

Potential Overreactions and Reversal Effects, Evidence from the Swedish Market

Filip Abrahamsson Kwetcz^{*} & Carl Åkerlind[†]

May 17, 2015

Bachelor Thesis

Stockholm School of Economics

Abstract

Ever since De Bondt and Thaler first formulated the Overreaction Hypothesis researchers have been studying different financial markets searching for evidence for an overreacting market. This paper examines if the OMXS30 stocks overreact to extreme events and if certain variables, such as the underlying causational event of the potential overreaction and furthermore the characteristics of the potential overreaction itself, can explain the probability of reversals taking place. The main result of this study is that on average there are no reversals taking place. Therefore, the Overreaction Hypothesis is rejected for the OMXS30 stocks. Reversals are however found to exist in over one third of the events examined which is considered a high fraction keeping in mind the size of the companies studied. Short time reversals occurred after 34.7% of the potential overreactions and long time reversals occurred after 43.3% of the cases. The main tests of the thesis show on a statistically significant level that increased traded volume on the event day increases the probability of reversals taking place. Some of the causational events are with statistic significance found to increase or decrease the probability of reversals. The conclusion that the likelihood of a reversal is dependent on the causational event is therefore drawn.

Keywords: Overreaction Hypothesis, Reversal effects, Causational events, OMXS30, Swedish Market

Tutor: Irina Zviadadze

Acknowledgements: We would like to express our gratitude to Irina Zviadadze for insightful comments and guidance throughout the entire project.

^{*}22800@hhs.se

[†]22707@hhs.se

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1 Introduction

Observing the movements of stocks' prices subsequently to major price changes this thesis investigates the stock market's reactions to extreme events. The main interest concerns the nature of reversals, i.e. rebound effects in the opposite direction of the initial price movement. Furthermore, the thesis also endeavours to shed light on some explanations as to when reversals are to be expected. The question whether the market is efficient or if mispricing sometimes occurs is one of the most, if not the most, extensively debated questions within the field of finance. The three forms of the Efficient Market Hypothesis (EMH) put forward by Fama (1969) represents one of the most fundamental theories within financial economics. This thesis examines the aspect of mispricing regarding the market reacting severely to spectacular events. This is of greatest interest since determination of future stock prices from past is a violation of the EMH and could lay a foundation to positive alpha trading strategies.

Ever since De Bondt and Thaler (1985) first formulated the Overreaction Hypothesis researchers have been studying different financial markets searching for evidence for an overreacting market. Arguments regarding the market's reactions to extreme events have been put forward for all of the three main competing theories, the EMH, suggesting that investors are unable to predict future returns, the Overreaction Hypothesis, suggesting that the market overreacts to new information and later on will correct these overreactions and the Underreaction Hypothesis, suggesting that the market underreacts to new information and later on will move in the same direction.

Atkins and Dyl (1990) as well as Lehmann (1990) claims that the U.S. market is overreacting to extreme events and also find support for the existence of a reversal effect, defined as a price decrease if the initial overreaction is positive or a price increase if the initial overreaction is negative, taking place. On the one hand Cox and Peterson (1994) find evidence for reversals taking place the first three days following a large one-day stock price decline. On the other hand they claim that on average there are no reversals to be found after 1987. Not only have our predecessors examined whether the market overreacts or not but also investigated the effect of different factors, such as market liquidity and bid-ask spread, on the characteristics

of the reversals.

This paper sets out to examine the behaviour of the stocks of the 30 largest companies on the Swedish stock market (the OMXS30 stocks) in a short time period after the stocks experience severe change in prices. In line with the method used by Bremer and Sweeney (1991) a pre-set trigger level of $\pm 5\%$ is defined. Price movements passing this threshold value and fulfilling further criteria of being the sole such movement in a 40 days window are then investigated to see if the market overreacts to extreme events related to the OMXS30 companies. Moreover, the thesis addresses the relation between major price changes and reversals to the underlying explanation of the initial price movement, i.e. causational event, and the market liquidity measured by the quantitative variables traded volume and bid-ask spread. The two main features that distinguishes this thesis from previous work in the field are i) the market where it is conducted, the authors are not aware of any similar study being conducted on the Swedish market, and ii) the endeavour to explain outcomes by the causational events of the initial price change.

Using the trigger level of $\pm 5\%$ and applying the criterion of only one potential overreaction per event window 150 potential overreactions are found in the period between 2010-2014. Furthermore, reversals are found during the examined time period. In total, short time reversals (defined as cumulative abnormal return closer to the zero level 5 days after the event day than on the event day) occurred after 34.7% of the potential overreactions and long time reversals (defined as cumulative abnormal return closer to the zero level 20 days after the event day than on the event day) occurred after 43.3% of the cases. However, this means that on average there are no reversals after an initial price movement of $\pm 5\%$.

Furthermore, some variables of interest are found on a statistically significant level to either increase or decrease the probability of a reversal after a potential overreaction. The main tests of the thesis shows that traded volume and some of the causational events have a significant impact on the probability of the existence of reversals. The ability to link the probability of reversals to the causational event is an important result and differentiates a lot from previous research and findings in the field. Worth to notice is that even though bid-ask spread seemed to have an impact on the probability of reversals occurring in the descriptive statistics no

statistically significant results could be attained.

The obtained results show that there on average have been no reversals during the last five years for the 30 largest firms on the Stockholm stock exchange. This means that the Overreaction Hypothesis can be concluded not to be valid for these firms. However, since this thesis considers very large firms it is possible that the outcome had been quite different if smaller firms would have been considered. Finding that more than one third of all potential overreactions in fact were overreactions has to be seen as a quite large fraction considering the size of the companies observed.

The remainder of this thesis is organized as follows, in section 2 related literature is reviewed and the most important results of previous research is presented. After that follows section 3 containing an outline of the hypothesis of this thesis. Moreover, in section 4 the data used in the study is presented and some potential biases are discussed. Section 5 contains a description of the methodology used in order to receive the results which are to be found in section 6. In section 7 follows the conclusions, and their implications, which are reached from the results. Finally, the last section contains the appendix where most of the graphs, tables and some detailed calculations are to be found.

2 Previous Literature

Numerous authors have explored the area of research concerning the reversal process following large movements of stock prices. Their findings sometimes seem to differ. Empirical evidence have been found both in favour of a financial market that seems to overreact to certain events as well as of a financial market that seems to underreact. Either of these scenarios causes effects that are violations of the EMH. Researchers who have found evidence for reversals taking place are in favour of the Overreaction Hypothesis whereas researchers who have not found these evidences but rather suggest momentum in returns are in favour of the Underreaction Hypothesis. Often, market capitalization, bid-ask spread, stock illiquidity and similar cross-sectional aspects are referred to as explanation for over- and under reactions.

2.1 Studies Conducted within the U.S. Market

De Bondt and Thaler (1985) was first to formulate the Overreaction Hypothesis. The hypothesis suggests two things: *"Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction."* and furthermore *"The more extreme the initial price movement, the greater will be the subsequent adjustment."* The Overreaction Hypothesis is regarded as a violation of the EMH since it contradicts the part of the EMH stipulating that stock prices cannot be predicted from historical prices. Moreover, De Bondt and Thaler (1987) denies that price reversals are caused by size effect, seasonality or change in market risk.

Atkins and Dyl (1990) found evidence of the stock market overreacting in the short run. The effect was especially visible for stocks experiencing large price declines. Though, the authors did not find evidence for the market being inefficient when transaction costs were taken into account since traders were unable to profit from the price reversals as a result of the magnitude of the bid-ask spread. In contrast to Atkins and Dyl, Lehmann (1990) suggests that arbitrary profits can be made on trading on reversal patterns despite the existence of transaction costs.

Bremer and Sweeney (1991) examines reversals after large stock price decreases. The authors use a pre-set trigger level return and examine the subsequent returns of the stocks passing the threshold value. In their study they find statistically significant reversals for stocks experiencing a single day return of less than -10%. The cumulative reversals of these stocks equal a 2.2% price increase over the next two trading days (1.77% day one).

Cox and Peterson (1994) studies the impact of the market liquidity and bid-ask bounce on price reversals the following three days after large one-day declines in stock prices. Their sample consists of daily data for all AMEX, NYSE and NMS firms that are listed on CRSP between 1963 and 1991. Significant positive average cumulative abnormal returns are found for the following three days after a steep price fall. The cumulative abnormal returns for day four to twenty are however found to be negative. Moreover, the amount of reversals tends to diminish over time, following late 1987 there are on average no reversals. Cox and Peterson also claim that if liquidity is an important factor in the reversal process stronger reversals are to be expected in less liquid markets and for smaller firms. Furthermore, the

results claim that larger initial declines not necessarily lead to greater subsequent reversals in contradiction to the Overreaction Hypothesis.

Studying stock price overreactions and delayed reactions contribution to profitability of contrarian strategies Jagadeesh and Titman (1995) found that stock prices overreact to firm-specific information and react with a delay to common factors.

More recently, Pritamani and Singal (2001) and Larson and Madura (2003) found, in contrary to their predecessors, that large price changes following a public announcement are associated with continuation in the trend, i.e. no reversals. Their findings supports the theory of reversals being connected to uninformed events whereas informed events are connected to underreactions.

Benou and Richie (2003) found evidence largely consistent with the Overreaction Hypothesis when studying the long-run reversal patterns for a sample of large U.S. firms with a trigger level of -20%.

2.2 Non-American Studies

All the abovementioned papers have at least one thing in common, their samples are from the U.S. market. However, studies have been conducted for other markets as well, though the U.S. market is the by far most studied.

Brailsford (1992) and Allen and Prince (1995) find evidence for reversals using Australian data. Da Costa (1994) studies the Brazilian market and finds evidence for reversals. Bremer, Hiraki and Sweeney (1997) examines the Japanese market and finds evidence for reversals as well as claims that the reversals for losers is related to traded volume. However, as far as the authors are concerned, no similar studies have yet been conducted on the Swedish market.

3 Hypotheses

The research question this thesis sets out to answer is whether the Swedish stock market overreacts or not on extreme events concerning the OMXS30 companies. Moreover, do certain underlying causational events and furthermore the characteristics of the potential overreaction itself affect the nature of the reversal effect. In

order to answer the research question about potential overreactions and the reversal effects that might follow a set of hypotheses are developed. The hypotheses being tested within the thesis regard two different main aspects of reversals. First and foremost, it is examined whether there are any reversals or not on the Swedish market. Second, if reversals do happen, can they be explained and when are they to be expected?

3.1 The Existence of Reversals

The first hypothesis being tested is if there have been overreactions followed by reversals during the studied time period. Concerning the question whether overreactions happen frequently or more sporadically guidance can be obtained from previous research in the field. Since reversals have been found to exist in different markets (e.g. Atkins and Dyl (1990), Lehmann (1990) and Bremer and Sweeney (1991)) the hypothesis is in line with previous findings. Though, Cox and Peterson (1994) claims that there are on average no reversals in the years following 1987 which might indicate that the reversals might not be numerous relatively to the amount of potential overreactions. In accordance with the findings of Cox and Peterson the size of the companies being studied ought to speak against overreactions and reversals taking place. Since these are big companies their stocks are very liquid which usually causes the stocks to fluctuate less than the ones of smaller, more risky, firms. This statement is in line with Cox and Peterson (1994). With this in mind, the second hypothesis is that on average there should be no overreactions taking place for the OMXS30 firms.

When investigating the existence of reversals a distinction between potential overreactions following positive and negative abnormal returns can be made. It is possible that the likelihood of overreactions is different between the two cases. The underlying idea is that behavioural economic concepts such as loss aversion, tendency to hold on to losers and sell winners and other similar concepts can affect the likelihood of reversals in the two different scenarios.

3.2 Variables of Interest

Given that reversals exist it is logical to assume that certain variables might help to explain the probability of reversals taking place. Previous literature has found similar results, e.g. Cox and Peterson (1994) found that liquidity is a factor of interest and Bremer, Hiraki and Sweeney (1997) states that reversals are connected to traded volume. In line with the two recently mentioned papers both traded volume and bid-ask spread are believed to have influence on the probability of reversals taking place.

The hypothesis that the bid-ask spread affects the probability of a reversal is motivated in a similar way as in Cox and Peterson (1994). Since large one-day price movements are likely to be associated with substantial selling or buying pressure, enhancing the probability that a closing transaction is at a bid or an ask price and, consequently leading to a reversal the next day due to the bid-ask bounce. Furthermore, greater bid-ask spreads ought to indicate more separated beliefs about the proper value of a stock. This in turn could increase the probability of a reversal since more investors potentially complete deals at the wrong price. Thus, when the market later on settles the fair value the potential mispricing should be corrected.

Traded volume is also likely to have influence on the probability of whether there is a reversal or not. The hypothesis is based on the idea that investors are pushing each other as well as the stock price in a certain direction. Somewhere on the way the logic disappears and some investors might loose perception of what the fair price actually is. The higher the traded volume is the higher is the chance of the above-explained scenario and therefore also reversals.

The final hypothesis being tested is whether the cause of the potential over-reaction, i.e. the causational event, in some way affects the probability of reversals taking place. The underlying economic intuition for this is that the reaction to unexpected events should be greater than the reaction to expected events since expected events should be incorporated in the stock price according to the EMH.

4 Data

The data on the stocks being analysed in this report as well as the market proxy and the data used to calculate the Fama and French factors originates from *Thompson Reuters Datastream*. The main data being analysed in this thesis is the information concerning the OMXS30 stocks, i.e. the stocks of the 30 largest companies on the Stockholm Stock Exchange. However, the constitution of the OMXS30 might change over time, to secure having the same 30 companies for the entire period the constituents as of March 2015 were elected for the entire time period. Data regarding closing price, traded volume and bid-ask spread are collected on a daily basis. The sample constitutes of data from the five most recent years (January 2010 – March 2015), for choice of period of interest please consult the *Methodology section*.

Furthermore, the data required to compute the daily Fama and French factors, i.e. closing price, price-to-book, and market capitalization, are gathered on a daily basis for all companies listed on the Stockholm Stock Exchange. In the cases no price-to-book is available this figure is calculated by dividing market capitalization with book value. Important to notice is that if data is not available for the entire period of interest the stock is not included in the sample. One might argue that this gives a survivorship bias. The effect is however mitigated since the period of interest is relatively short and thus the survivorship bias effect ought to be relatively small. Another attenuating effect is that in the end the factors will have minor impact on the result. This causes the eventual impacts of survivorship bias to be negligible. Additionally, if parts of the required data are missing and not possible to calculate, the stock is left out. Also, in line with Fama and French (1993) negative book value firms are not considered.

As a proxy for the market the OMXS index is being used, price is collected on a daily basis. Quite frequently the OMXS30 index itself is used as market proxy for the Swedish market. The reason not using OMXS30 in this thesis is that some of the companies of interest would make up a significant large proportion of the market itself.

Regarding a proxy for the risk-free rate the daily STIBOR rate is used. Since daily returns are analysed the risk-free rate should have the same term. The

STIBOR figures are collected from the website of Riksbanken¹ (the Swedish central bank) and then adjusted by hand within Excel to fit the data set from Datastream, which is not corrected for Swedish holidays.

Finally, *Retriever* is used to gather the information concerning causational events, mostly being articles from news agencies and press releases.

5 Methodology

In the following section the methodology used in our empirical tests is described. First, the general framework used to find abnormal returns is described. After that comes a part containing the necessary information about the Fama-French Three-Factor model and how expected returns are determined. The section then proceeds with the abnormal returns and the concept of a trigger level of $\pm 5\%$ for extracting the interesting parts of the data from the total sample is introduced. The terms causational event and reversal is then further defined and put into context. After that follows a description of the Linear Probability Model and how it is used in the thesis to test the statistical significance of the descriptive results. The section ends with the Probit Model which is used to test the robustness of the results.

5.1 General and Prerequisites

In order to study potential overreactions the returns qualifying for being studied need to be separated out. This is done by finding daily abnormal returns defined as daily actual return less daily expected return.

$$AR_{i,t} = r_{i,t} - E[r_{i,t}] \quad (1)$$

In (1) $r_{i,t}$ denotes actual return for stock i on day t computed as $r_{i,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$. Here $P_{i,t}$ is the closing price for stock i on day t .

Furthermore, daily expected returns need to be calculated for all 30 stocks throughout the entire time period of interest. In order to estimate the expected

¹<http://www.riksbank.se>

returns the Fama-French Three-Factor Model is used,

$$E[r_{i,t}] = \alpha_{i,t} + \beta_{i,t}^{MRP} MRP_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + r_{f,t-1} \quad (2)$$

where MRP_t is the market risk premium on day t defined as the return of the market on day t less the risk-free rate on day $t - 1$, i.e. $MRP_t = r_{m,t} - r_{f,t-1}$. The market return on day t is defined as $r_{m,t} = (P_{m,t} - P_{m,t-1})/P_{m,t-1}$. Furthermore, HML_t and SMB_t are the Fama-French factors on day t .

5.2 The Fama-French Framework

According to the framework introduced by Fama and French (1993), factors are created for the OMXS. Swedish factors are used since domestic factors in the model of interest better explain stock and portfolio average returns than world-based factors according to Griffin (2002). Note that the factors do not exist to download for the Swedish market and therefore are created. The reason for choosing the Fama-French Three-Factor Model is that it has a higher explanatory value than other models, for example the CAPM, according to Fama and French (1992a). Furthermore, the article argues that the beta (the slope coefficient in the CAPM) has little information about average stock returns, regardless if it is used alone or in combination with other variables. The factors in the Fama-French Three-Factor Model depend on market risk premium (MRP), firm size, which is measured by market equity (ME) (i.e. market capitalization) and the book-to-market equity ratio (BE/ME).

$$ME = \text{stock price} \times \text{number of shares outstanding} \quad (3)$$

$$\begin{aligned} BE/ME &= \text{the ratio of the book value of a firm's} \\ &\text{common stock, } BE, \text{ to its market value, } ME \end{aligned} \quad (4)$$

In Fama and French (1993) the authors argue that ME and BE/ME have explanatory power and that they explain the cross-section of average returns. However, ME and BE/ME cannot explain the great difference between the risk-free rate and the stocks average return, which is why the MRP is important in the model. Fama

and French argue that firms with higher BE/ME are more likely to be in a financial distress than firm with a lower ratio, and that larger stocks are less sensitive to changes in business conditions than smaller ones. Therefore, the factors based on ME and BE/ME capture the sensitivity of risk factors in the macro economy.² For further details on constructions and calculations of the Fama-French factors please see *2 Appendix*.

5.3 Robustness Test of the Model and Implications

The findings of the robustness test of the model (see *2 Appendix*) show that the model is rejected for the Swedish market. However, this is not surprising, Fama and French (2012) show that the Fama-French Three-Factor Model and its subsequent versions with even more factors are rejected. However, the Fama and French factor models are widely used in both research and applications in order to explain returns. The differences between the three-factor model and models of a higher degree are minor according to Fama and French (2012). In Fama and French (2014) evidence is presented for the five-factor model providing acceptable results when using the model for applied purposes, as is the case in this thesis. Since the differences between the models are minor, and the application of the model within this study is to set off the trigger level of $\pm 5\%$, the small constant terms that ought to be zero (average size magnitude of 0.32%), will neither misguide this study nor its results. Therefore, the Fama-French Three-Factor Model can still be used even though it is rejected.

5.4 Finding the Expected Returns

Using the Fama-French Three-Factor Model the daily expected return is defined as follows,

$$E[r_{i,t}] = \alpha_{i,t} + \beta_{i,t}^{MRP} MRP_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + r_{f,t-1} \quad (5)$$

²Bodie, Kane and Marcus, 2014, Investments, 10th Global Edition, p. 341

In order to get the slope coefficients in (5) the following regression is performed,

$$E[r_{i,t}] - r_{f,t-1} = \alpha_{i,t} + \beta_{i,t}^{MRP} MRP_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \epsilon_{i,t} \quad (6)$$

In the abovementioned regression the time period is defined on a quarterly basis, i.e. quarterly betas are calculated from the daily data. There are several arguments in favour of using quarterly betas. First, the study benefits from recalculating the betas quite frequently since the more accurate the betas are the more accurate will the estimation of the local behaviour be. Secondly, in order to mitigate the impact of extremely deviating daily returns the time period for the betas must not be too short. Therefore, the conclusion is that quarterly betas are best suitable. It is possible that monthly betas had performed even better but since the impact of individual deviations risk to be bigger using monthly betas the risk is further reduced using quarterly betas.

5.5 Trigger Level and Finding the Abnormal Returns

Using (1) and (5) the abnormal returns are retrieved. In order to select the potential overreactions to study a certain predetermined trigger level is established. This is in line with the methodology used by Bremer and Sweeney (1991) and many of their successors. The trigger levels used in previous studies vary and there does not exist a norm on what magnitude to use. Since this study examines the 30 largest listed companies in Sweden the deviations from the expected returns are expected to be relatively low compared to smaller companies. Therefore, the trigger level being used is set to $\pm 5\%$. If the absolute value of an abnormal return is greater than the trigger level the return is considered as a potential overreaction according to,

$$|AR_{i,t}| \geq 5\% \implies \text{potential overreaction} \quad (7)$$

After studying the results the years of the time period prior to and including the financial crisis are removed from the original sample. This is due to the problems associated with an extremely volatile market. During the removed period, the number of potential overreactions was approximately three times as many than during the more normal financial period following in 2010-2014. However, defining

the period of interest to 2010-2014 there are still enough potential overreactions to study.

5.6 Causational Events and Event Windows

After having identified the potential overreactions the following action is to identify the real event, i.e. the causational event, which caused the potential overreaction. The causational events found are then sorted into five categories depending on what type of event that occurred. The five categories are: *Report*, *News release*, *Dividend record date*, *Result indications* and *Environment change*. The event is categorised as a report if the event causing the potential overreaction is a quarterly report or similar. An event gets categorised as a news release if there is a piece of news published from the company or regarding the company on the day of the potential overreaction. If a company indicates something about their performance prior to the result is published officially or there are some other indications (for example the performance of the sector) the event is defined as a result indication. Finally, events regarding change in sector structure, legislation and judgements following judicial process are defined as environment change. The reason for only having five different categories is that with too many the number of observations in each category would be too few to be able to find accurate results.

The causational events are further used to filter away identified potential overreactions that have no causational event but rather are responses to earlier movements. More important, the causational events are used to determine which potential overreactions to study. The criterion for the potential overreactions is that they need to be the sole potential overreaction for a company in a time span reaching ± 20 days from the event day. A time span meeting the criterions is defined as an event window. This implies that if two potential overreactions for the same company are within a time span of 40 days from each other both events are excluded from further analysis. The reason for only allowing one potential overreaction in each time span of ± 20 days is that it otherwise would be impossible to distinguish the movements deriving from each separate event. From this point, the event windows are the time intervals of interest.

5.7 Cumulative Abnormal Returns and Reversals

The cumulative abnormal return CAR_i for stock i from day t_1 to day t_2 is defined as,

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \quad (8)$$

Having obtained the cumulative abnormal returns for all event windows it is possible to define a reversal. A reversal is defined as a rebound towards the zero CAR level after a potential overreaction. In this thesis two different reversals are being studied, short time reversals and long time reversals. A short time reversal prevails if the CAR is closer to zero five days after the potential overreaction than on the day of the potential overreaction. The case is similar for long time reversals, except for the time period being changed to 20 days. The reason to studying two different time spans is to see if there are any differences. If there is a reversal the conclusion that the potential overreaction in fact was an overreaction can be drawn.

In order to be able to study general tendencies of the identified potential overreactions denote \overline{CAR} as the average cumulative abnormal return across all event windows for all companies.

$$\overline{CAR}(t_1, t_2) = \sum_{t=t_1}^{t_2} \overline{AR}_t = \frac{1}{N} \sum_{i=1}^N CAR_i(t_1, t_2) = \frac{1}{N} \sum_{i=1}^N \sum_{t=t_1}^{t_2} AR_{i,t} \quad (9)$$

Important to notice is that a necessary distinction between positive and negative abnormal returns on the day of the potential overreactions needs to be done in order for the abnormal returns not to offset each other.

5.8 Further Variables of Interest

In order to seek to answer if reversals are more likely to occur under some particular circumstances than others two additional variables are defined, relative traded volume and relative bid-ask spread. Relative traded volume is defined as the traded volume on the event day divided by the average volume of the previous days of the event window, and similar for the relative bid-ask spread. Mathematically, these

variables are defined as,

$$\frac{Volume_0}{\frac{1}{|N|} \sum_{t=N}^{-1} Volume_t}, \text{ where } N = \min(t \in \text{event window}) \quad (10)$$

$$\frac{BA_0}{\frac{1}{|N|} \sum_{t=N}^{-1} BA_t}, \text{ where } N = \min(t \in \text{event window}) \quad (11)$$

respectively. The reason for defining the variables in this way rather than just comparing traded volume and bid-ask spread in absolute terms between the events is to normalise the substantial differences especially in traded volume between the companies. Furthermore, the variables are defined in a way making it possible to relatively compare traded volume and bid-ask spread on the day of the potential overreaction across different event windows. Moreover, the variables measure the impact of the relative change in traded volume and the relative change in bid-ask spread on the event day compared to the average of the days in the event window prior to the event day as can be seen from (10) and (11).

5.9 The Linear Probability Model

In order to test if the descriptive results are statistically significant a regression model called the Linear Probability Model (LPM) is used. The choice of model is motivated by the LPM being a model for binary outcomes, which suits this study perfectly since either a reversal happen or it does not. The dependent side of the regressions, i.e. the reversal variable will be denoted as a dummy variable. Note that the use of big letters implies stochastic variables.

$$REVERSAL = \begin{cases} 1 & , \text{ if reversal} \\ 0 & , \text{ otherwise} \end{cases} \quad (12)$$

For the independent side of the regression, i.e. the right hand side, a vector \mathbf{x} that includes all variables of interest as components is created. The variables of interest are the causational events, the relative traded volume variable and the relative bid-ask spread variable. Furthermore, when doing the regression, the slope coefficients

will come out as a vector denoted as β .

$$\mathbf{x} = [Report, News\ release, Dividend\ record\ date, Result\ indications, Environment\ change] \quad (13)$$

$$\beta = [\beta_{Report}, \beta_{News\ release}, \beta_{Dividend\ record\ date}, \beta_{Result\ indications}, \beta_{Environment\ change}] \quad (14)$$

Let F denote the cumulate distribution function, let P stand for the probability and let E denote the expected value. Then the following holds,

$$P(REVERSAL = 1|\mathbf{x}) = F(\mathbf{x}, \beta) \quad (15)$$

$$P(REVERSAL = 0|\mathbf{x}) = 1 - F(\mathbf{x}, \beta) \quad (16)$$

From (15) and (16) one can see that β reflects impact on the probability of changes in \mathbf{x} . One possible way of using the LPM is to make the regression,

$$F(\mathbf{x}, \beta) = \mathbf{x} \cdot \beta \quad (17)$$

Since the following holds,

$$E[Reversal|\mathbf{x}] = 0 \cdot (1 - F(\mathbf{x}, \beta)) + 1 \cdot F(\mathbf{x}, \beta) = F(\mathbf{x}, \beta) \quad (18)$$

it is possible to construct the following regression model,

$$Reversal = E[Reversal|\mathbf{x}] + Reversal - E[Reversal|\mathbf{x}] = \mathbf{x} \cdot \beta + \epsilon \quad (19)$$

Note that there are some drawbacks of the LPM. In (19) ϵ is heteroscedastic and depends on β , and because $\mathbf{x} \cdot \beta + \epsilon$ must equal 1 or 0, ϵ equals either $1 - \mathbf{x} \cdot \beta$ or $\mathbf{x} \cdot \beta$, with probabilities F and $1 - F$ respectively. Thus, the variance of the model is,

$$Var(\epsilon|\mathbf{x}) = \mathbf{x} \cdot \beta(1 - \mathbf{x} \cdot \beta) \quad (20)$$

Also, the model might give probabilities outside of the span $[0,1]$. This is of course a major error. Though, the results of this report were never close to the critical values and therefore this drawback did not affect the outcomes. Even though the

model has drawbacks, it is widely used, for example by Caudill (1988), Heckman and MaCurdy (1985) and Heckman and Snyder (1997). Since the left-hand side is binary, the linear probability model is a suitable model for this thesis. When analysing the results, the main interest will be the sign of the slope coefficients and the confidence interval of the values of the slope coefficients.

5.10 The Probit Model and Robustness Test

The Probit Model is used to test the robustness of the results obtained from the LPM. The Probit Model is also a regression model for binary outcomes. As in the case of the LPM, the reversal variable is denoted as a dummy variable,

$$REVERSAL = \begin{cases} 1 & , \text{ if reversal} \\ 0 & , \text{ otherwise} \end{cases} \quad (21)$$

The variables of interest are included in a vector \mathbf{x} ,

$$\mathbf{x} = [Report, News\ release, Dividend\ record\ date, Result\ indications, Environment\ change] \quad (22)$$

and the slope coefficients from the regression will come out as a vector $\boldsymbol{\beta}$,

$$\boldsymbol{\beta} = [\beta_{Report}, \beta_{News\ release}, \beta_{Dividend\ record\ date}, \beta_{Result\ indications}, \beta_{Environment\ change}] \quad (23)$$

The underlying idea behind the Probit Model is the use of the standard normal distribution function, denoted by ϕ , where

$$\phi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \quad (24)$$

The Probit Model is defined as follows,

$$P(REVERSAL = 1) = \int_{-\infty}^{\mathbf{x} \cdot \boldsymbol{\beta}} \phi(t) dt = \Phi(\mathbf{x} \cdot \boldsymbol{\beta}) \quad (25)$$

where Φ is the cumulative distribution function of the standard normal distribution defined as,

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt = \int_{-\infty}^x \phi(t) dt \quad (26)$$

Since the standardized normal distribution function is used within the model, the outcomes are bounded between 0 and 1 Φ is the estimated probability that a reversal will happen. Furthermore, it is expected that following equations hold,

$$\lim_{\mathbf{x} \cdot \boldsymbol{\beta} \rightarrow +\infty} P(REVERSAL = 1 | \mathbf{x}) = 1 \quad (27)$$

$$\lim_{\mathbf{x} \cdot \boldsymbol{\beta} \rightarrow -\infty} P(REVERSAL = 1 | \mathbf{x}) = 0 \quad (28)$$

When comparing the results from the Probit Model and the LPM, the main concern will regard if the outcomes of the two models point in the same direction. Therefore, the significance of the results of the Probit Model will not be studied in great detail.

6 Results

In the following section the empirical results of the thesis will be described in detail. The section begins with the main descriptive results concerning if reversals exists or not. Results regarding the different causational events, relative traded volume and relative bid-ask spread are then presented. Later follows the results of the main statistical tests and a discussion of the robustness of the tests. The section is finally complete by a potential trading strategy taking the main results into consideration.

6.1 Descriptive Statistics

Using the trigger level of $\pm 5\%$, as described in the methodology section, 296 potential overreactions are found. Applying the criterion of only one potential overreaction per event window reduces the number of potential overreactions to 150. Thus, the final sample to be studied consists of 150 potential overreactions with related event windows. The overreactions are well diversified over the different companies and in total 27 out of 30 have potential overreactions associated with them.

In accordance with the first hypothesis presented, reversals are found during the examined time period. In total, short time reversals occurred after 34.7% of the potential overreactions and long time reversals after 43.3% of the cases. See *1 Appendix, Table 1*. This means that on average there are no reversals after an initial price movement of $\pm 5\%$. The following two graphs shows the average cumulative abnormal return following positive and negative potential overreactions.

Figure 1: Evolution of the average CAR following negative potential overreactions.

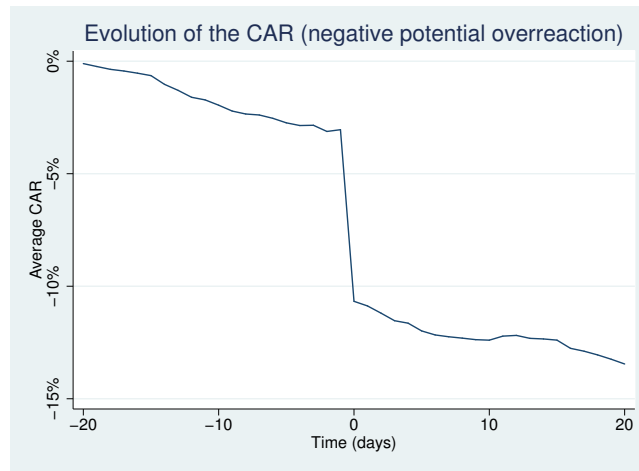


Figure 1 plots the average CAR for all the 82 negative potential overreactions in the time period 2010-2014. On the horizontal axis time in days is depicted.

Figure 2: Evolution of the average CAR following positive potential overreactions.

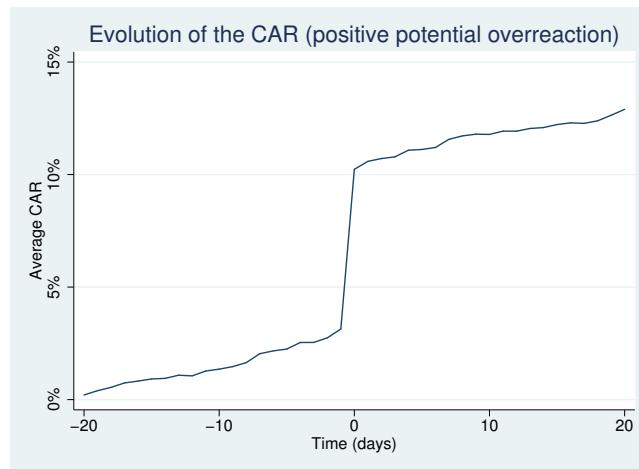


Figure 2 plots the average CAR for all the 68 positive potential overreactions in the time period 2010-2014. On the horizontal axis time in days is depicted.

The findings indicate continuation in trend after the initial price change on day zero. This is not in line with the Overreaction Hypothesis. However, it might be in line with the Underreaction Hypothesis though it cannot be concluded with certainty since the observed continuation in trend might as well originate from the trend from before the potential overreaction. However, even though there are no reversals on average the observed stocks have overreacted a considerable amount of times. This enables further studies on when to expect reversals.

When the sample is split up on the five different causational events there are indications that the potential overreactions of some causational events are more likely to be followed by reversals than others. In *1 Appendix, Figure 3-11* the average cumulative abnormal returns are shown for the different causational events after both positive and negative potential overreactions. If the potential overreaction is caused by a report, there are on average no reversal to be expected, indifferently of the potential overreaction is positive or negative. Furthermore, potential overreactions caused by news seem to be followed by reversals if the potential overreaction is positive but not if it is negative. The opposite seems to be true if the potential overreaction is caused by result indications. Negative potential overreactions are likely to be followed by a reversal while positive potential overreactions are likely to be followed by continuation in trend. If the initial price change is caused by environment change there are indications that reversals exist if the initial price change was positive but not if it was negative. Obviously, no positive potential overreactions exist for dividend record date. However, when a negative potential overreaction occurs and the causational event is dividend record date, it seems like on average reversals are taking place.

Finally, calculations regarding whether relative traded volume and relative bid-ask spread affects the chance of a reversal effect indicates that there is a correlation. The results are compiled in *1 Appendix, Table 2*. Calculating the relative traded volume it is found to be on average 4.286 times of normal on the event days after which no reversal effects occurs. However, when short time reversals occur the relative traded volume is on average 4.688 times higher on the event day than on average. Thus, the relative traded volume is on average 9.4% higher on the event day after which reversals follow than on an event days after which there are no

reversals. The case is similar for relative bid-ask spread. On event days followed by short time reversals the relative bid-ask spread is on average 1.171 times of normal whereas on event days not followed by short time reversals it is on average 1.064 times of normal. Thus, relative bid-ask spread is on average 10.1% higher on event days followed by short time reversals than on event days not followed by reversals. The results are similar when looking at long time reversals instead of short time reversals, as can be seen in the same table.

6.2 Main Statistical Tests

In order to find if the descriptive results are statistically significant the Linear Probability Model is used. The main findings are described in the following paragraphs and the results are summarized in *1 Appendix, Table 3-9*. Given that a negative potential overreaction has occurred it is found that the higher relative traded volume the higher is the probability of a short time reversal with a statistical significance of 15%. At the same significance level it is also found that if the causational event is a dividend record date the chance of a short time reversal is higher than for the other causational events. Please see *Table 3*.

In *Table 4* and *5* the following results can be found. Regarding the case of a negative potential overreaction on the event day the results are the same for both relative traded volume and dividend record date as above for long time reversals. Additionally, if the causational event is a result indication the probability of a long time reversal increases with a statistical significance of 5%.

In *Table 6* results concerning short time reversals after positive potential overreactions are found on a significance level of 1%. The causational events report and result indications are both found to decrease the probability of a short time reversal. The two mentioned causational events are therefore most likely followed by continuation in trend.

Table 7-9 contains the results regarding long time reversals after a positive potential overreaction. As before, both report and result indications are found to lower the probability of long time reversals with significance levels 1% and 10% respectively. Furthermore, as in the case of negative potential overreactions relative traded volume increases the probability of long time reversals. The higher the

relative traded volume, the higher the probability of a reversal on a significance level of 5%.

Generally, in three out of four different cases relative traded volume has a positive impact on the probability of reversals taking place. Important to notice is that even though relative bid-ask spread seemed to have an impact in the descriptive statistics no statistically significant results could be attained. Furthermore, even though it looked as if both the causational events news and environment change could have an impact on the probability of reversal effects taking place no results could be found on an acceptable significance level with the underlying sample.

6.3 Robustness Tests

In this subsection the results of the robustness tests using the Probit Model are presented. The results of the regressions are to be found in *1 Appendix, Table 10-13*. In the three scenarios negative potential overreaction, short and long time reversal, and positive potential overreaction short time reversal the results are very similar to the ones obtained using the Linear Probability Model. The same variables of interest are statistically significant in the same way as before. Since the Probit Model only is used to check the validity of already obtained results all tests are conducted on a 15% significant level. However, in the fourth case, positive potential overreaction and long time reversal the Probit Model does only find relative traded volume to be statistically significant. Some of the causational events are omitted in the regression. This might be the reason to why the regression does not give the same outcome in that case compared to the Linear Probability Model. Overall, the Probit Model gives very similar results as the Linear Probability Model which indicates that the previously presented results are robust.

A potential problem with the main results is that after dividing the final sample of 150 potential overreactions on the five different causational events some of the causational events contained quite few observations. Potentially, individual event windows risk being too influential when calculating the average cumulative abnormal return for these causational events. With a larger original sample this potential problem might have been smaller and consequently more and better statistically significant results might had been possible to find.

6.4 Potential Trading Strategy ideas

If a trading strategy were to be based on the findings of this thesis the results indicate that several factors should be taken into consideration. In this subsection some basic ideas will be outlined together with a primitive calculation to shed light on a potential application of the contents of this thesis. The development of a sophisticated trading strategy is however left to future researchers.

Since there on average are no reversals taking place the basic idea should be to trade on continuation in trend. Therefore, after a negative potential overreaction the stock in question should be shorted and after a positive potential overreaction the stock in question should be bought. If this would have been done consequently for all 150 potential overreactions with the same amount invested every time and the stocks had been held/shorted for 20 days the return would have been 410%, not taking trading costs into consideration.

There are however several issues with the figure calculated above. First and foremost, the return is only based on the final sample consisting of 150 potential overreactions. When calculating a proper trading strategy the potential overreactions that were removed from the sample as a result of not meeting the criterion of being the sole overreaction in a 40 days time span need to be taken into consideration. It would be impossible for an investor to know beforehand whether more overreactions were to expect in the near future or not. Moreover, a sophisticated trading strategy needs to take trading costs into consideration. Though, since the strategy outlined above only corresponds to 150 switches of position the trading costs are alleged to be fairly small.

A more sophisticated trading strategy should take more of the significant results into consideration. For example it is reasonable to trade on continuation in trend if the potential overreaction is positive and the causational event is a report whereas it would be wise to trade on a reversal if the causational event is a dividend record date. If the causational event is a result indication the trading strategy should be to trade on continuation in trend if the potential overreaction is positive whereas it should be to trade on a reversal if the potential overreaction is negative. Also, incorporating the relative traded volume aspect could improve the strategy since reversals are more likely the higher the relative traded volume on the

event day. However, since the development of a sophisticated trading strategy is beyond the scope of this thesis we leave that to future research.

7 Conclusions

This study sets out to investigate if the OMXS30 stocks overreact to extreme events and if certain variables can explain the probability of reversals taking place. Inspiration has been gathered from previous research and the study is based on the idea of a trigger level introduced by Bremer and Sweeney (1991). Moreover, the study extends the previous research in two ways. First, the Swedish market is being studied and second, causational events are viewed as potential explanatory variables for the probability of reversals. The results found are statistically significant and robust.

The main result of this study is that on average there are no reversals taking place. This is in line with the second hypothesis being presented. The economic interpretation of this result is that on average the market does not overreact to extreme events. Therefore, the Overreaction Hypothesis can be rejected for the OMXS30 stocks. However, as outlined in the first hypothesis, reversals are found to exist in over one third of the events examined which is considered a high fraction keeping in mind the size of the companies studied. The result that reversals actually are taking place is consistent with previous research. Moreover, a potential implication of the result is a trading strategy, which mainly takes advantage of that there on average are no reversals.

Some variables of interest are found, on a statistically significant level, to affect the probability of reversals taking place. In accordance with the hypothesis regarding the impact of traded volume the results show that increased traded volume increases the probability of reversals taking place. Furthermore, the outcome is the same of the hypothesis regarding causational events. Some of the causational events are found to increase or decrease the probability of reversals whereas others cannot be said to have a significant influence. The conclusion that the likelihood of a reversal is dependent of the causational event can therefore be drawn. This can be seen as a violation of the EMH since the results make it possible to predict

trends in the market. However, in contradiction to the hypothesis and previous literature regarding the impact of the bid-ask spread on the probability of reversals taking place, there are no significant results indicating that there is such a relation. One possible explanation for this is that the observed stocks are very liquid. The observed relative traded volume was around 450% of average on the day of the potential overreaction whereas the relative bid-ask spread was less than 112% of average which implies that the bid-ask spread does not change remarkably on the event day. Therefore the bid-ask spread lacks explanatory power as to when reversals are to be expected.

There are some limitations in the thesis that are important to shed light on. To begin with, using the approach with event windows only allowing for one potential overreaction per company in each event window almost 50% of the original identified potential overreactions was disregarded. However, having regarded these as well the main results still ought to be the very similar since the final sample still is a large fraction of the entire sample. Though, disregarding some of the potential overreactions prohibits the possibilities of forming a complete trading strategy. Moreover, another possible limitation is the time period over which the study is conducted. Since the time period is fairly short the market might have had certain characteristics during this period which are not necessarily true for other periods.

Even though the area of finance investigated in this thesis is quite well examined there are still interesting questions to seek answers to. In this thesis only stocks of large companies were considered. It would be interesting to compare the results of this thesis to a similar study regarding stocks of different sizes to see if the results found here would be similar or if there are some significant dissimilarities between firms of different sizes. Another interesting setting for future research would be to use a bigger sample. This would enable more specific categorizations of the causational events and not necessarily limit to the five causational event categories studied in this thesis. Finally, it would be interesting to develop a complete trading strategy based on the results of this thesis. If such a trading strategy would be found to perform successfully it would imply a violation of the EMH. This task is however left to future research to explore in greater detail.

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1 Appendix

Table 1: Number of Reversals

Type of reversal	N	Number of reversals	Frequency
Short	150	52	37.4%
Long	150	65	43.3%

Table 1 summarizes the number of reversals taking place. 52 out of the 150 potential overreactions, corresponding to 37.4%, were followed by a short time reversal. 65 out of the 150 potential overreactions, corresponding to 43.3%, were followed by a long time reversal.

Figure 3: Evolution of the average CAR following negative potential overreactions caused by Reports.

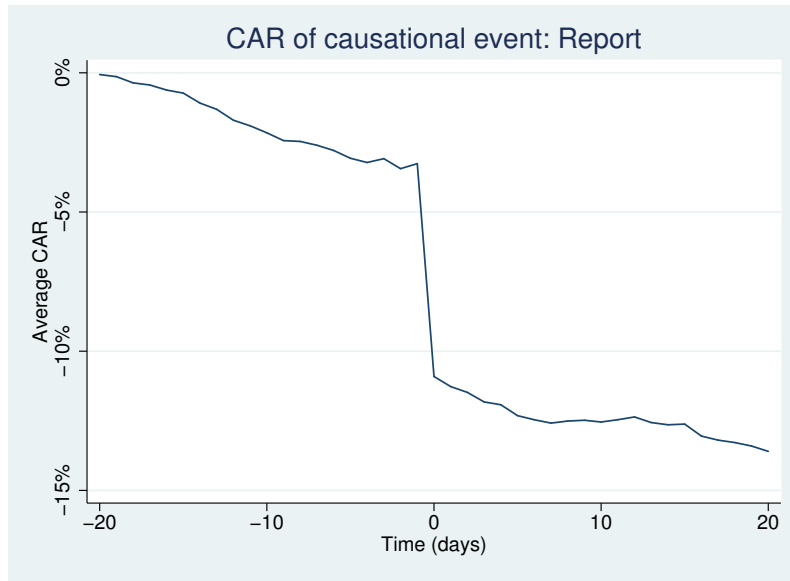


Figure 3 plots the average CAR for the negative potential overreactions caused by Reports in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 4: Evolution of the average CAR following positive potential overreactions caused by Reports.

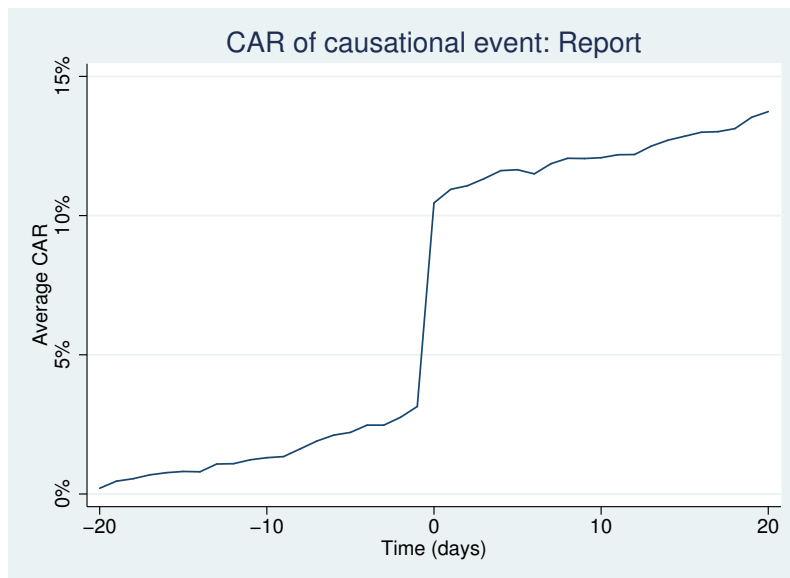


Figure 4 plots the average CAR for the positive potential overreactions caused by Reports in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 5: Evolution of the average CAR following negative potential overreactions caused by News.

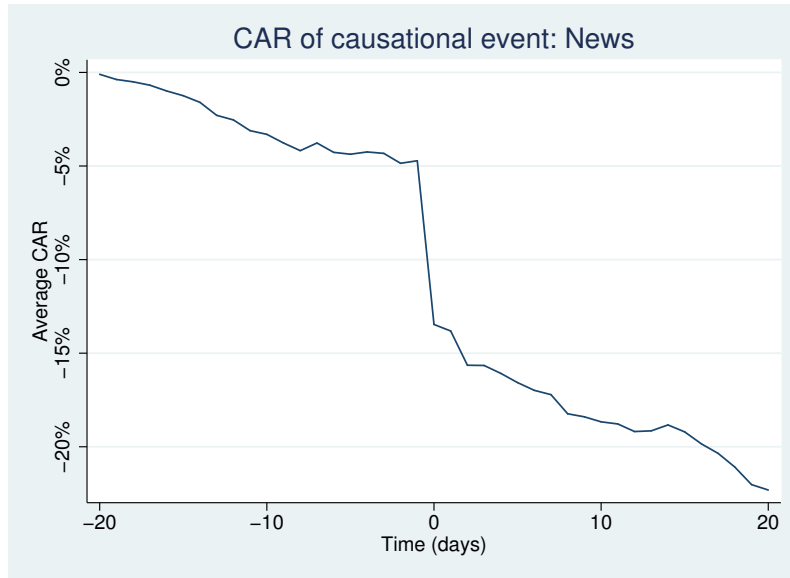


Figure 5 plots the average CAR for the negative potential overreactions caused by News in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 6: Evolution of the average CAR following positive potential overreactions caused by News.

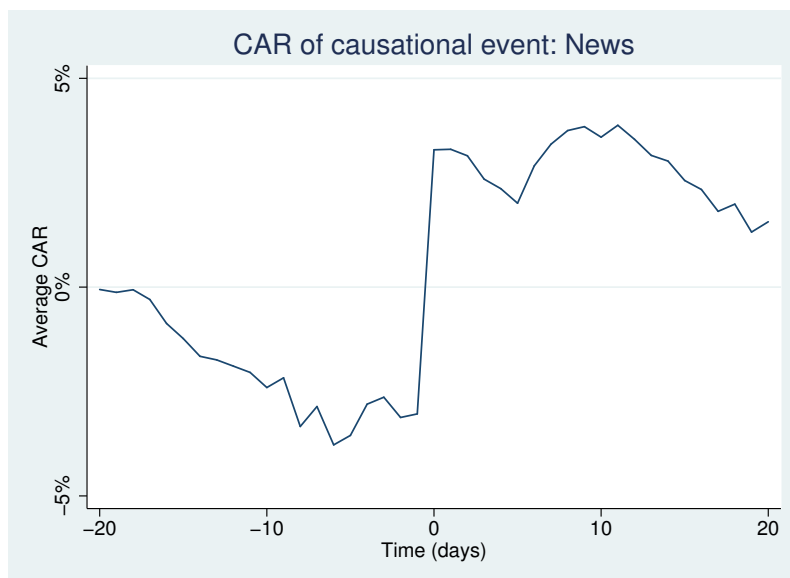


Figure 6 plots the average CAR for the positive potential overreactions caused by News in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 7: Evolution of the average CAR following negative potential overreactions caused by Result indications.

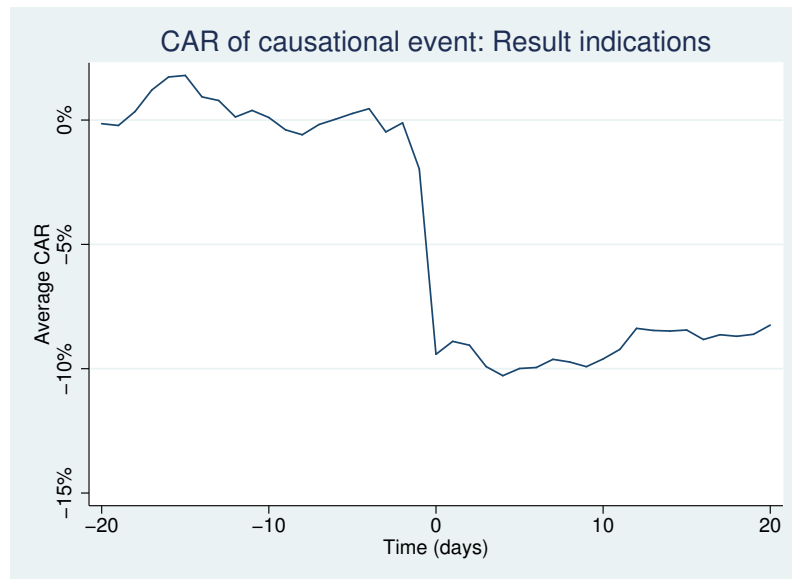


Figure 7 plots the average CAR for the negative potential overreactions caused by Result indications in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 8: Evolution of the average CAR following positive potential overreactions caused by Result indications.

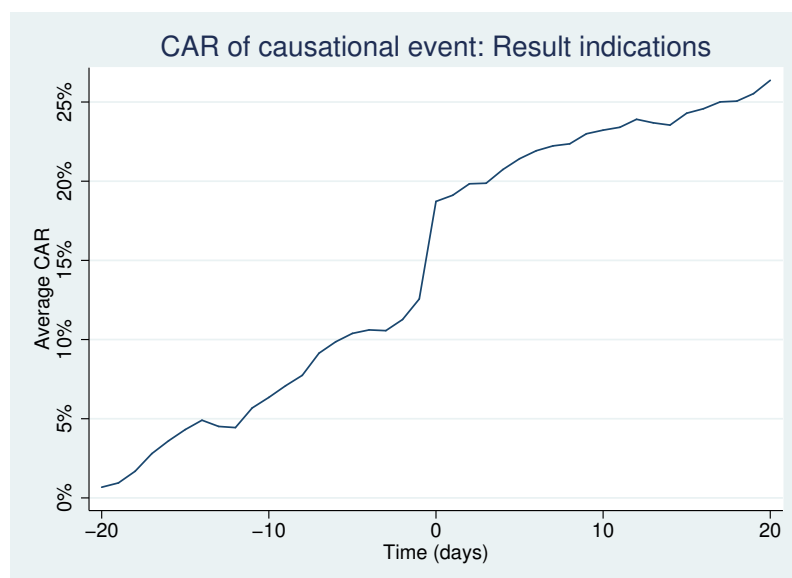


Figure 8 plots the average CAR for the positive potential overreactions caused by Result indications in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 9: Evolution of the average CAR following negative potential overreactions caused by Environment change.

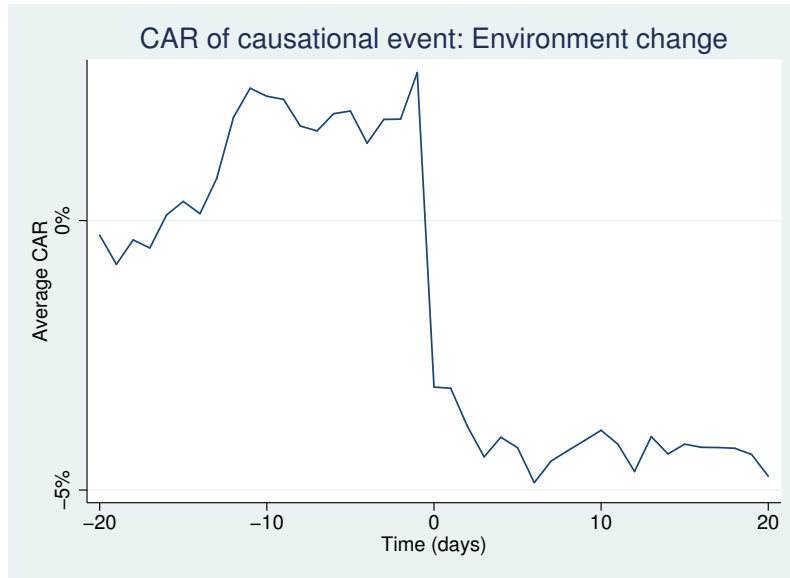


Figure 9 plots the average CAR for the negative potential overreactions caused by Environment change in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 10: Evolution of the average CAR following positive potential overreactions caused by Environment change.

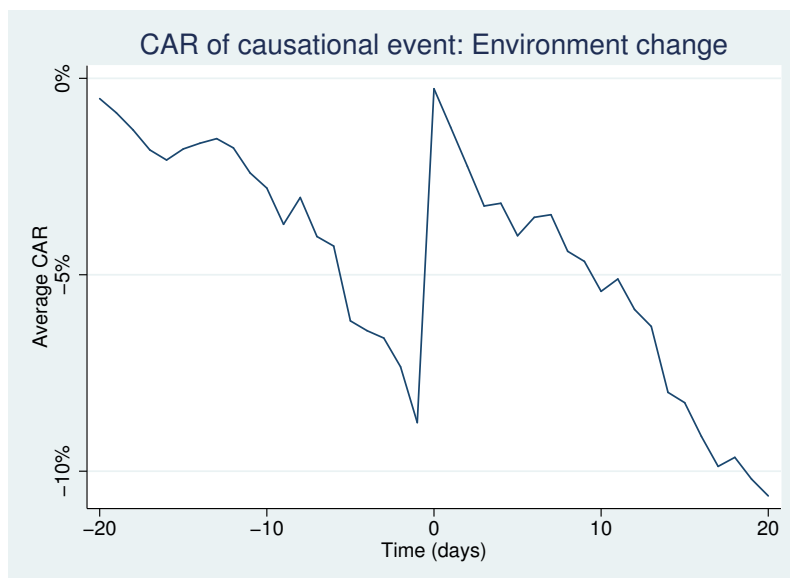


Figure 10 plots the average CAR for the positive potential overreactions caused by Environment change in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Figure 11: Evolution of the average CAR following negative potential overreactions caused by Dividend record date.

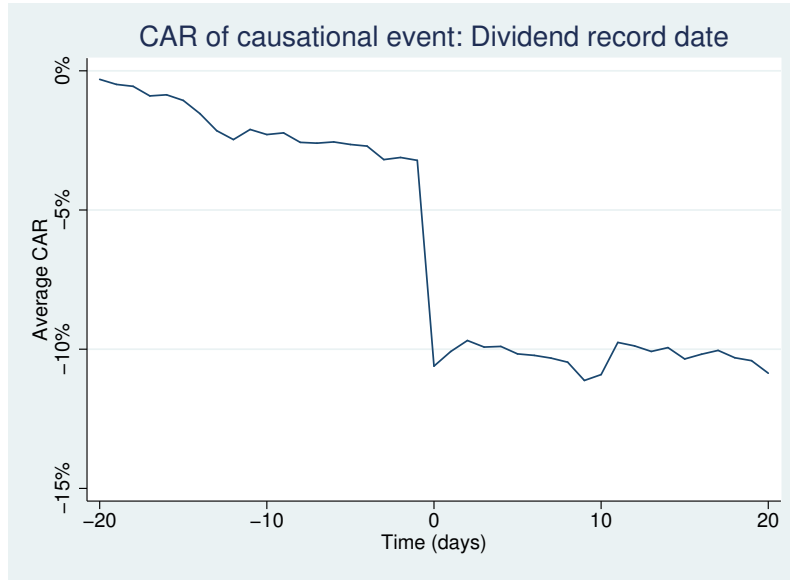


Figure 11 plots the average CAR for the negative potential overreactions caused by Dividend record date in the time period 2010-2014. On the horizontal axis the time in days from the event day is depicted.

Table 2: Relative traded volume and Relative bid-ask spread

VARIABLES	No reversal	Reversal	Relative difference
Relative traded volume (short)	4.286	4.688	9.4%
Relative bid-ask spread (short)	1.064	1.171	10.1%
Relative traded volume (long)	4.143	4.794	15.8%
Relative bid-ask spread (long)	1.086	1.120	3.1%

Table 2 depicts the Relative traded volume and the Relative bid-ask spread on the event day in comparison to their respective average of the 20 days prior to the event day. The figures calculated are divided between if the particular event is followed by a reversal or not. Also, a distinction between long and short time reversals has been made. The relative difference is the size difference of Relative traded volume/Relative bid-ask spread when the potential overreactions are followed by reversals and when they are not.

Table 3: Linear Probability Model: Regression analysis. Negative potential overreaction and short time reversals.

VARIABLES	Negative potential overreaction (short time reversal)
Relative traded volume	0.0303* (1.466) 0.000247 - 0.0604
Relative bid-ask spread	-0.0105 (-0.117) -0.141 - 0.120
Report	0.115 (0.666) -0.136 - 0.366
Result indications	0.342 (1.186) -0.0773 - 0.762
News	-0.111 (-0.524) -0.419 - 0.197
Dividend record date	0.367* (1.514) 0.0145 - 0.720
Environment change (omitted)	- - -
Constant	0.0426 (0.222) -0.236 - 0.322
Observations	82
R-squared	0.063

Robust t-statistics in parentheses and 85% confidence interval below

*** p<0.01, ** p<0.05, * p<0.15

Table 3 presents the results of the Linear Probability Model regression analysis of negative potential overreaction and short time reversals on a 15% significance level. Relative traded volume and Dividend record date are statistically significant at the given level. Since their signs are positive, the conclusion is that these two factors increase the probability of short time reversals after a negative potential overreaction.

Table 4: Linear Probability Model: Regression analysis. Negative potential overreaction and long time reversals.

VARIABLES	Negative potential overreaction (long time reversal)
Relative traded volume	0.0320* (1.533) 0.00164 - 0.0624
Relative bid-ask spread	0.00465 (0.0531) -0.123 - 0.132
Report	0.216 (1.268) -0.0319 - 0.465
Result indications	0.597** (2.258) 0.212 - 0.981
News	-0.115 (-0.655) -0.369 - 0.140
Dividend record date	0.373* (1.539) 0.0205 - 0.726
Environment change (omitted)	- - -
Constant	0.0215 (0.112) -0.258 - 0.301
Observations	82
R-squared	0.089

Robust t-statistics in parentheses and 85% confidence interval below

*** p<0.01, ** p<0.05, * p<0.15

Table 4 presents the results of the Linear Probability Model regression analysis of negative potential overreaction and long time reversals on a 15% significance level. Relative traded volume and Dividend record date are statistically significant at the given level. The causational event Result indications is statistically significant on a 5% level. Since their signs are positive, the conclusion is that these three factors increase the probability of long time reversals after a negative potential overreaction.

Table 5: Linear Probability Model: Regression analysis. Negative potential overreaction and long time reversals.

VARIABLES	Negative potential overreaction (long time reversal)
Relative traded volume	0.0320 (1.533) -0.00959 - 0.0737
Relative bid-ask spread	0.00465 (0.0531) -0.170 - 0.179
Report	0.216 (1.268) -0.124 - 0.556
Result indications	0.597** (2.258) 0.0703 - 1.123
News	-0.115 (-0.655) -0.463 - 0.234
Dividend record date	0.373 (1.539) -0.110 - 0.856
Environment change (omitted)	- - -
Constant	0.0215 (0.112) -0.361 - 0.404
Observations	82
R-squared	0.089

Robust t-statistics in parentheses and 95% confidence interval below

*** p<0.01, ** p<0.05, * p<0.1

Table 5 presents the results of the Linear Probability Model regression analysis of negative potential overreaction and long time reversals on a 5% significance level. Only the causal event Result indications is statistically significant on a 5% level. As showed in Table 4, since the sign is positive the conclusion is that the factor increases the probability of long time reversals after a negative potential overreaction.

Table 6: Linear Probability Model: Regression analysis. Positive potential overreaction and short time reversals.

VARIABLES	Positive potential overreaction (short time reversal)
Relative traded volume	0.0235 (0.629) -0.0759 - 0.123
Relative bid-ask spread	0.102 (1.113) -0.142 - 0.346
Report	-0.585*** (-5.125) -0.888 - -0.281
Result indications	-0.683*** (-3.343) -1.226 - -0.140
News	-0.262 (-1.137) -0.873 - 0.350
Dividend record date (omitted)	- - -
Environment change (omitted)	- - -
Constant	0.711** (2.547) -0.0308 - 1.453
Observations	68
R-squared	0.146

Robust t-statistics in parentheses and 99% confidence interval below

*** p<0.01, ** p<0.05, * p<0.1

Table 6 presents the results of the Linear Probability Model regression analysis of positive potential overreaction and short time reversals on a 1% significance level. Report and Result indications are statistically significant at the given level. Since their signs are negative, the conclusion is that these two factors decrease the probability of short time reversals after a positive potential overreaction.

Table 7: Linear Probability Model: Regression analysis. Positive potential overreaction and long time reversals.

VARIABLES	Positive potential overreaction (long time reversal)
Relative traded volume	0.0712** (2.388) -0.00805 - 0.150
Relative bid-ask spread	0.0291 (0.381) -0.174 - 0.232
Report	-0.368*** (-3.336) -0.662 - -0.0749
Result indications	-0.365* (-1.703) -0.933 - 0.204
News	-0.269 (-1.180) -0.876 - 0.337
Dividend record date (omitted)	-
Environment change (omitted)	-
Constant	0.509** (2.256) -0.0906 - 1.108
Observations	68
R-squared	0.110

Robust t-statistics in parentheses and 99% confidence interval below

*** p<0.01, ** p<0.05, * p<0.1

Table 7 presents the results of the Linear Probability Model regression analysis of positive potential overreaction and long time reversals on a 1% significance level. Report is statistically significant at the given level whereas Relative traded volume and Result indications are significant at the 5% and 10% level respectively. Negative signs for Report and Result indications indicates that these causational events decrease the probability of reversals whereas the positive sign of Relative traded volume indicates that higher Relative traded volume increases the probability of long time reversals after a positive potential overreaction.

Table 8: Linear Probability Model: Regression analysis. Positive potential overreaction and long time reversals.

VARIABLES	Positive potential overreaction (long time reversal)
Relative traded volume	0.0712** (2.388) 0.0116 - 0.131
Relative bid-ask spread	0.0291 (0.381) -0.124 - 0.182
Report	-0.368*** (-3.336) -0.589 - -0.148
Result indications	-0.365* (-1.703) -0.792 - 0.0633
News	-0.269 (-1.180) -0.725 - 0.187
Dividend record date (omitted)	-
Environment change (omitted)	-
Constant	0.509** (2.256) 0.0579 - 0.960
Observations	68
R-squared	0.110

Robust t-statistics in parentheses and 95% confidence interval below

*** p<0.01, ** p<0.05, * p<0.1

Table 8 presents the results of the Linear Probability Model regression analysis of positive potential overreaction and long time reversals on a 5% significance level. As previously stated in Table 7, Relative traded volume is statistically significant at the given level whereas Report and Result indications are significant at the 1% and 10% level respectively. Negative signs for Report and Result indications indicates that these causational events decreases the probability of reversals whereas the positive sign of Relative traded volume indicates that higher Relative traded volume increases the probability of long time reversals after a positive potential overreaction.

Table 9: Linear Probability Model: Regression analysis. Positive potential overreaction and long time reversals.

VARIABLES	Positive potential overreaction (long time reversal)
Relative traded volume	0.0712** (2.388) 0.0214 - 0.121
Relative bid-ask spread	0.0291 (0.381) -0.0986 - 0.157
Report	-0.368*** (-3.336) -0.553 - -0.184
Result indications	-0.365* (-1.703) -0.722 - -0.00716
News	-0.269 (-1.180) -0.650 - 0.112
Dividend record date (omitted)	-
Environment change (omitted)	-
Constant	0.509** (2.256) 0.132 - 0.885
Observations	68
R-squared	0.110

Robust t-statistics in parentheses and 90% confidence interval below

*** p<0.01, ** p<0.05, * p<0.1

Table 9 presents the results of the Linear Probability Model regression analysis of positive potential overreaction and long time reversals on a 10% significance level. As previously stated in Table 7, Result indications is statistically significant at the given level whereas Report and Relative traded volume are significant at the 1% and 5% level respectively. Negative signs for Report and Result indications indicates that these causational events decreases the probability of reversals whereas the positive sign of Relative traded volume indicates that higher Relative traded volume increases the probability of long time reversals after a positive potential overreaction.

Table 10: The Probit Model: Regression analysis. Negative potential overreaction and short time reversals.

VARIABLES	Negative potential overreaction (short time reversal)
Relative traded volume	0.0951* (1.651) 0.0122 - 0.178
Relative bid-ask spread	-0.0316 (-0.121) -0.408 - 0.345
Report	0.459 (0.771) -0.399 - 1.317
Result indications	1.078 (1.301) -0.114 - 2.271
News	-0.385 (-0.444) -1.634 - 0.863
Dividend record date	1.191* (1.583) 0.108 - 2.275
Environment change (omitted)	- - -
Constant	-1.441** (-2.084) -2.436 - -0.446
Observations	82

Robust z-statistics in parentheses and 85% confidence interval below

*** p<0.01, ** p<0.05, * p<0.15

Table 10 presents the results of the Probit Model regression analysis of negative potential overreactions and short time reversals on a 15% significance level. Relative traded volume and Dividend record date are statistically significant at the given level. Since this is in line with the results received using the Linear Probability Model the results are robust.

Table 11: The Probit Model: Regression analysis. Negative potential overreaction and long time reversals.

VARIABLES	Negative potential overreaction (long time reversal)
Relative traded volume	0.100* (1.747) 0.0176 - 0.183
Relative bid-ask spread	0.0127 (0.0548) -0.321 - 0.346
Report	0.749 (1.271) -0.0995 - 1.598
Result indications	1.788** (2.040) 0.526 - 3.049
News	-0.545 (-0.752) -1.589 - 0.499
Dividend record date	1.218* (1.619) 0.135 - 2.300
Environment change (omitted)	- - -
Constant	-1.511** (-2.195) -2.502 - -0.520
Observations	82

Robust z-statistics in parentheses and 85% confidence interval below

*** p<0.01, ** p<0.05, * p<0.15

Table 11 presents the results of the Probit Model regression analysis of negative potential overreactions and long time reversals on a 15% significance level. Relative traded volume, Result indications and Dividend record date are statistically significant at the given level. Since this is in line with the results received using the Linear Probability Model the results are robust.

Table 12: The Probit Model: Regression analysis. Positive potential overreaction and short time reversals.

VARIABLES	Positive potential overreaction (short time reversal)
Relative traded volume	0.0650 (0.652) -0.0786 - 0.209
Relative bid-ask spread	0.279 (1.225) -0.0488 - 0.606
Report	-0.845* (-1.622) -1.596 - -0.0951
Result indications	-1.187* (-1.851) -2.109 - -0.264
News (omitted)	- - -
Dividend record date (omitted)	- - -
Environment change (omitted)	- - -
Constant	-0.164 (-0.272) -1.032 - 0.704
Observations	65

Robust z-statistics in parentheses and 85% confidence interval below

*** p<0.01, ** p<0.05, * p<0.15

Table 12 presents the results of the Probit Model regression analysis of positive potential overreactions and short time reversals on a 15% significance level. Report and Result indications are statistically significant at the given level. Since this is in line with the results received using the Linear Probability Model the results are robust.

Table 13: The Probit Model: Regression analysis. Positive potential overreaction and long time reversals.

VARIABLES	Positive potential overreaction (long time reversal)
Relative traded volume	0.224* (1.885) 0.0529 - 0.395
Relative bid-ask spread	0.0845 (0.437) -0.194 - 0.363
Report	-0.280 (-0.531) -1.039 - 0.479
Result indications	-0.211 (-0.323) -1.153 - 0.730
News (omitted)	- - -
Dividend record date (omitted)	- - -
Environment change (omitted)	- - -
Constant	-0.817 (-1.296) -1.724 - 0.0903
Observations	65

Robust z-statistics in parentheses and 85% confidence interval below

*** p<0.01, ** p<0.05, * p<0.1

Table 13 presents the results of the Probit Model regression analysis of positive potential overreactions and long time reversals on a 15% significance level. Only Relative traded volume is statistically significant at the given level. This is partly in line with the results received using the Linear Probability Model.

2 Appendix

Construction and Calculation of Fama-French Factors

In March each year, from 2005 to 2014, all stock listed on OMXS are divided into two groups dependant on if they are smaller or bigger than the median value in terms of size, i.e. ME. The group with the smaller stocks (including the median stock) is denoted with an "S" and the bigger ones with a "B". At the same time, all stocks are divided into groups, dependant on their book-to-market value, i.e. BE/ME. The bottom 30% stocks with the lowest BE/ME are divided into a group denoted with an "L" for low. The middle 40% of BE/ME value are given an "M" for medium. The remaining 30% of the firms with the highest BE/ME value are divided into the group "H" for high. Finally, six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) are constructed as shown in the 2×3 matrix below. The reason for dividing BE/ME into three categories while ME in two is that Fama and French (1992a) have shown that BE/ME has a stronger explanatory value than ME.

Table 14: Fama-French Portfolios

		BE/ME		
		Low	Medium	High
ME	Small	S/L	S/M	S/H
	Big	B/L	B/M	B/H

After the yearly classifications of portfolios was made, all stocks on OMXS, which are analysed daily, are given their portfolio classification one year ahead, meaning that there are sixty different portfolios in total during the ten years of interest. Daily value-weighted returns (based on ME) are calculated for each of the portfolios.

After the portfolio construction and the determination of the daily value-weighted returns, the Fama and French factors SMB and HML can finally be determined. SMB stand for the return of a portfolio of small stocks in excess of the return on a portfolio of large stocks. HML is the return of a portfolio that includes stocks with a high BE/ME value in excess of the return of the portfolio of stocks with a low BE/ME value. The return of the small portfolio is,

$$R_S = \frac{1}{3}(R_{S/L} + R_{S/M} + R_{S/H}) \quad (29)$$

For the big portfolio the return is,

$$R_B = \frac{1}{3}(R_{B/L} + R_{B/M} + R_{B/H}) \quad (30)$$

The returns of the high and low portfolios are,

$$R_H = \frac{1}{2}(R_{S/H} + R_{B/H}) \quad (31)$$

$$R_L = \frac{1}{2}(R_{S/L} + R_{B/L}) \quad (32)$$

In the final step the factors SMB and HML could be determined on a daily basis.

$$SMB = R_S - R_B \quad (33)$$

$$HML = R_H - R_L \quad (34)$$

Finally, the last factor in the Fama and French Three-Factor Model is the MRP.

$$MRP_t = r_{m,t} - r_{f,t-1} \quad (35)$$

Robustness Test of Fama-French Three Factor Model

In order to check the robustness of the determined Fama-French factors, i.e. HML, SMB and MRP, the same procedure as in Fama and French (1993) is used. Instead of creating six portfolios, as was the procedure when determining the Fama and French factors, 25 portfolios are created. In March each year, from 2005 to 2014, all stock listed on OMXS are divided into five groups based on ME and five groups based on BE/ME. Portfolios are constructed as the intersections between the ME and BE/ME groups, which resulted in a 5×5 matrix, i.e. 25 portfolios in total are constructed on a yearly basis. For example, one portfolio includes the stocks with the lowest ME and the lowest BE/ME.

Daily value-weighted returns (based on ME) are calculated for each of the portfolios and further the excess return of each of the portfolios are determined as the difference between the expected return and the risk-free rate. When the excess return is determined for each of the 25 portfolios every year a regression is made in order to determine the quarterly betas for each of the factors in the Fama and French Three-Factor Model. Note that quarterly betas are used throughout the whole thesis.

$$E[r_{i,t}] - r_{f,t-1} = \alpha_{i,t} + \beta_{i,t}^{MRP} MRP_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \epsilon_{i,t} \quad (36)$$

In order to make the cross-sectional robustness test, a second pass regression is made, where the left hand side of the regression is the average excess return of each portfolio throughout the period of interest.

$$E[r_{i,t}] - r_{f,t-1} = \lambda_{0,t} + \lambda_t^{MRP} \hat{\beta}_{i,t}^{MRP} + \lambda_t^{SMB} \hat{\beta}_{i,t}^{SMB} + \lambda_t^{HML} \hat{\beta}_{i,t}^{HML} + \alpha_{i,t} \quad (37)$$

Table 15: Robustness test of Fama-French Three Factor Model

VARIABLES	Values
λ_t^{MRP}	-0.00350** (-2.539)
λ_t^{SMB}	0.000220** (2.169)
λ_t^{HML}	0.000190 (0.975)
Constant	-0.0139*** (-10.10)
R-squared	0.447
Robust t-statistics in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

From the table above, the R^2 value is satisfactory but the t -value of the constant term in the second pass regression implies that the model is rejected for the Swedish market since the constants on a statistically significant level are separated from zero.