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# Momentum

## Trendspotting in the Swedish Stock Market

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## Abstract

We set out to investigate the presence of momentum in the Swedish stock market in an attempt to distinguish whether the market displays the weak- and the semi-strong form of efficiency. Adopting a strategy similar to that of Jegadeesh and Titman (1993) and (2001), where past winners are bought and past loser are sold, we are able to show that momentum indeed is present, earning approximately 1 percent per month at a medium-term investment horizon. When investigating the sources of the momentum profits we find that neither the CAPM nor the Fama and French three-factor model are sufficient in explaining this phenomenon. After establishing that these profits were robust to these risk factors, we used the momentum factor in order to estimate the Carhart (1997) four-factor model. Comparing it to the three-factor model, we find that the momentum factor is significant and might be helpful in explaining variations in stock return.

**Keywords**: Momentum, Market Efficiency, Fama and French, Carhart.

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# 1. Introduction

## 1.1. Background

The idea of outperforming the market have since long been the objective for most investors within financial economics. As a consequence, many academics and private investors have tried to come up with a strategy with which they can accomplish this. Many of these attempts are concerned with the analysis of historical data, in which they are trying to find, and consequently exploit, patterns.

On the other side there are those who argue that the financial markets are efficient and that implementing such strategies is a waste of time. Only by taking advantage of temporary deviations from market equilibrium might one earn abnormal profits, but in the long run the market will adjust. This notion was and is still up for debate and a variety of evidence has been put forth from both sides. Historically, those arguing against market efficiency often point at certain anomalies that they find occurring on a regular basis while those in favor argue that these patterns, if they exist, are consistent with an efficient market.

While many of these anomalies appear to have been at least partially accounted for, the one that is hardest to explain is the so-called momentum effect in stock prices. Momentum builds on the assumption that over a medium-term investment horizon, past winning stocks continues to outperform past losers.

In 1993, Jegadeesh and Titman published a paper in which they investigated whether a strategy based on historical analysis of stock prices could be used to earn profits in the US market. By creating a zero-investment portfolio where past winners are bought and past losers are sold, they were able to obtain positive returns of up to 1 percent per month for periods up to one year.

Their discovery was given much attention, much due to the fact that the reverse pattern was observed a few years earlier, when DeBondt and Thaler (1985) showed that on longer horizons (three- to five years) past losing stocks outperformed past winners.

Following the influential works of Jegadeesh and Titman, several other studies conducted in different settings documented similar results, thus suggesting that their findings were not a fluke. In this context the choice of methodology has served as a major point of interest.

As one can expect, advocates of efficient markets have directed much critique towards the methodology used in these studies, putting their momentum findings down to either misspecified tests or data mining as they found no evidence of momentum.

Even among those in favor of the momentum anomaly lack a general consensus as to how profitable this strategy really is and whether it is implementable in reality. Some even argue that while there seems to exist a momentum effect in some markets, the profitability tends to disappear completely when adjusting for risk and when transaction costs are taken into consideration.

The reason as to why momentum is observed has also been up for debate. During the latter half of the 20$^{th}$ century, a new point of view in financial economics emerged. With its origin in behavioral psychology, this theory holds that it is the irrational behavior of investors that causes this anomaly, induced by the investors overreacting to information. Such an argument is particularly interesting considering that it questions the fundamental assumptions of one of the most widespread financial theories, the Efficient Market Hypothesis.

## 1.2. Purpose and Contribution

Primarily, we seek to test the weak- and semi-strong form of market efficiency by testing whether the Swedish stock market exhibits momentum. Should we find evidence of this, we will test if these results remain after adjusting for different risk factors. The two methods generally used for this purpose are the CAPM and the Fama and French three-factor model. Furthermore, we will use possible evidence of momentum and test whether this parameter could be used to explain variation in stock return, as proposed by among others Carhart (1997). This model will be tested on portfolios constructed on size- and book-to-market ratio and will later be compared to the Fama and French model to see whether the added factor adds to the explanatory power of the model.

Most of the major research has been conducted in the US and in larger western European markets, but there is less evidence of momentum in the Swedish market. While some have found that the zero-investment strategy yields positive monthly returns, these are not statistically significant.

During our chosen sample period, the Swedish stock market has experienced crashes (sub-prime crisis), bubbles (IT-bubble) and macroeconomic events that most likely affect the profitability of this strategy. Therefore, it is of great interest to us to test whether a possible momentum effect is persistent under different market conditions. By dividing the data into sub periods we hope to distinguish differences as to how these events affect the overall profitability of the momentum strategy.

## 1.3. Outline

The remainder of our thesis is organized as follows: In *Chapter 2* the reader is given the theoretical framework which we hope bring insight as to how the discovery of momentum questions the perceptions of efficient markets. In *Chapter 3,* we present the research that has been aimed at momentum, focusing on the most influential articles. We also present some research documenting the opposite behavior of stock prices, the so-called mean reversion phenomenon. In *Chapter 4* we present the data used throughout this thesis and discuss the manipulations that were undertaken. In *Chapter 5* the methodology used for constructing the portfolios and the statistical testing we perform is described. In *Chapter 6* the results from our tests are presented and analyzed. In the 7$^{th}$ and last chapter, we summarize and discuss our findings and offer suggestions for further studies.

# 2. Theoretical Foundation

*In this section we will present the theories that much of the current studies seek to falsify. These concepts have historically served as paradigms for much of the research conducted in this field.*

## 2.1. Efficient Market Hypothesis

Ever since the idea of efficient markets was expressed by Eugene Fama in his 1970's article '*Efficient Capital Markets: a Review of Theory and Empirical Work',* it has been a hot topic within financial economics. Before describing the theory behind it we believe that a definition of what constitutes an efficient market is necessary. Broadly speaking, an efficient market is one where prices fully reflect all available information. The term 'fully reflect' is a somewhat vague and at the same time a very strong assumption. Elton et al. (2007) argues that for investors to have an incentive to trade until this point, this would require that the cost of information and transaction is zero. Since it is not, they argue, they believe that this assumption is probably not valid.

As argued by Schleifner (2000), the assumptions of the EMH depend highly on the concept of investor rationality, which he divides into three types;

- Investors are rational and value securities rationally
- Irrational behaviour cancels each other out and does not affect the prices
- Arbitrageurs feed on the behaviour of irrational investors, which eliminates the latter's impact on prices.

While Fama (1988) argues that although the Efficient Market Hypothesis, in most cases, seems to stand up to the tests, he feels the need to categorize the hypothesis into three sub-categories.

In its *weak form*, today's prices reflect all historical information available, making it impossible to make arbitrage profits by studying historical data. While one might find temporary patterns, it is argued that when investors are exploiting this, prices would soon readjust to their equilibrium. Earlier tests of this assumption were based on technical analysis and appeared to conclude that stock prices followed a *random walk,* something that we will cover more thoroughly later on.

The *semi-strong* form of efficiency, which also incorporates the weak form, holds that all types of publically available information are reflected in stock prices. Testing this form of efficiency is mainly concerned with the speed of price adjustment to, for example, annual reports and financial statements. (Malkiel (2003))

It is assumed that the prices in a semi-strong efficient market adjust immediately after news are released, thereby making fundamental analysis, as well as the previously mentioned technical analysis, inadequate in the hunt for abnormal returns.

The third and final form of market efficiency is the *strong form*, in which not even monopolistic information, such as inside information, can be used to earn abnormal returns. Fama (1970) holds that while the two weaker forms have been proven to withstand most of its criticism the assumption of the strong form of market efficiency is too strong. Instead it should be viewed as a benchmark to the deviations of market efficiency.

## 2.2. Random Walk

Closely linked to the weak form of the efficient market hypothesis is the idea that stock prices follow a random walk. The idea of random walks means that changes in stock price are independent of each other and that they take a random and unpredictable path. If stocks were to follow a random walk, predicting future stock prices based on their historical prices would be impossible, thereby making technical analysis inadequate (Fama (1995)). Obviously, this stands in direct contrast to the momentum theory and other return predictability theories.

A random walk process is said to have a unit root, and inference based on a unit root process is unreliable. This becomes evident, as the asymptotic distribution of the t-statistic for the null-hypothesis is no longer normal. (Edgerton (2010))

Similarly to the EMH, the random walk can be divided into three categories based on how strong assumptions one makes. In the *strongest form* of Random Walk, the residuals are assumed to be independent and identically distributed (IID). The *second form* of random walk relaxes the assumption of IID returns. Instead, the error terms are considered independent and not identically distributed (INID). In its weakest form, the assumptions of independence and identical distribution are relaxed. The returns can have dependence, but have to be uncorrelated and cannot be identically distributed (DNID). (Asgharian (2010))

Clearly, any type of momentum patterns would question the validity of the Random Walk theory. If this theory were to hold empirically, it would not be possible to systematically earn profits by basing a strategy on technical analysis. As we will show later, many researchers disagree heavily with this theory and presents excessive proof to back up their opinions.

## 2.3. Behavioral Theories

In more recent years, alternative hypotheses as to why the market displays inefficiencies have been proposed and have become a topic of its own. Following the influential works of Kahneman and Tversky (1974), it has been proposed that possible market inefficiencies are due to investor irrationality. Since one of the primary assumptions of the EMH is investor rationality, these theories might serve as a tool to explain some of the documented anomalies.

In their 1974 paper, Kahneman and Tversky presents the idea of representative heuristics, which deals with the fact that individuals tend to make probability judgments which are based on the degree that they resemble something else. One problem with representativeness is that it could possibly lead to systematic biases. This since it implies that important issues such as sampling proportions are neglected. When an investor is faced by an investment opportunity he would, using Kahneman and Tversky's argumentation, tend to disregard information relevant for his future decisions and merely base them on his own probability assessments. In other words, he would base his decision on what he *thinks* is more likely to happen based on his own past experiences and confidence.

In 1979, the authors presented a new theory, which served as a critique of the Expected Utility Theorem. The main contribution of their *Prospect Theory* is the S-shaped utility curve, which introduces the concept of loss aversion. It has been shown empirically that investors attribute different weights to gains and losses in the sense that they tend to hold on to losing stocks and sell winning stocks, in fear of realization of a loss. This irrational behaviour clearly contrasts to the concept of rationality.

Another observation that is said to cause both the momentum-and contrarian effect is that investors both over- and underreact to information (see for example DeBondt and Thaler (1985) and Daniels et al. (1998). Since these observations have been used as evidence against the Efficient Market Hypothesis, the behavioural aspects might account for much of the documented anomalies. Fama disagrees with

the behavioural theorists stating that over- and under reaction should be viewed as market inefficiency. Instead, he argues that these anomalies are '*chance deviations*' in that they are equally frequent, and that they do not contradict the idea of an efficient market. Furthermore, he shows that the long-term anomalies either disappears or diminishes when using other models and/or statistical approaches.
Another explanation for these anomalies he says is that these patterns represent variations in rational risk premium.

Daniel et.al (1998) disagrees with both of his explanations and argues that imperfect rationality is a more likely explanation. Since several anomalies have been shown to occur not only regularly but also simultaneously, they argue that the market is both under- and overreacting. Taking a behavioural approach, the authors propose an integrated theory to explain the market reactions and predict when they occur. They argue the short-run momentum effects derive from two psychological biases which cause the security market to both under- and overreact:

- Overconfidence about the investor's private information
- Biased self-attribution that causes asymmetric shifts in investor confidence as a function of their investment outcomes.

The former bias emerges when an informed investor attributes past winning decisions to his or her skill, and past losses to bad luck, which then causes the investor to draw wrongful inferences about his forecasting abilities. This is not only applicable to agents in the financial context, but also to other so-called expert professions such as doctors who deals with predictions based on the current information set available.

While testing these behavioural models are beyond the scope of this thesis, we believe that the inclusion of these theories might serve as a mean of explaining any possible momentum- or contrarian effects further on, and the difficulties the testing for these presents. We believe that the human behaviour must have a large impact on the market behaviour even though the magnitude of this is impossible to measure. While the crucial assumption of rational investors sounds good and simplifies matters drastically, empirics tell a different story, something that is particularly evident with the crashes that the financial markets have experienced during its lifetime.

# 3. Previous Research

*The purpose of this section is to give the reader a review of the most influential research conducted in this field. For more elaborate information, please refer to the original texts given in the reference list.*

## 3.1. Introduction

The idea of forming trading strategies based on historical prices is by no means new. As early as in 1967, Levy found that when buying stocks whose prices were much higher than their average of the previous 27 weeks, he was able to yield significant abnormal returns. His results were later put into question when Jensen and Bennington (1970) showed that by extending the sample period, Levy's portfolios failed to outperform simple buy-and-hold strategies, consequently putting the findings down to sample bias (Jegadeesh and Titman (1993)).

As will become evident in the following section, there has been a wide range of research conducted towards return continuation. While many researchers have shown extensive proof of momentum, the significance of their results and the explanation to its existence are still widely debated in the academic world. Furthermore, the methodology used in respective study could possibly have a large impact on the profitability of the zero-investment strategy. Interestingly, the reverse phenomenon has also been observed; that prices tend to revert to their fundamentals at different horizons. Moreover, it has been shown that there is a link between price continuation and price reversals.

## 3.2. Price continuation

In 1993, Jegadeesh and Titman presented their first article, aiming towards investigating the profitability of momentum portfolios in the NYSE and AMEX during 1965-1989. They showed that when buying winner portfolios and selling loser portfolios, they were able to yield abnormal returns with formation- and holding periods ranging from 3-12 months. The six-month strategy earned approximately 1 percent per month and showed such a high t-statistic that it leads the authors to strongly reject the Efficient Market Hypothesis. Of all their different portfolios, the most successful proved to be a strategy that uses a twelve-month evaluation period and a three-month holding period. The main critique of their findings can be

attributed to two things. Namely that the results are either due to so-called data mining or, as argued by Fama, that they are due to compensations for risk. If one is dealing with a data-mining problem, this complicates matters since non-experimental tests such as this depend highly on available data.

As a response to the critics, Jegadeesh and Titman (2001) followed up on their previous article, and were able to give further support of their earlier findings. With their new study, the authors included an additional nine years of data, which helps in overcoming the data mining problem and solving two issues. Firstly, they are able to perform out-of-sample tests. And secondly, they are able to '*…assess the extent to which investors may have learned from previous return patterns'*. In doing so, they are still able to show that winning stocks kept outperforming losing stocks by over 1 percent per month for twelve months. This suggests, they argue, that the return continuation is not entirely due to data mining and that investors might not alter their strategies to reduce the predictability.

Interestingly, the additional data leads to new discoveries. The small firm effect (where smaller firms outperform larger firms) found by Banz (1981) and that value stocks perform better than growth stocks are not observed in their new study. The anomaly has been shown to yield abnormal returns (see for example Fama and French (1993), Haugen (1997)). Strategies such as these are often based on price-ratios such as book-to-market (B/M), earnings-to-price (E/P) and dividend-per-price (D/P) where value shares show large ratios and vice versa. However, in the post-holding period (ranging from 13-60 months) they find that the cumulative returns are negative. Looking at the post holding performance, they are able to reject that the profits are due to cross-sectional differences in expected return, as proposed by Conrad and Kaul (1997). At the same time, these findings gives support to the findings presented by Daniel et al. (1998)) who propose that the post holding returns of momentum portfolios are negative. This would in turn imply mean-reverting returns on longer time-horizons.

In another setting, using the same method as Jegadeesh and Titman (1993), Rouwenhorst (1998) investigates the medium-term return patterns in and between twelve European countries between 1978 and 1995. This, he argues, helps in avoiding the aforementioned data-mining problem. In his study, he was able to show that an internationally diversified relative strength portfolio earns approximately 1 percent per month. Similar to the findings of Jegadeesh and Titman (2001), he finds that the

return continuation is present for 12 months. However, these are more obvious for smaller firms than for large firms. Thus, it appears as if the small firm effect is valid even when looking at several markets. In addition, he also finds that the abnormal returns increases for the relative strength strategies when controlling for market risk and exposure to size factors.

Another study in an international setting is that of Griffin et al. (2003) where they test whether or not there is a link between macroeconomic risk and momentum. Their study uses data from 39 countries in different continents. Their portfolios include more stocks than for example Rouwenhorst, as they put 20 percent in each portfolio. They found that on average, a winner-loser strategy is highly profitable in 31 out of 39 countries. Out of all countries, they find that those located in Asia displayed the weakest average monthly return whereas African countries displayed the highest. In total, the momentum returns of the full sample reach 0.49 percent and is clearly significant while the European countries have an average profit of 0.77 percent where all are significant. The authors found that the correlation between regions is quite low, which suggests that if momentum derives from risk, then it is merely country specific. Furthermore, they find that macroeconomic variables and the economic climate have little or no impact on the developed markets, while the latter has some impact on the emerging markets.

Moskowitz and Grinblatt (1999) find that there exists a momentum effect in industries, which has a large impact on the profitability of individual stock strategies. This is due to a high return correlation of stocks belonging to the same industry. A consequence of this is that since the winner and loser stocks are likely to come from the same industry, the strategies are not diversified.

It is important to stress that neither of the earlier studies incorporated important factors such as transaction costs, taxes etc. Conrad et al. (1997) argue that these short-term profits are merely a result from a bid-ask bounce, and when correcting for this, the profits would disappear. One way of dealing with this is by not forming the portfolios immediately at time t, but instead delaying the formation of the portfolio with a week or more. This approach lets the stock prices readjust and might decrease the short-term profits. However, Jegadeesh and Titman (2003) found that this had very little impact on the average monthly returns.

Momentum research investigating the Swedish market is available, but is rather limited and inconclusive. Rouwenhorst (1998) and Griffin et al (2003) both

strongly rejects that there is momentum in the Swedish stock market. Locke et al. (2009) gives partly support of their findings, documenting small but insignificant returns using a 6-6 strategy applying several test- methods.

While Fama and French (1995) argue that long-term return reversals can be consistent with a multifactor model of returns, their model fails to explain the momentum effects that have been documented in the medium term. Chan, Jegadeesh and Lakonishok (1996) find that a market underreacting to earnings information can partly explain return continuation. Similar conclusions were reached by Daniel et.al (1998) who argues that the previously mentioned biases, causes the investor to both over- and under react. However, Rouwenhorst (1998) argues that price momentum is not subsumed by earnings momentum.

The lack of agreement with regards to the momentum profitability led Locke et al. (2009) to test whether the different methods used in other studies were the point of difference. Their study looked exclusively at the 6-6 strategy, which was tested on 43 different markets. To summarize their findings they found that the composition of the portfolios as well as the return metrics indeed yields different results. They find that while Cumulative Abnormal Returns (CAR) returns yields slightly higher returns than Buy-and-Hold Abnormal Returns (BHAR), though not by much. Greater are the differences between value- vs. equally weighted portfolios and log vs. simple returns, where value-weighted portfolios and log returns yields greater returns. They also highlight the impact of currency and shows that the momentum profits are sensitive to the exchange rate.

## 3.3. Price reversals

While extensive evidence of momentum effects has been shown in the medium-term, others have found the opposite effects using a shorter and longer time horizon. As such, advocates of the contrarian strategy take a slightly different approach to trading than those of momentum as past losers are bought and past winners are sold.

In the 1980s, two what has come to be highly influential articles simultaneously documented evidence of price reverting to their mean. DeBondt and Thaler (1985) presented one of the more influential articles in this field, and found that with a holding period of between 3 to 5 years, past losing stocks were able to outperform past winners. This theory builds on the assumption that due to the investors overreacting to new information, prices tends to revert to their mean,

because of negative serial correlation in prices. Their finding has been heavily criticized by among others Chan et al (1996), and the main critique is that size effects and the systematic risk of their portfolios accounts for the positive returns. Another interesting discovery is that it was only in January that the long-term contrarian portfolios outperformed their winner dittos. Jegadeesh and Titman (1993) also noticed this pattern as the losing stocks in their zero-investment portfolios, for all other months the reversed behaviour was observed. The latter finding raises the question of whether this is due to investors overreacting or not.

Even research aiming at explaining momentum documents price reversals at different time lengths. Jegadeesh (1990) and Lehmann (1990) found that a short-term contrarian strategy yielded significant abnormal returns. However, it has been argued that the most probable explanation for these findings is lack of liquidity or price pressure in the short run rather than overreaction. Another explanation could be that stock prices react slowly to common factors, something that could explain a large part of the abnormal returns.

Fama and French (1988) presented evidence of mean reversion in the US market where up to 40 percent of variations in stock return could be predicted on past returns depending on the size of the firm

Whilst testing the random walk hypothesis in the Swedish stock market during 1919-1990, Frennberg and Hansson (1993) found support in favour of both momentum and mean-reversion. On shorter investment horizons, they found strong support of the returns being positively auto correlated. When increasing the investment horizons, they found evidence of the contrary, as the returns now appeared to be negatively auto correlated, i.e. mean reverting.

Similar result were obtained by Poterba and Summers (1988), who showed that when using variance-ratio tests on 17 different markets, stock returns showed a positive autocorrelation for shorter periods which was later reverted into negative autocorrelation for periods over one year.

Again, the data selection serves as point of critique. Kim et al (1991) argue that the findings of Fama and French were a pre-war phenomenon. When using post-war data, they find support of the opposite: a momentum effect in stock prices where above average returns appear to continue. Looking at the post-holding period, the predictions of the behavioural models are opposite to those of Conrad and Kaul (1998). While the latter suggests that the winners will have a positive post-holding

return, the behavioural models argues that after the prices have reverted to their fundamental values, the loser stocks yields a higher return than winners.

Lakonishok et al. (1994) argue that naïve investors are more likely to invest on firms with a low Book-to-Market ratio (B/M) since they historically have performed well. This behaviour has proved to push the prices up and lowering their expected return. (Asgharian (2010))

While Lo and MacKinlay (1990) argue that lead-lag effects between stocks reverts the price in the short run, others argue that they are due to investors overreacting to information (see for example DeBondt and Thaler (1985)). In the longer run, microstructure bias and time-variations in expected returns have been suggested as causes (Chan et al (1996)).

As can be seen the evidence and their explanations are rather inconclusive. It is clear that depending on what markets to test, what sample period is used and what strategy one implements, the results might differ considerably. As soon as an author presents what he calls a profitable strategy, this have time after another been if not falsified, then at least thoroughly questioned. Data selection and the restrictions on this obviously serve as a point of interest and appear to have a large impact on the momentum profits.

Other factors that affect the results are the various measures one uses to evaluate the performance of their portfolios as showed by Locke at al. (2009). Particularly the choice of return metric has been proven to yield different results, something that we noticed ourselves whilst writing this thesis.

# 4. Data

*In the following section, we describe the data sample used throughout this thesis and the manipulations that were undertaken in order to perform our tests*

## 4.1. Data description

The data used in this thesis was retrieved from *Thompson DataStream* and consists of all the stocks listed on the Stockholm Stock Exchange (SSE) between January 1991 and January 2011. The number of available stocks ranges from 115 in January 1991 to 437 in January 2011.

Instead of using a regular price index, we choose to use the Return Index provided by *DataStream* since it assumes that dividends are reinvested in the company. [1]

DataStream uses the following formula for calculating their return index:

$$RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * \left(1 + \frac{DY * f}{n}\right)$$

where RI denotes the return at time t and t-1 respectively, PI denotes the price, DY is the dividend yield of the price index, f is a grossing factor and n is the number of days in the financial year.

As the risk free rate we chose the 1 month Swedish treasury bill, which was retrieved from the Sveriges Riksbank website. [2] The OMXS price index is used as a proxy of the market index, and was gathered from the NASDAQ OMX website. [3]

## 4.2. Data treatment

In order to overcome a possible survivorship bias problem, stocks that were delisted during our sample period were also included in our data. While this increases the power of our tests, it also gives raise to some issues. The main reasons for delisting stocks are either bankruptcy or mergers; both playing a crucial role for the portfolio returns due to their pre-delisting price drifts Eisdorfer (2008). Where the former is

[1] DataStream offers the following description of the index: '*...a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit*

[2] http://www.riksbank.com

[3] http://www.nasdaqomx.com

often associated with negative abnormal returns before delisting, the latter usually displays the opposite pattern.

While we believe that the reliability of the DataStream data is good, we must stress that it is not without fault. As pointed out by Ince and Porter (2006), one problem involves the data for firms that are delisted sometime during the sample. The problem arises when a stock that is included in either portfolio is delisted during the holding period. To account for this problem, we had to manually delete data for the delisted firms. In most instances, DataStream offers a description of the stocks that have been delisted, is merged or becomes dead. But when examining our data, we noticed that the data for several companies remained unchanged for long periods of time. Since this is not very likely, we had to conclude that they were removed from the index and they were subsequently deleted from the first repetition.

All data used in this thesis was treated in either MS Excel 2007 or EViews 7 and the reliability of these programs is believed to be sufficient. The extensive manual work done in MS Excel as we sorted the data from dead and delisted stocks has been done cautiously, though we cannot disregard the possibility that mistakes were made.

# 5. Methodology

*In the following section, we give the reader a thorough description of the methodology used for the construction- and evaluation of our portfolios.*

## 5.1. Portfolio construction

In order to test the presence of momentum in the Swedish stock market, we adopt a strategy similar to those used in Jegadeesh and Titman (1993) and (2001). At time t, we evaluate the stocks performance over the past *J* months, where *J* equals one-, three-, six-, nine- and twelve months.

### 5.1.1. Stock return

The rank of the stocks between time t and at t-*J* is determined by the stock's return. The general metric for simple returns is given by:

$$R_t = \frac{P_t + D_t - P_{t-1}}{P_{t-1}}$$

where $R_t$ denotes the return at time t, $P_t$ denotes the price at time t, $P_{t-1}$ denotes the price at time t-1 and $D_t$ denotes dividends.

Since we are using a return index, where the dividends are reinvested in the asset, we do not have to take these into consideration when calculating the returns. Our choice of using discretely compounded returns (arithmetic returns) in favor of continuously compounded returns (log returns) are mainly for comparability reasons, since most of the earlier studies have used these. While the latter method allows us to assume that the return data represent the distribution of the returns for the coming period, are symmetric and makes it easier to derive time series properties; it is most suitable when the changes in return are small. As will become evident, our data sample contains very volatile stocks that would, using log returns, tilt the portfolio returns downwards. (Benninga (2000))

### 5.1.2. Formation of the portfolios

Based on their past performance, we rank them and sort them into ten groups, where those within the top quantile are placed in an equally-weighted winner portfolio, and those within the bottom quantile are placed in the loser portfolio.

By taking a long position in the winning portfolio and a short position in the losing portfolio we form so-called zero-investment portfolio. Following formation,

the portfolios are held for *K* months, where *K* equals one-, three-, six-, nine- and twelve months.

Jegadeesh and Titman excluded stocks that had a Market Capitalization below the 10th percentile at time t and stocks that were traded below $5 USD. The reason for their restriction was to get rid of stocks that are the least traded and thus more volatile. But due to a much smaller sample, excluding over 10 percent of our stocks would, at least in the beginning of our sample, mean that there are less than 100 stocks available. As a consequence, we choose to exclude only those with a Market Capitalization below the 5th percentile. Also, stocks with a return history of less than 12 months at the time of formation were excluded from the portfolios, seeing that this is common practice in all studies we have examined.

Our strategy uses overlapping portfolios, where new portfolios are constructed each month. An advantage of using overlapping portfolios is that it increases the power of our tests by offering more observations (Jegadeesh and Titman (1993) and (2001)). At the same time, it also increases the risk of inducing autocorrelation.

### 5.1.3. Treatment of delisted stocks

As mentioned in section 4.2, the inclusion of delisted stocks helps in overcoming a possible survivorship bias of the stocks included in the index. Including them also give raise to problems if stocks included in either portfolio are delisted during the holding period. To account for this, one can either reinvest the stocks portion of the portfolio or simply do nothing.

While the latter would be the simplest, the fact that DataStream do not offer any post-delisting returns, we believe that this approach would not be a good reflection of reality. Instead, we assume that at the time of delisting, the investor is able to sell this asset at the last traded price and reinvest this portion of the portfolio in a market index, which in our case would be the OMXS price index. Even though this might prove to affect the results we believe that this is the most realistic option.

## 5.2. Portfolio performance

At the end of each holding period the returns are estimated by taking the arithmetic average of the total return. Again, the choice of using arithmetic- instead of geometric averages is for comparability. The returns of portfolios with holding periods over one month are transformed to give us their returns on a monthly basis. This is done with the hope of distinguishing any differences across the different investment strategies.

When the profitability of our portfolios is estimated, the significance of these profits is tested with a Student's t-test, where we test the null-hypothesis that the returns are not significantly different from zero against the alternative hypothesis that they are.

The *t*-statistics are calculated using the following formula:

$$t = \frac{\bar{X} - \mu}{\sigma_p / \sqrt{N}} \sim t_{n-1,\alpha}$$

where $\bar{X}$ denotes the average monthly portfolio return, $\mu$ is set to zero, $\sigma_p$ denotes the standard deviation of the portfolio, and $N$ is the number of observations in.

With different evaluation- and holding periods, the number of observations for each strategy differs. Ranging from 239 observations for the 1-1 strategy to 217 observations for the 12-12 strategy. But given that both of these poles are large enough to draw statistical significance from them, we believe that the comparisons between the results ought to be accurate.

Another point to stress is that the monthly returns of the portfolios are affected by the time at which they were calculated. This is due to the use of quantile portfolios as well as the changing number of available stocks. For instance, the portfolios in the beginning of our sample consist of fewer stocks than towards the end. As a result, extreme returns in either direction have larger impact on the monthly return at that time since their weights in the portfolios are bigger. These outliers might also cause violations of the OLS assumptions used in our coming regressions.

## 5.3. OLS assumptions

Before undertaking any further tests, we must establish whether our time series fulfills the necessary OLS assumptions. Particularly, we will test whether the time series of the winner- loser- and zero-investment portfolios contains a unit root, if the error terms are heteroskedastic and whether there is autocorrelation in the error terms. As a final and formal test, we will check whether the error terms are normally distributed using the Jarque-Bera test.

Should any of these problems be present, our OLS estimates will be biased and wrongful inference from the results might be drawn. It is therefore important that we test these assumptions and correct eventual violations.

## 5.4. Risk-adjusted returns

After establishing whether or not the momentum portfolios generate positive returns, we seek to test if the source of these profits are due to the portfolios being riskier than the market portfolio. If this is so, then the profits should merely be viewed as the price for the additional risk.

For readability and comparative reasons, we will only consider three portfolios in the remainder of the thesis. These are the 3-6, 6-6 and 9-6 portfolios respectively. The purpose of choosing the 6-6-portfolio is that virtually all other studies have focused on this strategy. And since we do not want to deviate too much from these studies, this one is included in our study as well. The inclusion of the other two portfolios is our attempt to test if the length of evaluation periods affects the profitability for the same holding period, even after adjusting them for risk. In order to test this assumption we run regressions on both the CAPM equation as well as the Fama and French three-factor model.

### 5.4.1. CAPM regression

After checking whether these conditions are satisfied, we run the CAPM regression and test the significance of alpha for the three portfolio combinations. Considering that the CAPM states that the only relevant variable of the following equation is the return in excess of the market portfolio, a significant alpha value would suggest that the model do not hold, as all other coefficient should equal zero. (Verbeek (2008))

The CAPM equation is given by:

$$r_{p,t} - r_{f,t} = \alpha_t + \beta(r_{M,t} - r_{f,t}) + \varepsilon_t$$

where $r_{p,t}$ denotes the return on the zero-investment strategy, $r_{f,t}$ is the risk free rate and $r_{m,t}$ is the return on the market index.

In order to establish whether the returns of our zero-investment portfolios are due to the investments being riskier than the market, the beta measure is used.

β is given by:

$$\beta_i = \frac{cov(r_p, r_m)}{var(r_m)}$$

where the numerator shows the covariance between portfolio return and market return, and the denominator is the variance of the market index return.

In CAPM theory, beta accounts for the systematic risk and high values of beta would thus suggest that the returns of the investment are merely a compensation for increased risk.

**5.4.2. Fama and French regression**

Our next test is to see whether the three-factor model could help in explaining the sources of the momentum returns. Fama and French (1993) showed that the CAPM and its single factor, β, did not seem sufficient in explaining the cross-section of average stock returns.

When testing whether adding new factors could be used, they found that stocks with smaller Market Capitalization (MC) and a high Book-to-Market ratio (B/M) (*value stocks*) outperformed their counterparts. The intuition for adding these factors is that stocks with a high B/M ratio are believed to be undervalued by the market and thus have to become more expensive. The situation is reversed for low B/M stocks (growth stocks) as they tend to lose their value.

By including the two new factors to the CAPM equation, they were also able to account for some of the market anomalies previously discovered (Lam et al. (2009)).

When portfolios are formed on size alone, it appears as if the CAPM model prediction holds, and there is a positive relation between average return and beta.

However, when sorting the portfolios after size, their betas were almost perfectly correlated with size. This is problematic since tests on size portfolios fail to separate the effect of beta and the size effects on average returns. (Fama and French (1993))

These findings suggest that stock risks are multidimensional, where size accounts for one and B/M ratio for the other. It is possible that the risk captured by B/M is the relative distress factor where the earning prospects of firms are associated with a risk factor in returns. (Ibid.)

In order to test these assumptions, the following regression will be run for the winner-, loser- and winner-loser portfolio for our different evaluation- and holding periods:

$$r_{p,t} - r_{f,t} = \alpha_t + \beta\left(r_{M,t} - r_{f,t}\right) + \gamma_t SMB_t + \delta_t HML_t + \varepsilon_t$$

where $r_{p,t}$ denotes the return on the zero-investment strategy, $r_{f,t}$ is the risk free rate and $r_{m,t}$ is the return on the market index. SMB is the Small Minus Big factor and HML is the High Minus Low factor.

To construct the SMB and HML factors, we follow the methodology suggested in the Fama and French (1993) article: First, the company data is sorted according to size, represented by their market capitalization. Those with a market capitalization above the median in the period are placed in the *big group (B)*, and those below the median are placed in the *small group (S)*. The same companies are then sorted after their B/M ratio. Those with a B/M above the 70$^{th}$ percentile are placed in the *high value* (H) group, those below the 30$^{th}$ percentile in the *low value* group (L) and the remainder in the *medium value* group (M).

This results in six portfolios with approximately the same amount of stocks. Over the twelve months following formation, their returns are gathered on a monthly basis. This procedure is repeated every year which results in 240 return observations of the six portfolios. Their monthly returns are then used to derive the factors with the following formulas:

The SMB factor is given by:

$$SMB = \frac{(r_{S/L} - r_{B/L}) + (r_{S/M} - r_{B/M}) + (r_{S/H} - r_{B/H})}{3}$$

and the HML factor by:

$$HML = \frac{(r_{S/H} - r_{S/L}) + \left(r_{B/H} - r_{B/L}\right)}{2}$$

An important difference compared to the CAPM regression is the data availability. While DataStream offers all data types needed for these calculations, the B/M data was less extensive than for Market Capitalization and the Return Index. Since all data classes at time t have to be available for the stocks to be included in either portfolio, we are left with fewer stocks to choose from. This of course means that our factors will deviate from their 'true' values, and differences between the risk-adjusted measurements will not be exact.

## 5.5. Carhart's four-factor model

While the three-factor model has been successful in explaining some of the documented market anomalies, the momentum effect could still not be explained. By adding the momentum factor found by Jegadeesh and Titman (1993) to the three-factor model, Carhart's (1997) model proved to be very successful in explaining the persistence in mutual funds. He also found that the inclusion of the fourth factor reduced the average pricing errors compared to the three-factor model. Another advantage of his model is that it has helped in explaining return patterns following post-earnings announcements. (Lam et al (2009))

The construction of this factor is done in the same manner as for the zero-investment strategies. For this purpose, we use the 12-1 portfolio, which is in line with the procedure in both Carhart (1997) and Lam et al. (2009).

For obvious reasons, this model cannot be tested using a zero-investment strategy as the dependent variable. Instead, we follow the methodology suggested by Carhart (1997). We begin by dividing all the companies according to their size into three groups. The same companies are then divided into three groups based on their B/M ratio. This differs from the three-factor methodology in that now, we are looking for the intersection of these groups and this results in nine portfolios as opposed to the

six portfolios used earlier. We then regress these portfolios on the three-, and four-factor model to find out whether the momentum factor *WML* adds to the explanatory power.

The resulting 4-factor regression will look as follows:

$$r_{p,t} - r_{f,t} = \alpha_t + \beta\left(r_{M,t} - r_{f,t}\right) + \gamma_t SMB_t + \delta_t HML_t + \varphi \mathrm{WML} + \varepsilon_t$$

where the only difference to the three-factor model is the addition of a momentum factor (WML), which is the return on the momentum portfolio.

# 6. Results

*In the following section, we present the results from the zero-investment strategies and discuss our findings.*

## 6.1. Returns for the zero-investment strategies

### 6.1.1. Raw returns

After completing the steps described in section 5.1-5.2 for all combinations of evaluation- and holding periods, we have gathered average monthly returns for a total of twenty-five zero-investment strategies. Our findings are presented in the table below:

**Table 1. Momentum returns**

| Evaluation period (*J*) | Strategy | Holding period (*K*) | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 3 | 6 | 9 | 12 |
| | **W** | -0.24% | 1.37% | 1.77% | 1.70% | 1.74% |
| **1** | **L** | 2.32% | 0.82% | 0.84% | 1.21% | 1.28% |
| | **W-L** | -2.56%*** | 0.55% | 0.93%*** | 0.49%** | 0.46%** |
| | **W** | 1.33% | 2.05% | 2.17% | 2.14% | 2.02% |
| **3** | **L** | 0.89% | 0.24% | 0.56% | 1.27% | 1.08% |
| | **W-L** | 0.44% | 1.81%*** | 1.61%*** | 0.87%*** | 0.94%*** |
| | **W** | 1.99% | 2.56% | 2.21% | 0.28% | 2.19% |
| **6** | **L** | 0.66% | 0.25% | 0.83% | -1.27% | 1.33% |
| | **W-L** | 1.32%* | 2.31%*** | 1.38%*** | 1.55%*** | 0.86%*** |
| | **W** | 1.89% | 2.29% | 2.09% | 2.05% | 2.13% |
| **9** | **L** | 0.77% | 0.64% | 0.91% | 1.37% | 1.41% |
| | **W-L** | 1.12%* | 1.66%*** | 1.18%*** | 0.68%** | 0.72%*** |
| | **W** | 2.07% | 2.18% | 1.95% | 2.01% | 2.11% |
| **12** | **L** | 0.91% | 0.92% | 1.36% | 1.58% | 1.54% |
| | **W-L** | 1.16%* | 1.25%*** | 0.60%* | 0.42% | 0.57%** |

*This table shows the monthly returns of the winner and loser portfolios as well as for the zero-investment strategies in the Swedish stock market during 1991-2011. P-values for the zero-investment strategies are given where * is significant at the 10% significance level, **significant at the 5% level and ***significant at the 1% level.*

Similar to the results documented by Jegadeesh and Titman (1993) and (2001), the strategy that uses a one month evaluation period and one-month holding period yields a negative monthly return of -2.56 percent and is clearly significant. The returns for all other zero-investment strategies are positive, ranging from 0.42 to 2.31 percent with 21 strategies being significant. Strategies using a six-month evaluation period have the highest average return where all but the 6-1 strategy are strongly significant. With a twelve-month evaluation period, three out of five are positive and insignificant at 5 percent level, which means that the standard deviation is higher for longer holding periods. It is interesting to see that there is no clear pattern of the returns except for that those using a 6 month evaluation period seems to yield higher returns, were the highest returns are given by the 6-3 strategy. The three month holding period yields the highest return for all evaluation strategies, which differs from other studies

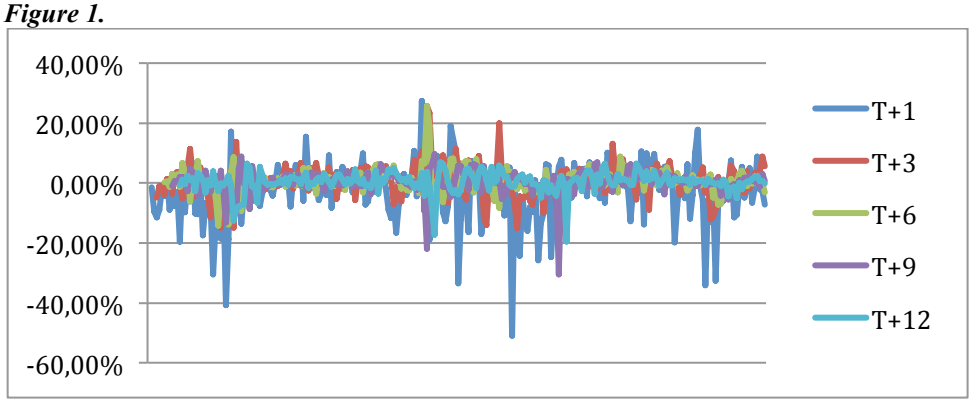
where the 12-3 was the most profitable. Looking at the 6-6 strategy, we find that it yields a positive return equal to 1.38 percent and is highly significant. This differs from the results obtained by Rouwenhorst who did not find evidence of momentum in Sweden for this strategy.

Apart from using different time periods, we can think over two main reasons for this difference. First, the fact that we reinvest delisted stocks in the OMXS index, which is likely to increase the portfolio return. Secondly, the fact that we impose fewer restrictions on the data, thus allowing more volatile stocks to be included in either portfolio increases the possibility of including stocks with extreme returns.

Our portfolios do have some outliers that of course affect the average monthly returns of the portfolios. As can be seen in the following graph for the t-1 evaluation period, shorter holding periods are clearly more volatile which supports the notion of Rouwenhorst and others.

On average, the zero-investment strategies yields an average monthly return of 0.87 percent, which is close to the 1 percent documented in other studies. Also noticeable is that the returns do not appear to diminish as the holding period is increased. Since it is shown that the momentum effect tend to dissipate after one year, we would have expected to see a decline at the twelve moth holding period. Instead, a few of them are slightly higher than for the nine-month holding period.

***Figure 1.***




*This figure illustrates the monthly return obtained from implementing the T-1 strategy with different holding periods between 1991-2011.*

One way of overcoming the volatility of the strategies might be accomplished if one would skip one week between evaluation and forming new portfolios, and allow for the bid-ask bounce as was shown by Conrad et al. (1998).

### 6.1.2. Persistence of the momentum returns

During our chosen sample, the Swedish stock market has experienced some macroeconomic events that might have had an impact on the results given in Table 1. In order to see whether the apparent momentum effect is robust under the full sample length, we divide it into four sub periods based on the growth and recession of the OMXS price index. Two of the more notable events were the IT-bubble at the start of the new millennium and the subprime crisis, which started around 2007.

The following table shows how the zero-investment strategies performed during our different sub samples.

**Table 2. Portfolio performance in sub samples**

| Evaluation period | Holding period (6) | | | | |
|---|---|---|---|---|---|
| | **Full sample** | **92-00** | **00-03** | **03-07** | **07-11** |
| **3** | 0.86%* | 1.30%*** | 0.81% | 0.53% | -0.53% |
| **6** | 1.65%** | 3.08%*** | 3.27%*** | 3.22%*** | 2.67%*** |
| **9** | 1.14%*** | 1.58% | 1.66%*** | 1.37%*** | 1.17%*** |

*This table shows the performance of three of our zero-investment portfolios during different time intervals. Their corresponding P-values are given where * is significant at the 10% significance level, **significant at the 5% level and ***significant at the 1% level.*

It is evident that the momentum effect is persistent for longer periods and our results suggest that the returns are correlated with the market. Clear is also that the returns from the millennium and onwards are declining. A possible reason for this apart from the most recent crisis is the development of the global economy. Thus, it appears as if the momentum returns are sensitive to dips in the market.

Only one of the portfolios, the 3-6, shows a negative yet insignificant return for the last four years. We can conclude that although the recent years have diminished the returns, most are still positive and significant, suggesting that the momentum effect is still valid even with shorter time periods.

## 6.2. OLS assumptions

While we did not find evidence of unit roots, our data was both significantly serially correlated and heteroskedastic for all portfolio strategies. Also, the residuals proved not to be normally distributed. By using the Newey-West (HAC) robust standard errors, we were able to obtain estimates that were consistent with OLS. Since the OLS estimates will be BLUE despite of the violation of non-normally distributed error terms, no correction for this was done. (Brooks 2008)[4]

[4] For a more elaborate discussion of the tests on the OLS assumptions, please refer to Appendix C.

## 6.3. Risk adjusted returns

### 6.3.1. CAPM regression

**Table 3. CAPM test results**

| Evaluation period (*J*) | Strategy | Holding period (6) | |
|---|---|---|---|
| | | α | β |
| 3 | W | 0.86%*** | 1.44*** |
| | L | -0.85% | 1.59*** |
| | W-L | 1.71%*** | -0.16 |
| 6 | W | 1.02%*** | 1.19*** |
| | L | -0.76%* | 1.77*** |
| | W-L | 1.77%*** | -0.58*** |
| 9 | W | 0.92%*** | 1.08*** |
| | L | -0.72% | 1.70*** |
| | W-L | 1.63%*** | -0.62*** |

*This table shows the outcome of the CAPM regression of our zero-investment strategies. Their corresponding P-values are given where * is significant at the 10% significance level, **significant at the 5% level and ***significant at the 1% level.*

As we can see, the betas for both the winner- and loser portfolios are all greater than the market beta where all are significant at the 1 percent level. Noticeably, for all formation- and holding periods, the loser portfolios have higher betas than winners, something that would suggest that these indeed are riskier than both the winning stocks and the market as a whole. The loser portfolio of the 9-6 strategy has beta equal to 1.7, which means that their portfolio return are almost twice as volatile than the market. Betas are decreasing for the winner portfolios as the evaluation period increases, though this pattern is not observed for losers. As for the zero-investment strategies, these are all negative which points to an inverse relationship between momentum returns and market movements. While 6-6 and 9-6 are significant at the 99% confidence level, 3-6 is not. In the CAPM framework, the momentum returns should be due to an increased risk taking which would be indicated by a β higher than one. While this appears to hold for the winner and loser strategy separately, the momentum returns cannot be explained using beta as the only measurement of risk. The CAPM β can thus not be used to explain the presence of return continuation.

When comparing these findings to other studies, we find that Jegadeesh and Titman (1993) and Rouwenhorst (1998) reached the same conclusion as they both documents negative betas for the 6-6 strategy however not as negative as ours. A likely cause of this difference, apart from putting different restrictions on the data, is their inclusion of many more stocks in their portfolios, where the diversification effect plays its part.

### 6.3.2. Fama and French regression

**Table 4. Fama-French test results**

| Evaluation period (*J*) | Strategy | Holding period (*6*) | | | |
|---|---|---|---|---|---|
| | | α | β | SMB | HML |
| 3 | W | 0.88% | 1.41*** | 0.10 | -0.03 |
| | L | -0.81% | 1.55*** | -0.15*** | -0.05 |
| | W-L | 1.69% | -0.14 | -0.05 | 0.02 |
| 6 | W | 0.98%*** | 1.17*** | 0.06 | 0.01 |
| | L | -0.74%* | 1.73*** | 0.16*** | -0.04 |
| | W-L | 1.72%*** | -0.55*** | -0.10 | 0.05 |
| 9 | W | 0.93%*** | 1.06*** | 0.07* | -0.02 |
| | L | -0.71% | 1.66*** | 0.15* | -0.04 |
| | W-L | 1.64%*** | -0.60*** | -0.08 | 0.01 |

*This table shows the results obtained from running the Fama and French regression for our zero-investment strategies. Their corresponding P-values are given where * is significant at the 10% significance level, **significant at the 5% level and ***significant at the 1% level.*

When adding the SMB and HML factors, we notice that the alphas for all investment strategies are bigger than from the CAPM regression and the raw returns. Similar results were obtained by Fama and French (1996) and Jegadeesh and Titman (2001), who all retrieved alphas higher than the corresponding raw return. The reason for this, they argue, is that the loser portfolios are more sensitive to the factors than winners.

This is partly true for our results as well since the betas of the losing stocks are greater than those of winners for all strategies. Our results differ in that our HML coefficients are only slightly positive and insignificant for all portfolio combinations, which would indicate that value stocks have no relation to the performance of our zero-investment strategies.

As was the case for the CAPM regression, the winner betas are all smaller than those of the loser portfolios, all being significant at the 99% confidence level. Since they are all considerably higher than the market beta this suggests that the smaller firms of our sample are included in the portfolios. We find that the betas are somewhat reduced which might be partly explained by the size effect of the loser strategies, although this conclusion is not very sound. However, it does not seem that the added factors shed new light on the source of the momentum effect in stock returns, and this phenomenon appears come from elsewhere. The insignificance of the majority of the size- and value factors might again be due to outliers in our returns and imposing stronger restrictions on the stocks available for selection might have given us different results. We notice, however, that the alpha from the three-month evaluation strategy is no longer significant. Looking at the highly significant SMB factor for the same strategy suggests that the sensitivity to the factor plays its part.

## 6.3. Size- and book-to-market portfolios

### 6.3.1Fama and French regression

**Table 5. Three-Factor model coefficients**

| Coefficient | Size (MV) | Book-to-market (B/M) | | |
|---|---|---|---|---|
| | | Low | 2 | High |
| α | Small | -0.20% | 2.04%*** | 0.58%** |
| | 2 | -0.29% | 0.38% | 0.69%*** |
| | Big | -0.19% | 0.02% | 0.20% |
| β | Small | 0.74*** | 0.87*** | 0.45*** |
| | 2 | 1.05*** | 0.92*** | 0.58*** |
| | Big | 1.10*** | 1.03*** | 0.55*** |
| γ | Small | 1.12*** | 1.35*** | 0.36*** |
| | 2 | 0.631*** | 0.34*** | 0.18*** |
| | Big | 0.10*** | 0.03 | -0.07** |
| δ | Small | -0.56*** | -0.71*** | -0.01 |
| | 2 | -0.43*** | -0.10** | -0.06 |
| | Big | -0.12*** | 0.06 | 0.14*** |

*This table shows the coefficients in 3-factor for 9 size/book-to-market portfolios. Their corresponding P-values are given where * is significant at the 10% significance level, **significant at the 5% level and ***significant at the 1% level.*

As can be seen in the above table, all betas are positive and highly significant. We observe that the beta coefficients are increasing as the size of the company gets bigger and the betas get smaller from low- to high B/M companies and from big- to small companies. The largest beta is observed for our B-L strategy (1.10) whilst the smallest was found for the S-H strategy (0.45). These results suggest that big companies with book value lower than market value are more volatile than the market index. It can be attributed to high volatility among stocks with low book-to-market ratios since the market overvalues them and any negative news can cause a drastic decrease in their stock prices.

In general, the size- and B/M portfolios are less volatile then market. All betas are positive and significant at very high levels so we can claim that portfolios built on size and B/M ratio follow the market index and are less volatile.

When comparing the betas and the SMB coefficients we can see that the relationship is almost inversed. It is logically, since bigger companies are less exposed to the SMB factor.

The values for the SMB coefficients for the B-H portfolio range from -0.07 to -2.54 strategies and 1.12 for S-L with strong significance, which is similar to what Fama and French observed in their 1993 article.

After controlling for size we can say that the HML factor has a bigger impact on the portfolio returns since it deviates from one more than the SMB factor. Six out

of nine of are negative where five of them are significant and four at the 99% confidence level.

We also observe that the HML coefficients increase with size- and B/M ratio. In the high group, two out of three have positive values and are close to zero with insignificant test statistics. A similar pattern was observed by Lam et al. (2009), who argued that the HML- together with the SMB factor could help in explaining additional variation in returns missed by market betas. Deeper insight can give us a hint that the portfolios consisting of stocks with higher B/M ratios slow down the price growing less than their counterparts. We interpret this as that the smaller risk protects the portfolios from bigger losses while preventing them from gaining larger returns. In other words, we can say that the HML factor has bigger impact on the portfolio return for the three-factor and explains more cross-sectional variation in stock returns.

### 6.3.2. Carhart regression

By including the momentum factor, we observe that the adjusted $R^2$ increases for all nine portfolios. Looking only at the regular $R^2$ would not tell us much, as the inclusion of additional variables increases the fit of the model. The adjusted version only increases if the new variable improves the model.

**Table 6. Four-factor model coefficients**

| Coefficient | Size (MV) | Book-to-market (B/M) | | |
|---|---|---|---|---|
| | | Low | 2 | High |
| α | Small | -0.05% | 2.17%*** | 0.08%*** |
| | 2 | 0.00% | 0.64%** | 0.97%*** |
| | Big | 0.00% | 0.43%* | 0.23% |
| β | Small | 0.70*** | 0.83*** | 0.38*** |
| | 2 | 0.99*** | 0.85*** | 0.52*** |
| | Big | 1.06*** | 0.94*** | 0.52*** |
| γ | Small | 1.08*** | 1.32*** | 0.32*** |
| | 2 | 0.56*** | 0.28*** | 0.13*** |
| | Big | 0.06 | -0.018 | -0.11** |
| δ | Small | -0.55*** | -0.69** | 0.01 |
| | 2 | -0.39*** | -0.08* | 0.08 |
| | Big | -0.10* | 0.076** | 0.16** |
| φ | Small | -0.09 | -0.10 | -0.12*** |
| | 2 | -0.14*** | -0.143*** | -0.11*** |
| | Big | -0.10** | -0.14*** | -0.09*** |

*This table shows the coefficients of the 4-factor model for 9 size- and B/M portfolios. Their corresponding P-values are given where * is significant at the 10% significance level, **significant at the 5% level and ***significant at the 1% level.*

Compared to the results of the three-factor model, the adjusted $R^2$ increased with nearly 5 percent for the 2-H portfolio whilst the change for the B-L strategy was more

modest (1 percent).[5] In the Fama and French's model, the adjusted $R^2$ ranged from 0.46 (2-H) and 0.81 (B-L). In the four-factor model it ranges between 0.51 (S-H) and 0.83 (B-L), which is similar to the results of among others Lam et al. (2009) where it ranged from 0.44 to 0.88 with the same peaking portfolios.

The alphas for all combinations are close to zero, while the betas remain highly significant though slightly lower than in the three-factor model. We interpret this as an increase in the explanatory power from the momentum factor that captures some of the variation in beta.

The tendencies observed in the three-factor model are preserved with slight changes for the four-factor model. The SMB coefficients range from -0.11 to 1.32 where seven out of nine are significant and six of them at the 99% level. The two insignificant values are both in the big group, indicating that they are less exposed to the small-firm effect.

When it comes to the HML coefficients in the high group, they range from -0.55 to 0.16 where all but two are highly significant and we can reject the null-hypothesis at the 99% confidence level.

As for the momentum coefficients, seven out of nine are significant at the 99% confidence level. The strongest momentum effect is observed in B-2 group with a coefficient equal to -0.14. This is in line with theory as big companies are more stable at generating returns and are more tilted to lasting relative strength phenomena. The fact that all coefficients are negative suggests that the momentum returns are negatively correlated with the market and with the return on portfolios. This pattern cannot be seen in the MC or the B/M groups. Our results thus indicate that all four factors are significant and add to the explanation of variation in returns.

[5] The list of the adjusted $R^2$ for the different regressions is given in Appendix C together with information about the portfolio compositions.

# 7. Conclusions

*In this section we summarize and discuss our findings. Finally, suggestions for future research are presented.*

## 7.1. Summary

The first step taken in order to determine whether the Swedish stock market exhibits the weak- and semi-strong form of market efficiency was to test the profitability of the momentum strategy. Through buying past winners and selling past losers we were able to yield positive and statistically significant result on 21 out of 25 zero-investment strategies, where only the 1-1 strategy yielded a negative return. The most steady momentum effect was observed for strategies using a six-month evaluation period, where the highest return was obtained from the 6-3 strategy, with a monthly return of 2.31 percent. For almost all evaluation periods, holding the portfolios for three months proved to be the most profitable strategy.

Considering that almost all of the zero-investment strategies were profitable and significant, we wanted to test whether they were persistent during shorter time intervals. In order to test this we focused on three strategies, the 3-6, 6-6 and 9-6. We found that while the profits diminished during the later years of our sample, only one turned insignificant, thus suggesting that the profits are persistent during our chosen sample.

The next step was to check whether the source of profits could be explained by the investments being riskier than the market portfolio. For this we first used the CAPM framework on the three portfolios where we tested whether the risk-adjusted returns would shed new light on the matter. Looking at the winning- and losing strategy separately, we found that both of them are more volatile than market index since they all had betas larger than one. However, the betas of the zero-investment strategies were all negative, and we could thereby conclude that the CAPM beta did not suffice in explaining the variation in momentum portfolio returns.

Due to the documented shortcomings of CAPM, we also chose to test this using the Fama and French three-factor model in which one includes factors for size and value into the regression. This has previously proved to capture variations in stock return not explained by beta. The results of this test showed that due to nearly

all coefficients being insignificant and close to zero, the model did not contribute much to the previously performed CAPM test. Therefore, our results are in line with previous studies and the momentum returns are not related to market capitalization or B/M ratio.

This finding logically led us to test Carhart's (1997) extended version of the Fama and French (1993) model were a momentum factor is added into the equation. To do so we constructed nine portfolios on the intersection on size- and B/M ratio. We then tested if the momentum factor added any explanatory power to this model using the adjusted $R^2$ as an indicator. All variables had sufficient coefficients and the momentum coefficient captured parts of the cross-sectional variation in stock returns. Also, we found that the HML factor has higher explanatory power than the SMB factor and the insignificant alphas indicate that abnormal returns are not related to skillful investors. Seven out of nine WML coefficients are strongly significant which suggest that Carhart's model is more successful in explaining the variation in returns on the Swedish market than the more traditional Fama and French model.

## 7.2. Concluding remarks

While our results are in line with the research in this field, we wonder whether these are due to the restrictions that were put on the data. When testing the strategies without any restrictions, all portfolios portfolio combinations displayed a negative and in most cases statistically significant return. We also tested whether the weights in respective portfolio had any impact. For this we altered the number of stocks included in the portfolios from 10-50 %. As expected, the increased number of stocks had the diversification effect that theory suggests. This of course speaks in favour of Jegadeesh and Titman's argumentation where the most volatile stocks should be excluded from the experiment.

We firmly believe that our choice of methodology has a lot of impact on the final results. As pointed out by Locke et al (2009), depending on whether one uses BHAR or CHAR, log returns or simple returns, arithmetic average or geometric average, the final result might differ considerably. As mentioned previously, when using log returns on the unrestricted data sample, we found strong support of momentum for all strategies while the simple returns gave us the opposite result. It was only when we imposed restrictions on the data, where we excluded those with a

return history of less than 12 months and with a Market Capitalization below the 5th percentile that we obtained positive results.

The advantage of putting these restrictions on the data is that it noticeably reduces the number of outliers. Because of these outliers, our return series violated the OLS assumptions. While we were able to correct for these, it was at the cost of lower significance of our coefficients.

However, while the momentum strategy appears to be profitable in the medium term, applying it in practice is a lot harder. When taking factors such as taxes, commissions and other transaction costs into consideration, we believe just as Conrad and Kaul (1997), that these profits would if not disappear then at least decrease drastically. The use of overlapping portfolios might be good from a research perspective but from a private investor point of view the strategy appears to be much harder to implement due to it being a very capital-intensive operation.

We believe that the question of whether or not the Swedish stock market exhibits the weak- and semi-strong form of market efficiency is hard to answer, and that it depends highly on how you define these forms. If the definitions are still valid even after putting the restrictions on the data, then yes we believe that one can use the zero-investment strategy in order to gain profits.

## 7.3. Suggestions for future research

We have found this study interesting on many levels, especially since the common models could not bring any clarity to the existence of momentum on the Swedish market. Almost all studies have used monthly data, and by looking at weekly and even daily observations of stock prices one might reach new conclusions. From a private investor perspective research directed at the cost of implementing the zero-investment strategies would be useful as one would thereby see whether this strategy is applicable in real life. From a financial economics perspective, research aiming at finding new factors to explain the variations in returns would be of great interest. We would also like to see more studies similar to that of Locke et al. (2009), which takes a variety of methodologies and markets into consideration. But as for the cause of this phenomenon, we believe that the answer lies within the behavioural finance department rather than traditional financial economic research. As such, we believe that the question is much harder to answer since it involves quite sophisticated and hard-to-estimate models.

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# Appendices

## Appendix A

**Table A1. Annual Stock Returns**

| Year | Average | Median | Std.dev | Max | Min |
|---|---|---|---|---|---|
| **1991** | -13.0% | -16.4% | 40.4% | 106.6% | -96.0% |
| **1992** | -11.5% | -20.6% | 101.4% | 1001.8% | -98.2% |
| **1993** | 141.3 | 93.5% | 134.8% | 762.9% | -44.7% |
| **1994** | 17.1% | 9.5% | 41.5% | 233.4% | -69.9% |
| **1995** | 9.7% | 3.3% | 42.0% | 240.1% | -59.3% |
| **1996** | 58.2% | 49.1% | 58.1% | 378.1% | -54.2% |
| **1997** | 23.9% | 18.7% | 45.4% | 193.7% | -63.3% |
| **1998** | -3.0% | -13.8% | 51.6% | 200.7% | -99.6% |
| **1999** | 73.3% | 24.0% | 357.7% | 5755.9% | -75.4% |
| **2000** | -11.2% | -17.9% | 60.3% | 497.3% | -98.9% |
| **2001** | -15.1% | -18.7% | 49.8% | 218.8% | -94.5% |
| **2002** | -28.1% | -30.8% | 41.5% | 150.0% | -97.0% |
| **2003** | 47.5% | 30.1% | 105.1% | 1242.9% | -92.8% |
| **2004** | 33.9% | 21.0% | 87.3% | 1000.0% | -87.7% |
| **2005** | 58.3% | 42.7% | 78.6% | 488.8% | -76.1% |
| **2006** | 21.9% | 18.1% | 67.9% | 709.6% | -90.0% |
| **2007** | -9.3% | -15.5% | 53.5% | 463.3% | -95.3% |
| **2008** | -45.6% | -49.2% | 33.2% | 259.7% | -99.5% |
| **2009** | 62.2% | 48.1% | 98.1% | 674.7% | -90.7% |
| **2010** | 14.1% | 8.9% | 69.4% | 485.4% | -96.7% |
| **Total** | 23.1% | 10.5% | 83.0% | 787.0% | -83.36% |

*This table shows yearly statistics for the data included in our sample.*

## Appendix B

### Stationarity

Stationarity is an important assumption in time series data. Should the instead be non-stationary then they are said to be unit root processes. For this test, we choose the Augmented Dickey-Fuller (ADF) test. The regular D-F is only valid when we are dealing with an AR(1) process and if our error terms are auto correlated this test will not work. By using the ADF we obtain a test that corrects for higher orders of autocorrelation by assuming that $y_t$ follows an AR(p) process.

Specifically, the following regression is used:

$$\Delta y_t = \alpha y_{t-1} + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + v_T$$

Where the null-hypothesis of non-stationarity is tested against the alternative of stationarity.

**Table B1. Unit Root Test Statistics**

| Evaluation period (*J*) | Holding period (*6*) | | | | |
|---|---|---|---|---|---|
| | **W** | **L** | **WML** | **SMB** | **HML** |
| **3** | -5.30 | -5.39 | -5.84 | -5.27 | -5.32 |
| **6** | -5.85 | -5.13 | -7.03 | -13.59 | -15.04 |
| **9** | -4.11 | -4.36 | -5.72 | -13.54 | -14.96 |

*This table shows the test-statistics from the Augmented Dickey-Fuller Unit Root test.*

As can be seen in above table none of our zero-investment strategies suffer from unit roots and no corrections were undertaken.

## OLS assumptions

In order for the results of the CAPM and Fama and French regression to be valid, the Gauss-Markov assumptions have to be fulfilled. In the following section, we present these assumptions and our results from testing these.

**Assumption 1**

$$E\{\varepsilon_i\} = 0. \quad i = 1. \dots N$$

This assumption states that the error term of the regression, on average should equal zero. As our regression allows for an intercept, this condition is fulfilled and no tests or corrections have to be performed.

**Assumption 2**

**Homoskedasticity**

$$V\{\varepsilon_i\} = \sigma_i^2$$

The assumption that the error terms are homoscedastic, i.e. have the same variance. If we are dealing with heteroskedastic errors, then the OLS estimates are valid while their standard errors are not. In order to test this assumption, White's test is used.

**Table B2. White Test Statistics**

| Evaluation period (*J*) | Strategy | Holding period (6) | |
|---|---|---|---|
| | | CAPM | Fama-French |
| 3 | W | 154.56 | 28.67 |
| | L | 3.03 | 1.12 |
| | W-L | 31.21 | 8.42 |
| 6 | W | 13.72 | 5.45 |
| | L | 16.56 | 3.20 |
| | W-L | 33.77 | 9.12 |
| 9 | W | 7.10 | 1.83 |
| | L | 5.64 | 2.76 |
| | W-L | 9.90 | 5.21 |

*This table shows the outcome of the White's test for our 3-6, 6-6 and 9-6 portfolios.*

Judging from the above table, it is clear that our portfolios suffer from severe heteroskedasticity. From this follows that our estimates of beta will be biased and the OLS estimates are no longer BLUE.

By assuming that the errors are uncorrelated, White (1980) was able to derive estimates of the covariance matrix that are robust to heteroskedasticity of unknown form. (EViews Users Guide II. pp.37)

Luckily, this option is available in EViews and by using White's errors we are able to obtain estimates that are free from heteroskedasticity without changing the coefficients. The only downside to this method is that it increases the standard errors and reduces the significance of the estimates.

**Assumption 3**

**Serial correlation**

$$cov\{\varepsilon_i . \varepsilon_j\} = 0 \quad i.j = 1. \ldots . N. i \neq j$$

The assumption of no serial correlation holds that that error terms at different times are uncorrelated. In the presence of autocorrelation, the OLS is no longer efficient among linear estimators and the standard errors are not correct. (EViews Users Guide II pp.65)

As there are no lags of our dependent variable on the right hand side of the equation, the Durbin-Watson (DW) statistic is valid for our test of serial correlation. A limitation of the DW is that it has an inconclusive region, in which we can neither accept nor reject the null-hypothesis. But as we can see in table B3, we have no difficulties rejecting the null and the returns from the zero-investment strategies are all positively auto correlated.

**Table B3. Durbin-Watson Test Statistics**

| Evaluation period (*J*) | Strategy | Holding period (6) | | | |
|---|---|---|---|---|---|
| | | CAPM | Fama-French | $D_L$ | $D_U$ |
| 3 | W | 0.61 | 0.65 | 1.66 | 1.68 |
| | L | 0.69 | 0.70 | 1.66 | 1.68 |
| | W-L | 0.74 | 0.73 | 1.66 | 1.68 |
| 6 | W | 0.65 | 0.67 | 1.66 | 1.68 |
| | L | 0.58 | 0.62 | 1.66 | 1.68 |
| | W-L | 0.73 | 0.73 | 1.66 | 1.68 |
| 9 | W | 0.84 | 0.54 | 1.66 | 1.68 |
| | L | 0.51 | 0.52 | 1.66 | 1.68 |
| | W-L | 1.16 | 0.61 | 1.66 | 1.68 |

*This table shows the Durbin-Watson test-statistics obtained from running the OLS regression on the 3-6, 6-6 and 9-6 strategies.*

Clearly, the use of overlapping portfolios induces positive autocorrelation in the residuals for all strategies. To deal with this problem there are several approaches. Again, EViews comes to the rescue. Using the built-in Newey-West (HAC) option, we are able to obtain coefficient estimates robust to both heteroskedasticity and autocorrelation. Just as in the case with heteroskedasticity, this transformation does not come for free. While our estimates now are robust and the same as when performing the OLS regression, the standard deviation and t-statistics of our coefficients are reduced.

**Assumption 4**

**Normality**

$$u_t \sim N(0.\sigma^2)$$

The fifth and final assumption states that the error terms must be normally distributed. To determine if this assumption is fulfilled, the Jarque-Bera test is conducted. Using the following test-statistic, Jarque-Bera checks the errors for excess skewness and kurtosis. (Verbeek (2008)):

$$Jarque - Bera = \frac{N-k}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

where S denotes the skewness, K is the kurtosis and k is the number of estimated coefficients. (EViews Users Guide I pp. 312)

The hypothesis being tested is that the error terms are normally distributed against the alternative that they are not.

**Table B4. Jarque-Bera Test Statistics**

| Evaluation period (*J*) | Strategy | Holding period (6) | |
|---|---|---|---|
| | | CAPM | Fama-French |
| **3** | **W** | 775.78 | 926.91 |
| | **L** | 917.73 | 915.69 |
| | **W-L** | 158.36 | 153.73 |
| **6** | **W** | 773.57 | 494.41 |
| | **L** | 466.65 | 970.62 |
| | **W-L** | 93.19 | 70.61 |
| **9** | **W** | 24.10 | 28.88 |
| | **L** | 1042.06 | 737.98 |
| | **W-L** | 131.65 | 90.18 |

*This table shows the outcome of the Jarque-Bera Normality test of our 3-6, 6-6 and 9-6 strategies.*

It is obvious that our results from the Jarque-Bera tests imply strong non-normality of the residuals. As argued by Brooks (2008), one likely cause of non-normality using financial data is outliers, which causes the kurtosis to increase. Given our data, the many instances where the monthly returns increased and/or decreased drastically are likely to cause this violation. The same can be said with regards to the issue of heteroskedasticity that we encountered previously.

While correcting for non-normality is possible, it is not necessary. Given enough observations the OLS is still BLUE even though this assumption is violated, thus allowing us to proceed with our tests. (Brooks (2008))

# Appendix C

**Table C1. Number of companies on the intersection of size and book-to-market groups**

| Year | Number of companies | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Total | S-L | S-2 | S-H | 2-L | 2-2 | 2-H | B-L | B-2 | B-H |
| **1991** | 108 | 4 | 6 | 24 | 5 | 9 | 18 | 17 | 11 | 14 |
| **1992** | 105 | 1 | 6 | 26 | 7 | 8 | 14 | 17 | 12 | 14 |
| **1993** | 106 | 0 | 6 | 23 | 7 | 14 | 14 | 19 | 7 | 16 |
| **1994** | 118 | 2 | 6 | 23 | 11 | 11 | 16 | 18 | 9 | 22 |
| **1995** | 142 | 5 | 7 | 29 | 11 | 7 | 25 | 18 | 16 | 24 |
| **1996** | 157 | 4 | 4 | 34 | 12 | 12 | 26 | 20 | 14 | 31 |
| **1997** | 181 | 8 | 10 | 32 | 14 | 15 | 28 | 23 | 18 | 33 |
| **1998** | 240 | 15 | 14 | 48 | 25 | 18 | 27 | 22 | 26 | 45 |
| **1999** | 286 | 10 | 11 | 73 | 28 | 29 | 30 | 33 | 23 | 49 |
| **2000** | 328 | 17 | 18 | 75 | 32 | 28 | 37 | 40 | 32 | 49 |
| **2001** | 356 | 20 | 26 | 80 | 31 | 35 | 42 | 43 | 28 | 51 |
| **2002** | 338 | 21 | 21 | 75 | 38 | 33 | 31 | 38 | 32 | 49 |
| **2003** | 322 | 23 | 14 | 69 | 26 | 35 | 45 | 41 | 39 | 30 |
| **2004** | 306 | 23 | 16 | 52 | 27 | 35 | 42 | 39 | 38 | 44 |
| **2005** | 324 | 23 | 22 | 50 | 35 | 37 | 37 | 38 | 38 | 44 |
| **2006** | 352 | 25 | 19 | 52 | 37 | 40 | 37 | 44 | 44 | 54 |
| **2007** | 388 | 22 | 24 | 70 | 36 | 42 | 43 | 55 | 50 | 46 |
| **2008** | 446 | 41 | 37 | 40 | 48 | 42 | 51 | 47 | 57 | 53 |
| **2009** | 439 | 50 | 40 | 66 | 47 | 47 | 51 | 40 | 51 | 47 |
| **2010** | 424 | 43 | 33 | 66 | 44 | 45 | 51 | 44 | 51 | 47 |

This table shows number of stocks included in the nine portfolios formed on the intersection of size- and B/M ratio.

**Table C2. Adjusted $R^2$ for the 3- and 4-factor model**

| Size | | Book-to-market | | |
|---|---|---|---|---|
| | | Low | 2 | High |
| **Three-factor model** | **Small** | 0.606 | 0.538 | 0.459 |
| | **2** | 0.696 | 0.658 | 0.478 |
| | **Big** | 0.811 | 0.759 | 0.642 |
| **Four-factor model** | **Small** | 0.627 | 0.540 | 0.505 |
| | **2** | 0.729 | 0.697 | 0.514 |
| | **Big** | 0.826 | 0.797 | 0.685 |

This table shows the Adjusted $R^2$ obtained from running the OLS regression on the three- and four-factor model on our nine portfolios formed on the intersection of size- and B/M ratio.