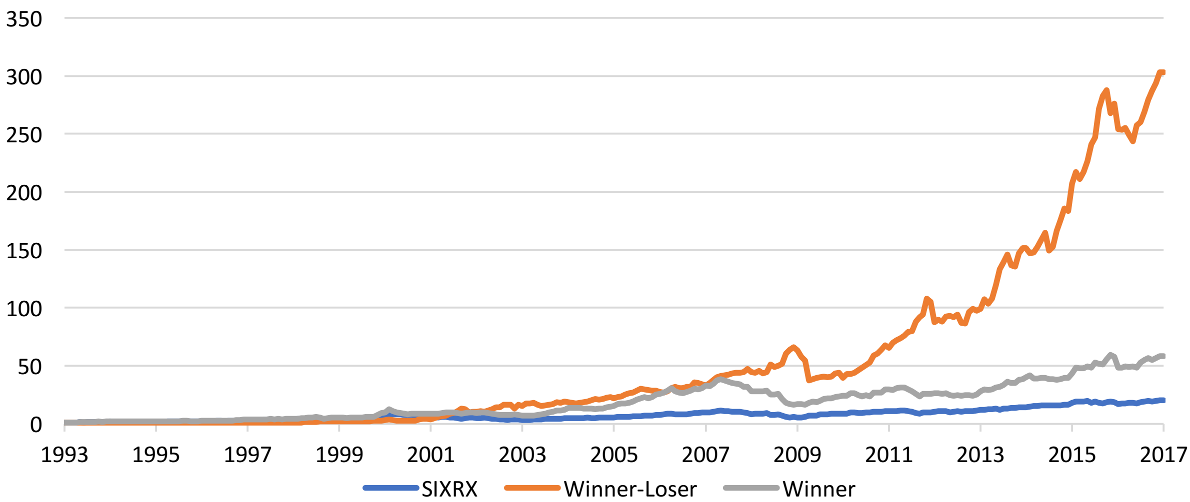


## 7.4 Appendix 4 - Performance overview

**Figure 7**

# Performance Overview

Illustration of cumulative return from January 1993 up until December 2016 for a 1 USD investment in the benchmark portfolio and the best performing zero-cost portfolio and winner portfolio. That is, the SIX Return Index, J6/K3 WL portfolio and J6/K3 Winner portfolio. In December 2016, the investment has grown to 20.081, 303.13 and 59.14 USD, respectively. Descriptive statistics are presented below.




**Descriptive Statistics**

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| SIXRI | 288 | 7.61 | 4.921 | .981 | 20.085 |
| WL | 288 | 53.956 | 74.702 | .812 | 303.137 |
| Winner | 288 | 18.915 | 15.218 | 1 | 59.143 |