Profitability of Technical Trading Strategies in the Swedish Equity Market

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Abstract

This study aims to see if it is possible to generate abnormal returns in the Swedish stock market through the use of three different trading strategies based on technical indicators. As the indicators are based on historical price data only, the study assumes weak market efficiency according to the efficient market hypothesis. The study is conducted using daily prices for OMX Stockholm PI and STOXX 600 Europe from the period between 1 January 2010 and 31 December 2019. Trading positions has been taken in the OMX Stockholm PI index while STOXX 600 Europe has been used to represent the market portfolio. Abnormal returns has been defined as the *Jensen’s α* in a Fama French three factor model with Carhart-extension. This period has been characterised by increasing prices (a *bull market*) which may have had an impact on the results. Furthermore, a higher frequency of rebalancing for the Fama-French and Carhart model could also increase the quality of the results. The results indicate that all three strategies has generated abnormal returns during the period.

**Keywords**

Trading, Technical analysis, stocks, stonks, Equity markets, abnormal returns, moving average, RSI, relative strength index, MACD, moving average convergence divergence
Sammanfattning


Nyckelord

Trading, teknisk analys, aktier, aktiemarknaden, överavkastning, glidande medelvärde, RSI, relative strength index, MACD, moving average convergence divergence
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Chapter 1

Introduction

1.1 Background

The global financial market is a behemoth that is hard to gauge as the number of participants as well as traded volumes fluctuates depending on which markets are included. Markets and traded assets combine a dynamic universe which is under constant evolution. From the early futures contracts which allowed farmers to lock in profits, the East India Companies and the Dutch Tulipomania, to cryptocurrencies and SPACs today.

Traders can be split into three different categories: hedgers, arbitrageurs and speculators. Hedgers participate in the market in order to reduce or eliminate risks (for example a farmer selling futures contracts on future harvests in order to hedge against price fluctuations). The second category is the arbitrageurs. These are actors looking to profit from inefficiencies in the market, such as the same asset trading on different prices in different locations. Finally, there is the speculator. The speculator participates in the market with the objective of making a profit in future price movements [9].

The notion “trader” in this study refers to actors belonging to the speculator category rather than the two other categories of market participants. Throughout history there have been multiple traders reaching some levels of notoriety for their entanglement in the markets. Either be it by being highly profitable or by the daunting size of the bets they have placed. These include Jesse Livermore, Ed Seykota from Jack D. Schwager’s Market Wizards as well as the “London Whale”, a CDS trader from JP
CHAPTER 1. INTRODUCTION

Morgan [12][20][10].

Given the secrecy surrounding the trading industry in combination with the large bets that can be placed has resulted in a certain interest from the general public. This imagery is reinforced by several incarnations within the media industry, such as the movie "Wall Street" and the TV Series "Industry" [22][11]. These depictions constantly and to various degrees fail to showcase the deeper mechanics of these markets and instead focuses on the outcomes in terms of profits and losses. In this study the focus is instead on a few selected tools used by traders and whether these can be used in order to obtain an edge in a market. In one aspect this report could be viewed as an inverse to the aforementioned depictions as there is a clear focus on the trading strategy.

Typically, the analysis of assets can be split into two groups. Fundamental analysis, which focuses on reading through different sources of information in order to arrive at a fair price for the asset [15]. Simplified, if this price is higher than the current price it is a buying opportunity. The second subset of analysis is the more debatable technical analysis. Technical analysis aims to forecast future price movements based on historical data.

Technical analysis is somewhat of an umbrella term as it includes multiple kinds of analysis such as identifying support and resistance levels where the price could likely turn or trigger a breakout. There is also the pattern analysis which aims to identify some patterns within price movement which indicate some sort of future price development. A third leg of technical analysis is the use of indicators in order to forecast price movements.

Indicators are different calculations done on historical data which are then interpreted by the trader or analyst in order to decide on which way to trade the market. The simplest of these may be a moving average which reflects the average price over the $x$ last time periods. This can then be modified into a more agile exponential moving average and by combining two moving averages, a moving average convergence/divergence indicator may be created. There could also be other properties used in indicators, such as volume or volatility, meaning that the imagination of the constructor is the limitation in what can be created.

After calculating the indicators, these need to be interpreted by the trader in order to make a trade. In this project some popular indicators are used in order to see both if their traditional interpretation gives the trader an edge.
1.2 Purpose and Problem Statement

The aim of the study is to examine whether it is possible to generate abnormal returns in the Swedish stock market using three different commonly found trading strategies. All three trading strategies are based on technical indicators which are calculated from historic price movements. This implies that it should not be possible to generate abnormal returns according to the efficient market hypothesis, assuming weak market efficiency. The research question is then formulated as:

Is it possible to generate abnormal returns with these traditional technical trading strategies?

In order to gauge abnormal returns the study uses the Fama-French three factor model with Carhart extension. Abnormal returns are then defined as the intercept, Jensen’s $\alpha$. Upon answering the first research question a second question is also discussed:

Does the result differ between strategies in terms of, for example, generated $\alpha$ and $\beta$?

1.3 Scope

1.3.1 Market Demarcations

For the study to be relevant, a number of markets would have to be examined, however in order to address time and capacity constraints two relevant European equity indices have been selected. The time period included in the study is 1 January 2010 to 31 December 2019.
CHAPTER 1. INTRODUCTION

Market Geography Description

<table>
<thead>
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<th>Market</th>
<th>Geography</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>OMX Stockholm PI</td>
<td>Sweden</td>
<td>Also called Stockholm all-share. This index weighs together the value of all shares listed on the Stockholm Stock Exchange. Provides an overall picture of developments on the stock exchange [19].</td>
</tr>
<tr>
<td>STOXX Europe 600</td>
<td>Europe</td>
<td>A subset of STOXX Global 1800 Index. Represents small, medium and large cap companies operating in various industries in 18 different European countries. Covers ~90% of the free-float market capitalization of the European stock market [21].</td>
</tr>
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Table 1.3.1: Equity indices used in the study
Chapter 2

Theoretical Framework

2.1 Technical Indicators

2.1.1 Moving Average

The moving average indicator is the average of the $x$ last time periods. There are multiple variants of the moving average such as the exponential moving average and smoothed moving average. The calculation can also be conducted in different ways, for example through using open or closing prices. Finally, there is also a choice of number of periods included in the moving average [7].

In this study, a simple moving average is used. Simple moving average with the period of $n$ can be defined as

$$MA(t, n) = \frac{1}{n} \sum_{i=1}^{n} S_{t-i}$$

where $S_t$ denotes the stock price at time $t$. This is commonly referred to as MA-$n$ and has been calculated as the average of closing price in the last $n$ trading days. This study uses days as time periods.
2.1.2 Relative Strength Index

The Relative Strength Index, RSI, was first presented by American technical analyst J. Welles Wilder in his 1978 book “New Concepts in Technical Trading Systems”. The RSI is an indexed indicator that always assumes a value between 0 and 100 [8]. Typically, a period where the price of the underlying instrument is increasing the RSI level will increase as well. The calculation is done in multiple steps. First the Relative Strength, \( RS \), is calculated. This is done through computing the fraction between the average increase and the average decrease over the \( n \) last periods:

\[
RS(n) = \frac{\text{Average gain } n \text{ last time units}}{\text{Average loss } n \text{ last time units}}.
\]

After the Relative Strength has been calculated this is indexed in order to obtain the Relative Strength Index,

\[
RSI(n) = 100 - \frac{100}{1 + RS(n)}.
\]

From the calculation of relative strength, it is clear to see that if the period used for the indicator is dominated by larger increases than decreases, the RSI level will increase. There is also the case where decreases in the included period do not exist which will result in the denominator being equal to 0 in the Relative Strength calculation. In this case the RS is assumed to approach infinity and the RSI subsequently set to 100, the maximum value.
2.1.3 Moving Average Convergence Divergence

Moving Average Convergence Divergence, MACD, is an indicator based on three different exponential moving averages, EMA, and is expressed through two lines (referred to as the MACD-line and the signal-line) and a histogram [14]. The MACD-line is defined as the difference between a shorter, commonly known as “fast”, EMA and a longer, commonly known as “slow”, EMA. The MACD-line is then calculated as

$$EMA_{fast} - EMA_{slow} = MACD.$$

As the shorter moving average is quicker to react to a price movements, increased prices in the underlying will result in a higher value for the MACD-line. The common practice is to use a 12-period EMA as the “fast”-EMA, and a 26-period EMA as the “slow”-EMA.

The second line is known as the signal-line and is an exponential moving average of the MACD-line. The common setting is for the signal-line to be based on the nine last notations of the MACD-line.

Finally, the histogram is defined as the difference between the MACD-line and the signal-line:

$$Histogram = MACD - SignalLine.$$
2.2 Efficient Market Hypothesis

The efficient market hypothesis is associated with American economist Eugene Fama, who in 1970 presented his efficient market hypothesis. It argues that the market discounts all available information in the current market price. This means that over a long timespan, an investor will fail to achieve returns that deviate from the expected return (i.e., failure to generate alpha). A market is said to be efficient if there is an information set, $\phi$ that could be revealed to investors without affecting the pricing of the market. The information set used in the hypothesis is commonly split into three distinct settings: Weak, Semi-strong and Strong efficiency. Weak market efficiency assumes that only historical price data is available, semi-strong efficiency assumes that all public information is priced in and strong market efficiency also includes private information (i.e. inside information) [16].

As the focus of this study is the use of technical indicators, which are only based on historical price data, the study assumes weak market efficiency. Given the theory of efficient markets it should not be possible to generate abnormal returns by deploying trading strategies based on these indicators.
2.3 Previous research in predictability of Stock movements

In this section previous work on the use of technical trading strategies are reviewed.

2.3.1 Revisiting the Performance of MACD and RSI Oscillators

One of the more extensive work on using technical analysis for trading was published in an article in by three researchers in the Journal of Risk and Financial Management [4]. The article differs from this study in that it uses slightly different trading rules (for example a holding period of 10 days) and is based on other markets equity markets. The period in the study is also longer, ranging from 1976 to 2002. Nonetheless the results are relevant as the article found that a MACD strategy similar to that used in this study managed to outperform a buy and hold strategy in both the Milan Comit General and the SP/TSX composite index. The article also finds abnormal returns from deploying a different RSI strategy in these markets leading to a discussion surrounding the validity of the efficient market hypothesis.

2.3.2 Profiting from Serial Correlation

A study from Umeå Universitet examines a number of technical indicators in order to create a profitable strategy for trading the German DAX index. Among the tested indicators are both the RSI and the MACD indicators [3]. The study deploys both the same RSI strategy used in this study as well as the "50 crossover" strategy not used here. The MACD strategy is the same as used in this study. However, the holding period for each trade seems to be longer than in this study. After initially planning to combine the different indicators in order to build a strategy the author changed into relying on a single indicator after failing to find success in using RSI and MACD. Instead the final strategy was based on a linear regression of the price itself, which managed to outperform a buy and hold strategy over the ten year period used in the study.
CHAPTER 2. THEORETICAL FRAMEWORK

2.4 Mathematical Theory

In this section, the mathematical theory used in this study are presented. The source for the section as a whole is the book Introduction Linear Regression Analysis by Montgomery, D.C, Peck, E.A and Vining, G.G [18].

2.4.1 Multiple Linear Regression

The multiple linear regression model is an extension of the simple linear regression model and deploys more than one regressor variable. This adds additional $\beta$’s and $x$’s, resulting in a model that might look like

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \epsilon.$$  

This is the model used in this study with the regression variables, $x_{1,2,3,4}$, replaced by the different factors in the model described in 3.3.1, 3.3.2 and 3.3.3. From there it is also clear that the intercept, $\beta_0$ has been replaced by Jensen’s $\alpha$. There is also five major assumptions made in order for the regression model to work:

- The relationship between the response variable $y$ and the regressors are, or are approximately, linear
- The mean value of the error term, $\epsilon$, is equal to 0
- The variance of the error term, $\epsilon$, is constant and $\sigma^2$
- The errors, $\epsilon$, are not correlated to each other
- The error terms, $\epsilon$, is normally distributed

2.4.2 Ordinary Least Squares Estimation

In order to estimate the values of the regression coefficients, $\beta_j$, ordinary least squares estimates is used. In plain text this means that $\beta$ is selected so that the sum of all squared errors is minimised.

By rewriting the equation,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \epsilon$$
in to

\[ y = X\beta + \epsilon \]

were \( X \) is matrix where the echelons represent \( x_{1,2,3,4} \) and each row is an observation. \( \epsilon \) is a vector of the error in each observation. From this the least square estimation, \( \hat{\beta} \), is obtained from

\[ S(\beta) = \sum_{i=1}^{n} \epsilon_i^2 \]

which can be simplified to

\[ X'X\hat{\beta} = X'y \]

leading to the estimation of \( \beta \)

\[ \hat{\beta} = (X'X)^{-1}X'y \]

### 2.4.3 \( R^2 \) and adjusted \( R^2 \)

\( R^2 \) is known as the coefficient of determination and can be said explain how much of the variability is explained by the regression. A such \( R^2 \) takes values between 0 and 1, where a higher value means that the regression explains more of the variability. However this does not mean that a higher value of \( R^2 \) is always better as it can be manipulated through adding a larger number of regressors and is also effected by the spread in \( x \). The formula for calculating \( R^2 \) is

\[
R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_{Res}}{SS_T}
\]

where \( SS_T \) is the total variation, \( SS_R \) the variation of the regression and \( SS_{Res} \) the variation of the residual. \( SS_R \) and \( SS_{Res} \) are defined as

\[
SS_R = \hat{\beta}_1 S_{xy}
\]
\[ SS_{Res} = SS_T - \hat{\beta}_1 S_{xy} \]

In order to combat the problem of a large number of regressors inflating \( R^2 \) an adjusted \( R^2 \) can be used which also reflects upon the number of regressors used. Adjusted \( R^2 \) is calculated as

\[ R^2_{Adj} = 1 - \frac{SS_{Res}/(n - p)}{SS_T/(n - 1)} \]

### 2.4.4 Residuals

The residual is the difference between the difference between the value suggested by the regression model and the actual value of the observation. The value of the residual for observation \( i \) is calculated as

\[ e_i = y_i - \hat{y}_i \]

with the approximated average variance

\[ MS_{Res} = \frac{SS_{Res}}{n - p} \]

This deviation from the value proposed by the model can also be viewed as the error of the model. Given that the error is expected to behave in a certain way, examination of the residuals can offer valuable clues as to the models validity. The above equation is only one way to calculate the residual, other modified ways of calculating residuals offer additional insights.

**Standardised Residuals**

The standardised residual, \( d_i \) is the normal residual scaled by \( MS_{Res} \),

\[ d_i = \frac{e_i}{\sqrt{MS_{Res}}} \]

This makes the average variance of \( d_i \) equal to zero and the average variance approximately equal to 1. From this it is easier to find large deviations, meaning a standardised residual much larger than 1, which may indicate an outlier.

**Studentised Residuals**
CHAPTER 2. THEORETICAL FRAMEWORK

The studentised residual is an improvement of the standardised residual. It is more thorough than the standardised residual as it calculates the exact standard deviation of the $i$th residual rather than assume it has the variance $MS_{Res}$. Assuming that the vector of residuals can be written

$$e = (I - H)y$$

where $H$ is the hat matrix the variance of $e$ is

$$Var(e) = Var[(I - H)e]$$

which implies that the exact variance of the $i$th residual is

$$Var(e_i) = \sigma^2(1 - h_{ii})$$

The value of the studentised residual compared to the standardised or normal residuals is that it is good at highlighting leverage and influential points. These points typically lie towards the outer edges of $x$ which causes them to have an unproportional impact on the regression. This is adjusted for in the studentised residuals which adjusts for the distance between $x_i$ and the centre of all $x$.

### 2.4.5 Normal Probability Plot

The normal probability plot plots the residuals with the probability on the y-axis. Ideally the plot will be a perfect line but small deviations are standard and causes limited issues when evaluating the model. Larger deviations poise a bigger issue as this means that the residuals are not distributed as expected by F statistics and confidence intervals which can cause errors in later analysis.

### 2.4.6 Fitted Values Plot

By plotting the residuals against the fitted values, $\hat{y}$, eventual inadequacies can be found. For example, outliers will be seen as they will have a larger than average value. If the plot seems non-linear this may indicate that the relationship between $y$ and $x$ is in truth non-linear rather than the assumed linear relationship.
2.4.7 Added Variable Analysis

The partial regression plot examines the relationship between a regressor, \( x_j \) and other regressors used in the model in order to analyse the impact of the regressor \( x_j \). An example with two regressors is a model defined as

\[
y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon
\]

in order to examine the marginal relationship of \( x_1 \) we first regress \( y \) on \( x_2 \) and obtain

\[
\hat{y}_i(x_2) = \hat{\theta}_0 + \hat{\theta}_1 x_{i2}
\]

\[
e_i(y|x_2) = y_i - \hat{y}_i(x_2), \quad i = 1, 2, \ldots, n
\]

\( x_1 \) is now regressed on \( x_2 \) and new residuals obtained:

\[
\hat{x}_{i1}(x_2) = \hat{\alpha}_0 + \hat{\alpha}_1 x_{i2}
\]

\[
e_i(x_1|x_2) = x_{i1} - \hat{x}_{i1}(x_2).
\]

2.4.8 Cook’s Distance

Cook’s distance is a tool to find points of interest that have an disproportional impact on the regression model. The Cook’s distance for an observation, \( i \), is measured as the distance between the estimated coefficient for all observations, \( \hat{\beta} \), and the estimated coefficient when excluding the \( i \)th observation, \( \hat{\beta}_{(i)} \). This distance can be calculated as

\[
D_i = (M, c) = (\hat{\beta}_{(i)} - \hat{\beta})'M(\beta_{(i)} - \beta)
\]

typically with

\[
M = X'X
\]

and

\[
c = pMS_{Res}.
\]

A larger value for \( D_i \) means that the \( i \)th observation has a large impact on the estimated coefficients with \( D_i > 1 \) a typical cutoff for points that need to be examined further and maybe removed from the data.
2.4.9 **DFFITS**

*DFFITS* is another way of examining and expressing the effects of excluding one observation, *i*, from the sample. *DFFITS*$_i$ is calculated as

$$DFFITS_i = \frac{\hat{y}_i - \hat{y}_{(i)}}{S(\hat{y}_{(i)}, h_{ii})}$$

where the denominator adjusts the variation so that *DFFITS*$_i$ is the number of standard deviations that \(\hat{y}\) would be moved if the observation *i* was excluded. One strength of *DFFITS* is that it considers both the error in prediction as well as the leverage of the point. As for many other measurements larger values require more attention with a threshold of \(|DFFITS_i| > 2\sqrt{p/n}\) suggested by the inventors.

2.4.10 **Heteroscedasticity**

A key assumption in the analysis of a regression model is that the residuals have a common variance, known as being homoscedastic. This is an assumption that needs to hold true in order for different measures such as F statistics to be true. Should the variance of the residuals be heteroscedastic rather than homoscedastic these measurements and tests cannot be used. By plotting the residuals against the response variable this can be examined.

2.4.11 **Multicollinearity**

Multicollinearity is inference caused by a almost linear dependence among regressors which can have an effect on the model. Therefore, this has to be kept under surveillance in order to ensure that model remains valid. There are multiple causes behind multicollinearity. In order to assess if there is a problem with the model stemming from multicollinearity different methods can be deployed.

**Correlation Matrix**

One of the methods to detect multicollinearity is examining the correlation between regressors in a traditional correlation matrix. By examining the \(X'X\) matrix the correlation of all regressor pairs is evident. What is not detected by the correlation matrix is correlations that involves more than two regressors.

**Variance Inflation Factor, VIF**
CHAPTER 2. THEORETICAL FRAMEWORK

The Variance Inflation Factor, VIF, is another metric for determining multicollinearity. VIF consists of the inverse of the $X'X$ matrix and becomes larger with increasing multicollinearity. Typically, a VIF of more than 10 is said to indicate large multicollinearity issues. The formula for calculating VIF is

$$VIF_j = C_{jj} = (1 - R_j^2)^{-1}$$

where

$$C = (X'X)^{-1}$$

and $R^2$ is the coefficient of determination for the remaining $x$.

**Eigenvalues**

The final way of examining multicollinearity used in this study is to analyse the eigenvalues of the $X'X$ matrix. The eigenvalues will be smaller if there is multicollinearity between regressors. In order to analyse this the condition number is sometimes calculated as

$$\kappa = \frac{\lambda_{max}}{\lambda_{min}}$$

with a value above 1000 indicate very serious problems with multicollinearity and a value below 100 indicate only limited problems.

### 2.4.12 Variable Selection and Evaluation

When building a model from scratch it is not always possible to know which regressors are important and therefore should be included in the model. Selecting the wrong or too many regressors may have an adverse effect on the quality of the final model. Therefore, it is important to acknowledge this possibility and have a systematic way to choose regressors. It is also important to evaluate different versions of the model in order to find out which regressors optimise the quality of the model.

**All possible regressions**

"All possible regressions" is a way to determine what regressors to include in the model. As indicated by the name this method is based on trying all possible combinations of regressors which are then evaluated on some pre-defined metric, in this study $MSE$, and the best model selected. As the number of possible models is $2^K$, where $K$ is the number of potential regressors, this method has become more practical with the aid of faster computation.
Cross-validation
Cross-validation is a tool to evaluate the quality of the model. The method splits the data set into \( k \) different sets at random. One set is then selected as the evaluation set and the others are then used as training sets. The model is optimised over the training sets before being evaluated over the evaluation set. The procedure is then reiterated but with another set as the evaluation set.

Akaike information criterion (AIC)
Akaike information criterion (AIC) is also known as Bayesian Information Criteria and calculates the additional information obtained from adding an additional variable as defined by the Kullback-Leibler information measure. The AIC is defined as

\[
AIC = n \ln \left( \frac{SS_{Res}}{n} \right) + 2p
\]

\( SS_{Res} \) cannot increase as the number of regressors, \( n \), increases. However, AIC also penalises the use of more regressors through the \( n \) in the denominator.

Mallow’s \( C_p \)
Mallow’s \( C_p \) is a criterion which examines the variance of an observation. The criteria is defined as

\[
C_p = \frac{SS_{Res}(p)}{\hat{\sigma}^2} - n + 2p
\]

assuming that \( \hat{\sigma}^2 \) is a valid estimate of \( \sigma^2 \). If visualising \( C_p \) plotted as a function of \( p \), biased points will be pencilled above the line \( C_p = p \). Generally, small values of \( C_p \) is desired as this minimises the total error even though this may force an acceptance of a higher bias.

2.4.13 Test of Significance
A test of significance is to determine if a linear relationship exists between the response \( y \) and any of the regressor variables. The standard hypotheses are:

\[
H_0 : \beta_1 = ... = \beta_k = 0
\]

\[
H_1 : \beta_j \neq 0, \text{ for at least one } j
\]

If there exists a linear relationship between at least one \( x \) and \( y \), the null hypothesis
will be discarded.
Chapter 3

Methodology

In this chapter the methodology for the thesis is presented. The methods and processes are based on the theoretical framework in Chapter 2. Assumptions, limitations, strategies, data and the model used in this study are described successively.

3.1 Trading Strategies

The following subsections include descriptions of the trading strategies used in the study.

3.1.1 MA-20 and MA-50 Crossover Strategy

The moving average crossover is a trading strategy containing two data manipulations: a short and a long term exponential moving average where \( n_{\text{long}} > n_{\text{short}} \). Recent closing prices of a stock are highly weighted in the short term moving average line while the long term moving average is a more smoothed line representing the long term closing price trend [17].

This technical trading strategy can be used to recognize changes in trends which can be translated to two signals:

*Buy signal (Up-trend)*: Short term moving average line crosses the long term moving average line from below. This indicates a short term up-trend relative to the long term. In this particular event the investor should buy the stock. This signal can be described mathematically with the following conditions:
CHAPTER 3. METHODOLOGY

\[ MA(t-1, n_{\text{short}}) < MA(t-1, n_{\text{long}}) \]

and

\[ MA(t, n_{\text{short}}) > MA(t, n_{\text{long}}). \]

\textit{Sell signal (Down-trend):} Short term moving average line crosses the long term moving average line from above. This indicates a down-trend and signals the investor to sell the stock. The mathematical conditions for this signal is:

\[ MA(t-1, n_{\text{short}}) > MA(t-1, n_{\text{long}}) \]

and

\[ MA(t, n_{\text{short}}) < MA(t, n_{\text{long}}). \]

Figure 3.1.1: MA Crossover strategy. Chart from Investing.com

\[ \text{Figure 3.1.1: MA Crossover strategy. Chart from Investing.com} \]

3.1.2 The RSI-14 Overbought and Oversold Strategy

RSI-14 (daily) is a momentum indicator that measures the relative strength of a share price in relation to the price’s own historical development the last 14 time units and will be used in our second technical trading strategy. An RSI value of over 70 indicates that the share is overbought and an RSI value of less than 30 indicates that the share is oversold. That a share is overbought or oversold means that it commutes far from its equilibrium position and becomes expensive or cheap in relation to its current trend [13]. We clarify this in two type of signals:
Buy signal (Oversold): RSI-14 crosses the value 30. This indicates that the share is oversold and that there is theoretically a high probability for the stock to bounce up to equilibrium. The investor should in this case buy the stock. This event is described mathematically with the following formula:

\[ RSI(t - 1, n) > 30 \]

and

\[ RSI(t, n) \leq 30. \]

Sell signal (Overbought): RSI-14 crosses the value 70. This indicates that the share is overbought and that there is a high probability for the stock to recoil to equilibrium. In this case the investor should sell the stock and the mathematical expression of this event is:

\[ RSI(t - 1, n) < 70 \]

and

\[ RSI(t, n) \geq 70. \]

Figure 3.1.2: RSI strategy. Chart from Investing.com
3.1.3 The MACD Crossover Strategy

The MACD used in the study is constructed with the MACD-line as the difference between a 12-period exponential moving average and a 26-period exponential moving average. The signal line is then defined as the 9-period exponential moving average of the MACD-line. The strategy could be said to be trend following as it generates buy signals when the market starts to trade up and sell signals when the market trades down. This is due to the definition of the indicator. As the price increases the fast exponential moving average increases faster than the slow exponential moving average which causes the MACD-line to rise. As the signal-line is in turn an exponential moving average of the MACD-line, the signal-line will lag the MACD-line. When the MACD-line crosses the signal-line a signal is generated. The buy and sell signals can be defined as the following [5]:

**Buy signal (Up-trend):** MACD-line crosses the signal-line from below. This indicates a short term up-trend relative to the long term. In this particular event the investor should buy the stock. This signal can be described mathematically with the following conditions:

\[
MACD(t - 1, n) < SignalLine(t - 1, n)
\]

and

\[
MACD(t, n) > SignalLine(t, n).
\]

**Sell signal (Down-trend):** MACD-line crosses the signal-line from above. This indicates a down-trend and signals the investor to sell the stock. The mathematical conditions for this signal is:

\[
MACD(t - 1, n) > SignalLine(t - 1, n)
\]

and

\[
MACD(t, n) < SignalLine(t, n).
\]
3.2 Holding Periods and Trading Assumptions

Different investments have different time horizons. Generally for the decisions based on technical indicators, the holding period is relatively short term. Volatility is often not high enough for RSI, for example, to have an effect that is oversold or overbought in the longer term (longer periods). For this study a deterministic holding period is set and applies to all trades for a more comfortable and robotic trading style. The reason for this is to exclude all investing behavioral biases. The following ground assumptions are set to avoid any obfuscation:

- The holding period is set to 5 days.
- If there is a new trend detected (buy/sell signal) while there is an active trade, the position is closed.
- When there is no active trade, the investor takes a neutral position by taking a risk-free position (UK 3-month Treasury Bill rate).
- No short positions are allowed.
- No margin.

3.3 Performance Model

The study focuses on trading with market indices, the index price of the market will be used to compute the return of each trade. Mathematically speaking, the return of a
trade is calculated by dividing the selling price (5 days after taking the bullish position) with the buying price (whenever the indicator signals an upward-trend). Since short-selling is not allowed in this strategy, the sell signal is only used if an indicator signals a downward-trend while there is an active trade. The return of a trade is defined as

$$R_{t,i} = \frac{P_{s,i}}{P_{t,i}} - 1,$$

s=selling time, t=buying time, i=trade number,

and since the selling time s cannot exceed the holding period it is restricted to $t < s \leq t+5$. In order to measure the excess returns using these trading strategies, all returns in a month will be accrued into a monthly return. We define the monthly return as

$$R_p = \prod_{i=1}^{n} (1 + R_{t,i}) - 1.$$ 

The trading strategies used in this study will generate different trades and returns such that comparison is possible. When the monthly return is computed the monthly excess return can be calculated by subtracting the monthly return with the risk-free rate (UK 3-month Treasury Bill rate). The monthly excess return is defined as

$$\text{Monthly excess return} = R_p - R_f.$$ 

In order to study if any trading strategy generates abnormal returns (Jensen’s Alpha), the excess return is adjusted for risk by considering the Sharpe ratio. The exact purpose of this consideration is to isolate the returns associated with risk-taking activities. The Sharpe ratio is computed by dividing the monthly excess return with the standard deviation of the index price. The ratio explains the average return earned per volatility unit. Sharpe ratio[7] is defined as

$$\text{Sharpe ratio} = \frac{R_p - R_f}{\sigma_p}.$$ 

### 3.3.1 Capital Asset Pricing Model

Capital Asset Pricing Model asserts that assets with higher systematic risk should earn higher returns [1]. This risk-return relationship can be applied in this study by assuming that OMX and CDAX indices have a systematic relationship to the European
markets. In order to test if a trading strategy generates any abnormal returns (Jensen’s Alpha), the risk should be controlled by using CAPM, particularly by using the CAPM assumption that the asset’s sensitivity to systematic risk is measured by the $\beta$ multiplier [1]. The $\beta$ multiplier is computed by means of the monthly excess return of the market return. In this particular study, as mentioned in previous sections, the market is defined as the STOXX Europe 600 Index since it is a broad representation of European small-, medium- and large cap stocks. The CAPM is defined as

$$R_{Pt} = R_{ft} + \beta_1(R_m - R_f).$$

The theoretical return is explained and predicted by the market model. If the performance of a specific portfolio or strategy is considered, one should apply the single-index model (SIM) which is derived from the CAPM (William Sharpe, 1963). This simple asset pricing model will be used to investigate the abnormal returns by measuring both the risk and the return of the indices. The formula is rewritten as

$$R_{pt} - R_f = \alpha_j + \beta_1(R_{Mt} - R_{ft}) + \epsilon_p$$

$$\epsilon_p \sim N(0, \sigma^2_p)$$

$R_{Pt} - R_{ft} =$ Total monthly excess return using technical trading strategies

$R_{Mt} - R_{ft} =$ Monthly excess return of the market

$\alpha_j =$ Jensen’s Alpha (the estimated abnormal return, CAPM intercept)

$\beta_1 =$ Estimated trading portfolio beta responsiveness to the STOXX 600 Europe return

$\epsilon_{Pt} =$ Error term (assumed to be independent normally distributed, zero mean).

The regression model will generate both, $\alpha_j$ and $\beta_1$, however, the parameter in interest is the Jensen’s Alpha, $\alpha_j$, as it is an indication of the abnormal returns gained by trading with technical trading strategies, after controlling the market risk.

### 3.3.2 Fama and French Three Factor Model

The Fama and French 3-Factor Model is a model developed by Fama and French (1992) and expands the CAPM by adding size- and value risk to the CAPM[6]. Generally, the main consideration made by this model is the fact that value stocks outperform growth stocks and small cap stocks tend to outperform large cap stocks. These considerations
are realized by deriving size and value factors into the CAPM. The size-factor should capture the outperformance of small cap stocks over large cap. The factor is computed by constructing 15 portfolios from the STOXX Europe 600 Index ranked on Market capitalization and Price-to-Book ratio (which are rebalanced yearly). A large cap company is associated with high Market capitalization or Market Equity and a growth stock is associated with a high Book-to-Market ratio [6].

The size factor \( \text{SMB}_t \) is computed by subtracting the average monthly return on portfolios containing small cap stocks with the average monthly return on portfolios containing large cap stocks. The averaging is done between value and growth for a more weighted and adequate representation of small and large cap. The size-factor, \( \text{SMB}_t \), is defined as

\[
\text{SMB}_t = \frac{1}{2}(R_{\text{small, value}} + R_{\text{small, growth}}) - \frac{1}{2}(R_{\text{large, value}} + R_{\text{large, growth}}).
\]

The tendency of value stocks outperforming growth stocks is realized by adding the value-factor to the model. The value-factor \( \text{HML}_t \) is computed from the same 15 constructed portfolios by subtracting the average monthly return on value portfolios minus the average monthly return on growth portfolios. Also here the averaging is done for a more weighted and adequate representation of value and growth stocks. The value-factor, \( \text{HML}_t \), is defined as

\[
\text{HML}_t = \frac{1}{2}(R_{\text{value, small}} + R_{\text{value, large}}) - \frac{1}{2}(R_{\text{growth, small}} + R_{\text{growth, large}}).
\]

Including these factors to the CAPM model, the Fama and French 3-Factor Model is obtained, which is the second model tested in this study. The final regression model is

\[
R_{pt} - R_f = \alpha_j + \beta_1(R_{Mt} - R_{ft}) + \beta_2\text{SMB}_t + \beta_3\text{HML}_t + \epsilon_{pt}.
\]

This model yields estimates of \( \alpha_j, \beta_1, \beta_2 \) and \( \beta_3 \) where the main focus will be aimed at Jensen’s Alpha as it is the reflection of abnormal returns using technical trading strategies.
3.3.3 Carhart Extension

The Carhart 4-Factor characteristic model is an extension of the Fama and French 3-Factor model which implies that recent winners in the stock market have a tendency to outperform recent losers [2]. This implication includes a momentum factor for asset pricing of stocks which can be realized by adding a new variable to the Fama and French 3-Factor model. The momentum-factor (winners minus losers, $UMD_t$) is computed by subtracting the weighted average of the highest performing companies (lagged one month) with the weighted average of the lowest performing companies [2].

For this particular factor, 4 portfolios are constructed based on market capitalization and the prior returns (12 month), where these portfolios are rebalanced yearly. The main interpretation of this factor is that if a stock has shown a positive 12 month average of returns, then the stock is considered to show momentum. In this study the momentum is computed by subtracting the average monthly return of two portfolios containing stocks with higher prior returns with the average monthly return of two portfolios containing stocks with low prior returns. The averaging is done between small- and large cap companies for a more equal representation of the momentum.

$$UMD_t = \frac{1}{2}(R_{\text{HighReturn, small}} + R_{\text{HighReturn, large}}) - \frac{1}{2}(R_{\text{LowReturn, small}} + R_{\text{LowReturn, large}}).$$

The momentum-factor is added to the Fama and French 3-Factor Model and the following regression model is obtained

$$R_{pt} - R_f = \alpha_j + \beta_1(R_{Mt} - R_{ft}) + \beta_2SMB_t + \beta_3HML_t + \beta_4UMD_t + \epsilon_{pt}.$$  

This model yields estimates of the same parameters as the Fama and French 3-Factor Model but also a coefficient $\beta_4$ for the momentum factor. Also here the main focus is on Jensen’s Alpha as it is the reflection of abnormal returns using technical trading strategies. This is the initial model used in this study.
3.4 Data and Tools

In this section, the data and tools used in this study is presented.

3.4.1 Data

Since this study is mainly for inexperienced private investors, advanced financial derivatives are excluded for testing. As mentioned before the study will focus on trading with the OMX Stockholm PI index because of its broad representation of small, medium and large cap companies across Sweden and Germany. Data for STOXX Europe 600 Index will also be needed for this study, functioning as a control variable explaining the market risk. The data is retrieved from Yahoo! Finance. The time period included in the study is 1 January 2010 to 31 December 2019. The reason for excluding the market year 2020 is because of the high error generated when trading with technical trading strategies. The Cook’s Distance is presented below for a regression analysis with regressor: distance between Moving Average 50 and 20, and dependent variable: Market return (OMXSPI).

Figure 3.4.1: Cook’s distance highlighting the 2020 volatility
As observed above one can see that the Cook’s Distance is strongly deviant between 1 February 2020 to 31 March. It is therefore more adequate to apply this study on the time interval 1 January 2010 to 31 December 2019 for more accurate results.

### 3.4.2 Software

The software used for linear modeling, model analysis and assessment is R. The following packages are used: devtools, dplyr, GGally, knitr, car and kableExtra.
Chapter 4

Results

In this chapter the empirical results of the study is presented and the Carhart 4-Factor model is analyzed. This section is divided into firstly presenting and analyzing the raw excess returns by trading using technical indicators and, secondly, analyzing the abnormal returns retrieved with the performance models provided in Section 3.3.

4.1 Preliminary Raw Results

The results for the full regression model for the three different technical trading strategies are presented below.

The table shows that the Carhart-4 Factor full regression model generates positive abnormal returns (positive Jensen’s Alpha intercept) when trading with the Moving Average Crossover strategy, the RSI-14 strategy and the MACD strategy. One can see that there is a great significance on the p-value of the explanatory market variable which also is close to zero for the three trading strategies. This indicates that the null hypothesis (regressors coefficient is equal to zero) can be rejected which concludes that there is a linear relationship between the market returns and the technical trading returns. The model summaries are presented below.

One should particularly have in mind that the R-squared levels are low which is an indication of the models low explanation of the variance in the trading return. Furthermore, the adjusted R squared are lower than the R squared value for all three strategies which explains that additional input of regressors to the model are not adding value to the regression model. In order to understand and revise an optimized


| Strategy   | Coefficients | Standard error | t-value | Pr(>|t|) |
|------------|--------------|----------------|---------|----------|
| MA Strategy |              |                |         |          |
| $\alpha$ (Intercept) | 0.63009      | 0.27067        | 2.328   | 0.0217*  |
| $R_m - R_f$ | 0.47889      | 0.09508        | 5.037   | 1.77e-06 *** |
| SMB        | 3.12781      | 2.61371        | 1.197   | 0.2339   |
| HML        | -0.04139     | 3.26066        | -0.013  | 0.9899   |
| UMD        | -0.99675     | 3.35860        | -0.297  | 0.7672   |
| RSI Strategy |              |                |         |          |
| $\alpha$ (Intercept) | 0.8049       | 0.2622         | 3.070   | 0.00267** |
| $R_m - R_f$ | 0.4716       | 0.0921         | 5.121   | 1.23e-06 *** |
| SMB        | -1.6688      | 2.5317         | -0.659  | 0.51112  |
| HML        | 0.1544       | 3.1584         | 0.049   | 0.96109  |
| UMD        | 0.3900       | 3.2532         | 0.120   | 0.90479  |
| MACD Strategy |            |                |         |          |
| $\alpha$ (Intercept) | 0.64044      | 0.26913        | 2.380   | 0.019    |
| $R_m - R_f$ | 0.53255      | 0.09454        | 5.633   | 1.27e-07 *** |
| SMB        | 0.63258      | 2.59879        | 0.243   | 0.808    |
| HML        | 0.87882      | 3.24205        | 0.271   | 0.787    |
| UMD        | 2.18205      | 3.33943        | 0.653   | 0.515    |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ''

Table 4.1.1: The empirical results for the full Carhart-4 Factor model for the three technical trading strategies.

<table>
<thead>
<tr>
<th>Model</th>
<th>MA strategy</th>
<th>RSI strategy</th>
<th>MACD strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual standard error</td>
<td>1.516 on 115 DF</td>
<td>1.469 on 115 DF</td>
<td>1.508 on 115 DF</td>
</tr>
<tr>
<td>Multiple $R^2$</td>
<td>0.2012</td>
<td>0.1871</td>
<td>0.227</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.1734</td>
<td>0.1588</td>
<td>0.2001</td>
</tr>
<tr>
<td>F-statistic</td>
<td>7.239 on 4 and 115 DF</td>
<td>6.618 on 4 and 115 DF</td>
<td>8.444 on 4 and 115 DF</td>
</tr>
<tr>
<td>p-value</td>
<td>3.096e-05</td>
<td>7.888e-05</td>
<td>5.216e-06</td>
</tr>
</tbody>
</table>

Table 4.1.2: Model summaries

In this section, the model is evaluated and developed. The main purpose is to get a model that best explains the data points. The methods used in this section are explained in the chapter on mathematical theory, 2.4.

### 4.2 Model Analysis

In this section, the model is evaluated and developed. The main purpose is to get a model that best explains the data points. The methods used in this section are explained in the chapter on mathematical theory, 2.4.

#### 4.2.1 Residual Analysis

In this section the linearity between the response and the regressors and the distribution of the residuals are to be analyzed. Residual plots of the full model fit for all three strategies are presented below.
Figure 4.2.1: Residuals against fitted values and residuals against theoretical quantiles plots for all three strategies. The first row represents the plots for the MA-strategy, second row represents the RSI-strategy and the last row represents the MACD-strategy.
For the presented residuals against theoretical quantiles plots (Normal QQ-plot), one can see that the residuals form an approximately straight line. There are some departures from the line on the tails, which indicates that the studentized residuals have a distribution with heavier tails than the normal distribution. This indicates that the residuals are not perfectly normally distributed. For example for the RSI and MACD strategies, a considerable amount of residuals are above the straight line which identifies a right skewed distribution. The departures, however, are relatively small and we can say that the studentized residuals are approximately normally distributed.

The linear relationship between the response variable and the regressors can be analyzed with the above presented studentized residuals against fitted values plots. The data points seem to be randomly plotted around the horizontal line and no particular pattern (explained in the Mathematical theory section) are formed by the points for any trading strategy. Thus one can say that there is no indication of heteroscedasticity or nonlinearity and also conclude that the residuals have a constant variance.

4.2.2 Added Variable analysis

As mentioned above (in 4.1) the smaller adjusted R-squared value demonstrates that the number of regressors used are questionable. Therefore, an added variable analysis is relevant for this study. Partial regression plots for the regression model of all three trading strategies are presented below.

The partial regression plots (explained in the mathematical theory section, 2.4) of all regressors of the full Carhart 4-Factor model points out the potential points (red dots) that might have an influence on the full model. These points have shown a distantly large presence in the x-space and are considered as potential influential points. All three strategies have a strong positive slope on their added variable plot of the market regressor \( R_m - R_f \) which indicates the market regressor has a strong positive contribution on the model already containing the other regressors. For the regression model used on the Moving Average trading strategy one can see that the slope of the HML and UMD PR-plots are close to zero. Since there are no patterns of nonlinear trends, it can be assumed that the regressors HML and UMD does not contribute to the explanation of the trading returns using Moving Average. The PR-
Figure 4.2.2: Partial regression plots of the Carhart 4-Factor model used on the MA trading strategy.

Figure 4.2.3: Partial regression plots of the Carhart 4-Factor model used on the RSI trading strategy.
Figure 4.2.4: Plot 4: Partial regression plots of the Carhart 4-Factor model used on the MACD trading strategy.
plots of the same regressors when the model is used on the returns of the Relative Strength Index strategy also presents a slope close to zero for the HML and UMD regressors. Also for the model using this particular strategy the HML and UMD regressors might not have a considerable effect on explaining the response. When the model is used on the Moving Average Convergence Divergence trading strategy, the PR-plots show that the SMB and HML variable does not help explaining the returns obtained with the given strategy. However, it seems like the regressors are entering the model linearly, thus we choose to not transform or exclude any of the regressors from the model for the sake of further analysis.

### 4.2.3 Multicollinearity

A correlation matrix of the regressors used in the Carhart 4-Factor model is presented below.

![Correlation matrix of regressors](image)

Figure 4.2.5: Correlation matrix of regressors

As one can see on the correlation matrix, no considerable high correlation is noticed. Thus, the possibility of existence of multicollinearity is not identified. Another multicollinearity analysis of the regressors in the full Carhart 4-Factor regression model is performed by computing the condition number of the regressors correlation matrix (X'X). This resulted in a condition number above 100 which indicates that there might exist multicollinear relationships.
For further investigation the variance of inflation are computed and presented below with the eigenvalues.

<table>
<thead>
<tr>
<th></th>
<th>Market</th>
<th>SMB</th>
<th>HML</th>
<th>UMD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigen</td>
<td>1.1604515</td>
<td>1.0827623</td>
<td>0.9568753</td>
<td>0.7999109</td>
</tr>
<tr>
<td>VIF</td>
<td>1.024211</td>
<td>1.021729</td>
<td>1.018894</td>
<td>1.015671</td>
</tr>
</tbody>
</table>

Table 4.2.1: Variance inflation factors and characteristic eigenvalues of $XX$ for each regressor

The eigenvalues presented above are not particularly close to zero which is an indication of no existing near linear dependencies. The rule of thumb in variance of inflation analysis states that a VIF over 10 indicates that there appears to be multicollinearity in the OLS regression. Since the VIF values of the regressors are close to 1, it is said to be no existing correlation between the variables, and hence the variances of the coefficients are not inflated.

![Variance Inflation Factor Chart](image)

Figure 4.2.6: Variance of inflation

### 4.2.4 Diagnostics and Outliers

The Cook’s Distance and DFFITS plots are computed for the Carhart 4-Factor model of each trading strategy application and are presented below.
CHAPTER 4. RESULTS

Figure 4.2.7: Cook’s Distance and DFFITS when MA strategy is applied.

Figure 4.2.8: Cook’s Distance and DFFITS when RSI strategy is applied.

Figure 4.2.9: Cook’s Distance and DFFITS when MACD strategy is applied.

The four largest detected Cook’s distance observations are marked as red lines. The vast majority of the largest distances are detected in the period 2015-2019. This causal
relationship may indicate that the market is constantly changing and that the Carhart 4-Factor model does not have the same function as it had before. If Cook’s cut-off value of 1 is considered, one can assume that none of the observations are influential points. However, it is worth mentioning the four largest distances since it may affect the fit of the model.

The observations that are marked with green have a DFFITS value outside the recommended cut-off interval (Not influential when $-2\sqrt{\frac{p}{n}} < \text{DFFITS} < 2\sqrt{\frac{p}{n}}$). The majority of the DFFITS values outside the non-influential interval are observations in the period 2015-2019. Also here the assumption of the stock market constantly changing can be applied and that the Carhart 4-Factor model loses its function. Comparing the observations with reality, one can see that the outliers are not a result of mismeasurements and there is no qualitative or quantitative argument for removing them (the market should not be adjusted for the model, the model should be adjusted for the market).

### 4.2.5 Variable Selection

All possible regression method is implemented when selecting the variables for the model. In this specific analysis, all possible models are tested by first trying out one regressor, then two and so on. The measurements for Bayesian information criterion, Akaike information criterion, Mallow’s $C_p$ criterion and adjusted R-squared of the best subset of models for each trading strategy are presented below.

Many methodological considerations were involved in this particular step regarding the choice of variables. As mentioned before, removing influential- and outlier data points would reduce the mean squared error significantly, however, there exist no causality reason to discard these observations and therefore they will remain in the dataset. One could argue that a model that minimizes the mean squared error should be proceeded, but since the purpose of this analysis is not to use the performance model for future predictions and that the main focus is to explain the data rather than manipulating it for a better fit, there is no considerable need for minimizing the mean squared error. In fact, predictions made by the final model may still be approximately accurate even if the best fit is not obtained.
Figure 4.2.10: AIC, adjusted R-squared, C(p) criterion and BIC of the best subset models of the regression model when using MA trading strategy.

Figure 4.2.11: AIC, adjusted R-squared, C(p) criterion and BIC of the best subset models of the regression model when using RSI trading strategy.
Figure 4.2.12: AIC, adjusted R-squared, C(p) criterion and BIC of the best subset models of the regression model when using MACD trading strategy.
4.2.6 Final Models

The coefficients of the models with best performance evaluated with the cross-validated mean square error is presented below.

<table>
<thead>
<tr>
<th></th>
<th>MA strategy</th>
<th>RSI strategy</th>
<th>MACD strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$ (Intercept)</td>
<td>0.611403</td>
<td>0.936635</td>
<td>0.884428</td>
</tr>
<tr>
<td>$R_f - R_m$</td>
<td>0.389271</td>
<td>0.363150</td>
<td>0.470932</td>
</tr>
<tr>
<td>SMB</td>
<td>4.981507</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>HML</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>UMD</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>MSE</td>
<td>1.34632</td>
<td>1.51566</td>
<td>1.40745</td>
</tr>
</tbody>
</table>

Table 4.2.2: Final models

4.3 Final Results

In this particular section, each model for each strategy are analyzed and the results are interpreted.

4.3.1 Moving Average Strategy Analysis

The Efficient Market Hypothesis (EMH) asserts that trading with technical trading strategies in the equity market should not generate any abnormal returns. In order to test if this hypothesis for the moving average trading strategy, the monthly excess returns obtained when trading with the strategy over the time period 2010-2019 are regressed on the risk-adjusted Carhart 4-Factor model.

The moving average lines used in this particular investigation has the period of 20 respectively 50 days (since it is the most commonly used strategy set-up among beginners). The initial full Carhart 4-Factor model generated a positive intercept which is significantly different from zero. The market coefficient is also significantly different from zero, however the size-factor, value-factor and the momentum-factor is not. When the model is analyzed and revised, no outliers are removed from the dataset since there is no qualitative reason for that (the market should not adapt to the model). The multicollinearity analysis shows that no transformations of variables are needed for this model. The final model of the Carhart 4-Factor model when trading with the
moving average strategy is retrieved from the best performing model when the model is cross-validated.

When the raw linear model are compared to the final model, one can see that the parameterized value-factor and momentum-factor gets discarded from the model. A possible explanation of this is later discussed in Limitations (Section 5.1). However, the intercept, market coefficient and size-factor remains positive. The results shows that the Jensen’s Alpha is positive (positive intercept) which means that there exists an abnormal gain when trading with the moving average strategy, which also rejects the hypothesis of efficient markets. The interpretation of the low market beta value (<1) indicates that the trading portfolio is less volatile than the overall market. This can be explained since the trading portfolio is invested in the UK 3-month Treasury Bill when there is no active trade.

### 4.3.2 Relative Strength Index Strategy Analysis

In order to test if the hypothesis about efficient markets holds for the RSI trading strategy, the monthly excess returns when trading with the strategy is obtained and regressed on the risk-adjusted Carhart 4-Factor model over the time period between 2010-2019.

The RSI set-up period is set to 14 days (commonly used set-up among professional traders and beginners) and the initial full Carhart 4-Factor model generated a positive intercept which also is significantly different from zero. Also in this case, the market coefficient is significantly different from zero and positive. The rest of the factors does not show any significant results. The revised model does not exclude any outliers because of its lack of a qualitative reason. Since the strategies initially used the same regressors, the multicollinearity analysis remains the same and no variable are transformed or merged.

The final model obtained by cross-validating the Carhart 4-Factor model when trading with the RSI-14 strategy discards the size-factor, value-factor and the momentum-factor. Further discussion about the possible reasons for this elimination is discussed under Limitations (Section 5.2). The intercept and the market coefficient remains positive and does not change significantly. The final results indicates that the trading strategy generates a positive Jensen’s Alpha which implies that abnormal returns exists. Also for this model the market beta value is low, mainly because of its passive
investments in the UK 3-month Treasury Bill when no active trade is present.

4.3.3 Moving Average Convergence Divergence Strategy Analysis

Also for this strategy, the hypothesis is tested by obtaining the monthly excess return when trading with the Moving Average Convergence Divergence strategy and regress it on the risk-adjusted Carhart 4-Factor model of the period of 2010-2019.

The MACD-line is set to be the distance between the lines exponential moving average 26 and the exponential moving average 12 and the signal-line is set to be the exponential moving average 9. The initial full Carhart 4-Factor model generates a positive Jensen’s alpha which is also significantly different from zero. Also the market coefficient shows great significance on the p-value which is also close to zero likewise for the other strategies. As mentioned for the other strategies, the model does not exclude any outliers and no transformations or mergers of variables are done.

The final cross-validated version of the Carhart 4-Factor model when trading with the MACD-strategy excludes size-factor, value-factor and the momentum-factor. Potential reasons for this elimination are explained in Limitations (Section 5.2). However, the intercept remains positive which indicates that abnormal returns exists when trading with this particular strategy. As for this strategy, the market coefficient is low and can be explained of its passive positions in the UK 3-month Treasury Bill.
Chapter 5

Conclusions

This study investigated if technical trading strategies generate any abnormal returns when trading in the Swedish equity market. In addition, three different strategies are tested for a investigation if the result differ between strategies in terms of generated Jensen’s alpha and the market coefficient. The conclusions made from the results are presented in this Chapter.

5.1 Summary of Results

To summarize the key results of this study, the technical trading strategies with the predetermined trading rules did separately generate abnormal returns. The applied rules and assumptions were simplified such that individuals that are beginner in the field of technical trading does not have to be comfortable with advanced derivatives. The Jensen’s alpha retrieved from the regressed models also have a high level of significance. The final model (best fit model) presents the Jensen’s alpha and coefficients when the trader takes an neutral position (UK 3-month Treasury Bill) whenever there is no active trade. The trading strategies yields the following abnormal returns:

- Moving average 20 and 50 crossover strategy: 0.61 percent per month
- Relative Strength Index (14-period) strategy: 0.94 percent per month
- Moving average convergence divergence strategy: 0.88 percent per month

As one can see, the most profitable trading strategy obtained by the final model
is the RSI-14 trading strategy. The results obtained rejects the hypothesis of efficient markets, which accordance to literature should not generate any abnormal returns.

5.2 Limitations

In this section the limitations of the results will be disclosed. This part will be divided into three aspects; the model limitations due to its factorial limitations, mathematical limitations and lastly the limitations due to the data used in this study.

5.2.1 Variables

This study computes the monthly excess return based on the OMXSPI price movements when trading with technical indicators. The OMXSPI index is a capitalization-weighted index (not equal-weighted), in which the small capitalization stocks are not heavily represented. Small capitalization stocks capture greater risk and consequently have larger expected returns than large capitalization stocks. This also applies for STOXX Europe 600 index. The movements of large capitalization companies may explain the high significance on the market-factor (market excess return) and the disappearance of the other factors. The main reason of the disappearance may depend on the fact that the value-, size- and momentum-factor is not weighted in the same particular way as the indices.

Furthermore, parameterization of the brokerage commission is not done in this study. This means that the transaction cost for each trade is not included when trading with the indicators. This particular parameter has an direct relationship with the monthly excess return and the exclusion of this may have affected the generated abnormal returns. Since several brokerage accounts does not take fees (or take a very small fee) from beginners who invest a small amount of capital (for example Avanza courtage class Start), the transaction cost parameter is excluded.

5.2.2 Data

The dataset in this study have both up- and downsides. As mentioned in the theory, this particular field or area of trading investigation can be endlessly specified for greater results. But because of the lack of time and resources, many parts of the study are
simplified. For example, the excess return obtained when trading with the indicators are obtained month-wise, which leaves the study with only 120 observations. Also, the value-factor, size-factor and momentum-factor are rebalanced and computed yearly, which means that the data is annually static for these variables. This lead to an obscure parameterization of the factors and may misrepresent the market phenomenons.

5.2.3 Regression Model

The model developed by Fama and French (3-Factor model) and the Carhart Extension (4-Factor model) is practically and initially retrieved in the sole purpose of investigating and measuring fund managers performances. This study investigates the performances of technical indicators, so the suitability of the model can be discussed. Also, the excess return of the trading portfolio (the explanatory variable) should be computed of a stable portfolio containing an appropriate number of shares. One should have in consideration that this study use the excess return obtained when trading with OMXSPI index (for a more broad representation of the Swedish equity market). So the model can be questionable for this particular case.

5.3 Applications in Practice

New investors trading with the use of technical indicators in the stock market lose value relative to the well known buy and hold strategy [4]. One can argue that the reason for this is because of the non-functioning trading indicators. This particular study have shown that if the trader sticks to predetermined trading rules and trade consistently whenever a buy signal is shown, there exist an abnormal return relative to the market when trading with indicators such as MA, RSI and MACD. Therefore, the reason behind individuals losing value in the market may due to the excessive trading and behavioral biases like overconfidence, fear or FOMO (fear of missing out). A consistent technical trading strategy could make the investor overcome this problem since a strategy provides with objective trading signals rather than subjective. This would eliminate trading on intuition or biased signals retrieved from other psychological factors.

This study also contributes to the existing studies by investigating the profitability of technical trading strategies in the Swedish equity market. The strategies yielded
positive abnormal returns which goes against the Efficient market hypothesis. However, the results also supports earlier studies in this field, mainly in technical trading subject, which is highly discussed in today’s high frequency algorithmical world.

5.4 Further Research

As this Bachelor Thesis concludes that the Moving Average 20 and 50 crossover-, Relative Strength Index 14- and the Moving Average Convergence Divergence strategy generates positive abnormal returns, it is in high interest to investigate this subject with more parameterizations, modification of model, time periods and strategies. For example, further research could be more in-depth and zoom-in to a daily excess return basis for a more aggressive trading strategy specially made for excessive traders. In addition, researcher could investigate the insignificant factors and examine if its possible to increase the quality of the factors by a more in-depth analysis of the parameterization.

Another interesting field that can be further investigated is the abnormal returns when short-selling is allowed while trading with technical trading strategies. Mainly because it would arouse interest among professional traders which are also taking short position when trading with indicators. In a study with allowance of short-selling, the transaction cost should also be included in the model for a more accurate and adjusted representation of the returns.

Since 2010-2019 have been reflecting a bullish market, further researchers could investigate how the abnormal returns differ in a more volatile and bearish time period. An example of this could be the time period 2000-2010 where two large economic bubbles and crisis are involved in the data set. The performances and the hedging capabilities of the trading strategies under patchy circumstances and alternating movements can then be examined.
References


REFERENCES


