Bachelor Thesis in Economics

From Market Efficiency To Event Study Methodology
— An Event Study of Earnings Surprises on Nasdaq OMX Stockholm

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This report is written in very close collaboration between the co-authors as all text has been written with both of them attendant. This undeniably lead to several discussions regarding interpretation of information from the various sources as well as problem solving, although some sections were written individually. In addition, the procedure of writing has been proceeding sequential rather than parallel and with this in mind, Robin Jonsson is responsible for Chapter 1, while Jessica Radeschnig is responsible for Chapter 2, except for Section 2.5, which were carefully created through corporation. The reminder of this report is written word by word, by the two authors together.
ABSTRACT

The analysis of market efficiency helps researchers and investors to better understand the complexities of the financial market. This report tests market efficiency at the semi-strong degree by employing an event study with focus on surprises in quarterly earnings-announcements made by companies that are publicly listed on Nasdaq OMX Stockholm. The surprises are determined by comparing the earnings per share with its consensus estimate, for two positive and one negative panel respectively. The report also provides a robust methodology description of event studies in general, likewise a broad discussion about different types of biases that might occur. For determining estimated abnormal returns the market model is adopted, as most commonly done in event studies. The panels are statistically evaluated by the use of a non-parametric rank test and economically through cumulated abnormality. The authors statistically find semi-strong market inefficiency through the negative panel, as well as for the small positive panel when economical inferences are taken into account, where a slight post-announcement abnormal return can be achieved. The same could not be implied for the large positive panel.
ACKNOWLEDGEMENTS

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A fundamental need of this thesis in order to detect earnings surprise events was the ability of comparing the actual earnings versus the consensus estimates, causing these numbers to be necessities. Therefore we are beholden to Mrs. Helena Effert (SME Direkt), which permitted us access to the SME Direkt database as well as linked us to the source where it could be attained. This further leads our gratefulness to Mr. Erik Eklund (Stockholm School of Economics), which contribution involved supplying this database directly to the authors.

We moreover would like to thank Emeritus Professor Peter Jennergren (Stockholm School of Economics), which sent us copies of his articles from 1974 and 1975, in which he investigates returns, profitability, and weak market efficiency on the Swedish equity market. Since we have been experiencing a deficit of studies which examine the Swedish market, Emeritus Professor Jennergrens’ papers were highly appreciated and they could not have been obtained elsewhere.

At last we are turning the attention to Mr. Lars Pettersson (Asset Manager at IF Metall), whose enthusiasm and guidance through previous courses have increased the authors’ curiosity within portfolio theory. Mr. Pettersson has become a source of inspiration which encouraged the authors to the topic of this thesis.

– Jessica Radeschnig & Robin Jonsson, Västerås 2014
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INTRODUCTION

There is a common saying on the equity market that one should buy securities on rumours and sell them on the news. If this statement bears any truth, there should be evident inferences to draw from the distribution of returns surrounding the announcement of an event which is expected to move a security’s return from its equilibrium, given no event. An event is an informational announcement of any kind which occurrence is assumed to be unexpected by the market, that is, the announcement does not necessarily have to involve an immediate change in firm value, but rather cause investors to associate with successive expected positive or negative information. Examples of informational announcements are when companies go public with stock-splits, mergers, take-overs, new products, and earnings. The last one of these could also be thought of as an "earnings surprise" since earnings-announcements are made at a regular basis whereas they do not necessarily have to be unexpected.

The body of literature associated with event studies mainly focus on the market efficiency hypothesis (directly or indirectly), under which returns above expectations should not be possible to obtain. This phenomenon originates from that all information should already be incorporated in stock prices at the time a trade will occur, however, event studies question whether absorption of information into equity prices occurs before, around, or after a return influencing event.

Problem Formulation

Are there any possibilities for an investor to make abnormal returns on the Swedish stock exchange by examining surprises from earnings-announcements in relation to their estimates? If there is an abnormal return effect related to earnings surprises, when does it occur? If there is no abnormal return effect, does it render the market semi-strong efficient?

Review of Literature

The history of event studies tracks back all the way to Dolley (1933), cited in MacKinley (1997) p. 13, which is reported as "probably the first published study". According to MacKinley (1997), Dolley (1933) investigated how stock prices were affected by stock-splits using a total

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1 The theoretical sections of this report bring up many different event studies, where they will be distinguished through a specification of what kind of informational announcement it concerns. When no specification is given however, the "event" or "announcement" is referred to general information. Additionally, all circumstances concerning a "surprise" refers to an earnings surprise although not always explicitly written.

2 Event studies can also be applied to other financial instruments as well as in other fields of research. The application in this thesis is however on security prices at the financial market.
of 95 splits occurring over the period 1921 to 1931, where he found that an increase of the security price occurred in 60% of the cases.

MacKinley (1997) moreover argues that the event study methodology spanning from the 1930’s to the late 1960’s improved in context of identifying biases, where Myers & Bakay (1948) and Barker (1956) are mentioned examples during the era. However, it was Ball & Brown (1968) and Fama et al (1969) that outlined the event study procedure into the methodology that more or less is being applied today.

Assuming market efficiency and that returns are only affected by market wide information, Ball & Brown (1968) conducted a study based on accounting income numbers over the time January 1946 to June 1966, where 261 firms were analysed over the interval 1957 to 1965 using monthly return data adjusted for dividends and capital gains. The analysis covered average log abnormal returns using two different expectational models; a one factor model and one model assuming that the current year’s income will equal the income of the previous year. The writers concluded that the difference between the two regression models was small and that around 85% to 90% of the content from upcoming income reports was captured ahead of the release, caused by the market, which used other sources of information when making investment decisions rather than waiting for the income-announcement.

The pioneering attribute to event studies by Fama et al (1969) was that they investigated how fast security prices adjust to new information rather than to infer market efficiency based on the independence of event proceeding price changes. The event under consideration was stock-splits, which were defined as "an exchange of shares in which at least five shares are distributed for every four formerly outstanding", causing all dividends larger than 25% to be classified as a split. The study was based on 940 splits and a sample consisting of monthly data between 1926 to 1960, where stocks included had to have been listed at the New York Stock Exchange for at least one year before, and one year after the event since this was the interval of investigation. The model applied for calculating the abnormal returns was the market model with the use of logarithmic returns, and the conclusion drawn by the four authors were that the market is efficient in context of fast incorporation of information into stock prices and that the reaction was only due to the implications of the dividend. Further, no indication of that usage of the split-announcement could possibly increase expected returns was found, at least conditionally on the market to constitute a fair game in terms of insider trading.

The volume of papers performing event studies has through time become increasingly large and to track every one of them seems like an almost, if not impossible task. Eckbo (2007) reports 565 event studies (of varying events) that were published in five different journals between year 1974 and 2000, where he shows that around 10 studies a year were published in the late seventies, which grew to about 25-35 a year during the nineties. Some examples of such varying event studies include Kraus & Stoll (1972), which tested the impact of announcements on stock prices when financial institutions trade large blocks of equity. Grier & Albin (1973) made a similar large block trade analysis based on information given by the NYSE tape and its reaction in the share price. Firth (1973) studied the distribution of returns around announcements regarding large acquirements of firm equity, where he expected and found evidence of that such announcements yields premiums to stock prices. As an example of earnings-announcements, Elton et al (1981) suggest that unexpected earnings in excess of

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3The authors of this report have found no evidence indicating any dramatical restructuring of the event study methodology since MacKinley (1997) and the time being.

4In contrast to Ball & Brown (1968), the measurement of cumulative abnormal return was here being introduced.

expectations tend to give abnormal stock movements around the earnings-announcement, while Drakos (2004) investigated the risk effect on securities of 13 different international airline companies listed at different stock exchanges, after the September 11 terror attacks in the United States. Using daily return data from July 2000 to June 2002, Drakos (2004) showed that risk increased for the airline industry stocks because of the attacks and that the increase was partly due to an increase within the systematic portion of the risk.

The fast development of technology has also encouraged for some event studies, where Roztocki & Weistroffer (2009) contain a survey of literature from research related to IT, and in which 46 studies occurred during the current millennium while one was from year 1993.

Turning the focus towards very recent studies and particularly towards event studies on earnings surprises, Bartov et al (2002) shows that companies that meet or beat expectations of earnings consensus enjoy higher subsequent returns than their contradictory peers. Based on analysts’ average forecast sample of 130,000 estimates for a total of 65,000 quarters reported by firms between 1983 and 1997, they also show that forecasting errors decrease as the fiscal year develops and that more companies meet or beat their expectations in later quarters. The phenomenon was concluded to be over-optimism by analysts in the beginning of the fiscal year that turned more negative (or neutral) as more information became publicly available.

Della Vigna & Pollet (2009) used CRSP stock data and I/B/E/S earnings estimates to show that employing a post announcement drift strategy based on a Friday earnings-announcement, not only achieves abnormal returns in general, but in fact higher abnormal returns than earnings-announcements on other week days. The authors concluded the reason to be inattention by investors on Fridays, measured by immediate response to information (15% lower), delayed response to information (75% higher), and trading volume (8% lower).

Hou et al (2006) studied NYSE/AMEX stock portfolios on the basis of earnings momentum and standardized unexpected earnings for different trading volumes and concluded that earnings momentum (1) is a decreasing function of investor attention, (2) has a greater effect among low volume stocks, and (3) is more distinct in bear markets.

Aim of the Thesis

The purpose of this thesis is to test the fundamental theory around the efficient market hypothesis at semi-strong degree, which is central for any type of event study regardless of the event component, and give arguments for why or why not this hypothesis holds. This work is important from an investor perspective because the literature analysing smaller exchanges such as Nasdaq OMX Stockholm is very limited. If given insight into how investors react to surprises in earnings-announcements, one can (1) potentially use the information flow to develop active strategies taking advantage of these announcements, or "buy and hold" investment strategies that are at least on par with the market. If (2) such opportunities are non existing one can conclude that either the market absorbs information quicker than investors generate returns, or some investors have an informational advantage rendering the information absorbed before its released to the public.

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6 CRSP stands for the Center for Research in Security Prices. It is a Chicago based research entity that collects and stores historical security return information for academic research.
7 I/B/E/S is short for Institutional Brokers’ Estimate System. They collect earnings estimates made by analysts. The database has become a much needed resource for event studies on the U.S. equity market.
8 Earnings momentum is also known as post earnings-announcement drift.
9 The construction of optimum portfolio strategies is not attempted within this thesis (for a reader interested in such a thesis, Jonsson & Radeschung (2014) constitutes a more satisfactory content). The material more serves as a tool to investors interested in market behaviour and who potentially would like to utilize the information given in the authors’ conclusion in order to create a strategy of their own.
Methodology

As understood from previous literature, many event studies have been performed and the methodology of such studies has become fairly standardized over time. In this thesis the authors adopt this carefully chosen methodology as summarized below:

1. Identify the announcement day, define the event- and estimation windows
2. Compute the abnormal returns, the standardized abnormal returns, and the cross-sectional aggregated cumulative abnormal return
3. Compute the scaled ranks and the cross-sectional aggregated cumulative scaled ranks
4. Test the hypothesis and evaluate the results

This procedure as well as its limitations will be explained in more detail throughout Chapter 2 in this report.

The data of actual earnings as well as consensus estimates was received from Mr. Erik Eklund at Stockholm School of Economics, which originally was collected from a research database held by SME Direkt. The study covers earnings events during the financial years 2009 to 2012 which gave a total of 808 quarterly earnings surprises for 72 different securities, while the data of returns was collected from [http://www.nasdaqomxnordic.com/aktier/historiskakurser](http://www.nasdaqomxnordic.com/aktier/historiskakurser) over the period April 1st 2008 to February 20th 2013. The surprises were then sorted into three different groups; large positive surprises (232 samples), small positive surprises (231 samples) and negative surprises (345 samples). 50 events out of each group were then randomly selected with equal uniform probability as to constitute each event study sample. Further issues concerning the data sample and its construction is described with more details in Chapter 3.

Limitations

Any empirical research usually suffers from limitations, and the study of this thesis does not compose an exception. The authors have identified a number of limitations which here are specified without any particular order of severity.

Firstly, when testing for market efficiency the restriction to a subset of the market as a whole emerged. Since the sample was dependent on estimates within the SME Direkt database the authors only accessed earnings surprises for a total of 72 stocks listed on Nasdaq OMX Stockholm, while the entire population constitutes around 250 securities. Moreover, the return database does not provide data of higher frequency than daily which implication is that there possibly exist informational losses dependent on the the intra-day reaction to information releases. As an example there may be positive announcements released followed by negative information on the same day, which effect could cause the potential abnormal returns to cancel each other out.

Another data limitation of the study is that the only included event is earnings surprises, causing the test of market efficiency to only account for such events. Hence, the results can only measure if the market is efficient in respect to earnings-announcements rather than test if the market is efficient in context of all publicly available information.

Moreover, the authors had access to a total of 1058 consensus estimates which were utilized in order to detect a total of 808 earnings surprises. After separating these into a positive and a negative group respectively, the amount of samples within each group did limit the construction...
of the study in forms of whether the magnitude of the surprise matters (the authors wished to have a total of six panels; one small, one medium, and one large panel for each group).

Additionally, a time limitation set by the course description forces the study’s construction to test for abnormal returns using well diversified portfolios of securities. This means that no information concerning the ability to catch abnormal returns for individual stocks could be extracted, thus, speculators interested in such opportunities will not be satisfied after reading this report.

Some of these limitations occur when specifying the "normal" rate of return, which has to involve a return generating model including its underlying assumptions, likewise assumptions are present in the testing procedure of the study. Assumptions may circumscribe the results to a non real world phenomena causing bias in the produced estimators. Some of these assumptions however depend on different steps associated with the event study methodology, and may by construction be set in order for the assumption to hold. These assumptions and sources of bias are thoroughly described in conjunction with respective event study step in Chapter 2 while the implications and solutions concerning the study in this thesis are discussed in a special section within Chapter 3.


CHAPTER 1

EFFICIENT MARKETS

The concept of market efficiency refers to a level where the market price of an exchange traded asset is reflected by the information available to investors at the time being. Eugene Fama states that

"A market in which prices always "fully reflect" available information is called efficient." [Fama (1970), p. 383]

What is referred to in the quote is known in the literature as the efficient market hypothesis [Fama (1991)], however, another perhaps more sophisticated take on the hypothesis is given by Jensen (1978), which describes an efficient market as

"A market is efficient with respect to information set \( \theta_t \) if it is impossible to make economic profits by trading on the basis of information set \( \theta_t \)." [Jensen (1978), p. 3]

The concept as given above is vague in its description and if the sentences caused confusion, the reader may have realized that there is a controversy between the price, which is a measurable variable, and the information set which is not easy to quantify. The question that should have come to mind is how one can measure this Efficient Market Hypothesis with such a tussle between variables.

First of all one must consider investors’ incentives to engage in trading. If new information becomes available, investors will rationally engage in trading until the marginal benefits no longer exceed the marginal costs, and upon achieving that state, the market is once more efficient. [Fama (1970)] gives conditions which are sufficient for such a market to exist, which includes no transaction costs associated with trading\(^2\) all information is available to all investors at no cost and all investors have equal interpretations and expectations about the impact of information on the security price. Such a market is clearly efficient, however the conditions are obviously not very realistic. Some trading costs are present in a real market environment and informational access might also be charged. In addition, investors’ interpretations of information are most likely heterogeneous.

Moreover, there must be a decision made for how the set of information should be measured. It is a cumbersome, if not impossible task to value each piece of information as a price

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1 Even if not explicitly clarified in Jensen’s quote, the information set is understood to be available for all market participants.
2 Such costs include commission fees, spread costs, execution costs, taxes, etcetera.
fragment of a security. Instead, given that it is known to all investors, the information available is assumed to be incorporated into investor expectations of security returns, where such expectations can be measured by a two factor equilibrium model \cite{Fama1970}. Quantifying information by an equilibrium market model to measure market efficiency is so important in this field of research that it has been given a name; the Joint Hypothesis.

1.1 The Joint Hypothesis

The Joint Hypothesis implies that market efficiency cannot be measured by itself, but rather must engage in conjunction with an asset-pricing model in order to reach a state of equilibrium in which information can be "properly" measured \cite{Fama1991}. This is in fact exactly what was done in empirical studies [see for example Ball & Brown (1968) and Fama et al (1969)] of market efficiency prior to when the Joint Hypothesis was first coined as an expression by Jensen \cite{Jensen1978}. Jensen states that

"In most cases our tests of market efficiency are, of course, tests of a joint hypothesis; market efficiency and, in the more recent tests, the two parameter equilibrium model of asset price determination. The tests can fail either because one of the two hypotheses is false or because both parts of the Joint Hypothesis are false." \cite{Jensen1978}, p. 2

The first sentence describes the relationship between market efficiency and equilibrium models, while the second implies a very important notation made by Jensen. He reasonably questions whether the potential abnormal returns, and thereby market inefficiency, is due to that (1) the market actually is inefficient, (2) the equilibrium model might be bad, or (3) both. Since the nature of the first hypothesis (market efficiency) is not empirically testable without the equilibrium model, one must start by examining latter. To be more explicit, one must find an equilibrium price (or return) generated by an asset pricing model in order to specify whether deviations are due to new information or not. This "fact of life", as scholars put it, is of great concern and commonly known as the Bad Model Problem.

The Bad Model Problem

Fama \cite{Fama1998} provides a survey of the problem with the Joint Hypothesis, known as the Bad Model Problem, where the main concern is the very nature of the Capital Asset Pricing Model (CAPM). This model, which is the one for which the Bad Model Problem is most severe, relies on assumptions that are hard to test empirically. All known information is assumed to be contained in the expected returns computed by CAPM, where return is only awarded for bearing market related risk\footnote{The market risk is also known in the terminology as systematic risk.}. However, the security sensitivity to this risk (measured by beta) is only an estimate of the true value. In other words, if beta suffers from estimation bias, the return generating process has return elements not captured by the market and thus, tests of CAPM fails to properly measure market efficiency. An evident study by Banz \cite{Banz1981} shows that CAPM fails to explain expected returns of small stocks, while an even more serious critique is given by Roll \cite{Roll1977}. He argues that since the true market portfolio is unobservable\footnote{One assumption of CAPM is that all assets are marketable, including human labour, art, collections, and other objects with abstract valuation.},

\footnote{The Capital Asset Pricing Model is a model that given a set of assumptions, finds the equilibrium stock return, and is determined through the covariance with the market. For a rigorous explanation of CAPM, see Elton et al (2010) chapter 13, and/or Hillier et al (2010) chapter 10.}
the market proxy (consisting of some stock index) is mean-variance inefficient. In a financial context, a frictionless equilibrium can only hold if the market is mean-variance efficient, that is, all rational investors hold the same risky portfolio due to homogeneous expectations of information. The rising conclusion is that CAPM can only be properly used if one has access to the true market portfolio.

A way of decreasing estimation errors due to a bad model is to instead employ a firm specific market model, where the coefficients are estimated using firm- and market data outside the event period, and apply those coefficients to the firm and market data in the event period. Several studies have adopted some form of the market model, including [Ball & Brown (1968), Fama et al (1969), Elton et al (1981) and Atiase (1985)], to mention a few.

1.2 The Efficient Market Hypothesis

The hypothesis surrounding the theme of market efficiency has split the financial industry in two parts for decades. Basically there are those who believe that the market is efficient, and those who do not. It is up to scholars to determine which view is correct, however it is seemingly a very hard nut to crack. Burton Malkiel, famous for his book "A Random Walk Down Wall Street", explains the Efficient Market Hypothesis as

"The efficient market hypothesis is associated with the idea of a "random walk," which is a term loosely used in the finance literature to characterize a price series where all subsequent price changes represent random departures from previous prices. The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today." [Malkiel (2003), p. 59.]

The quote implies that if the hypothesis is correct, investors have no means of constantly over-perform the market expectation. In other words, in absence of superior information investors have to settle with attaining a return premium in line with that of a well diversified stock market index.

From "Fair" Games Theory...

By intuition, a stock market where firms go to raise capital should price equity "fair" in terms of capital allocation. Likewise, investors are expected to be paying "fair" prices since the price of equity should reflect its fundamental value [Fama (1976)]. A fair game in its financial context is such that a market equilibrium exists and can be expressed in terms of expected returns. Regardless of which model one prefers, the expected price can in theory be expressed as

\[ E[P_i(t+1) \mid \Omega(t)] = (1 + E[R_i(t+1) \mid \Omega(t)])P_i(t), \] \quad \forall i \in \mathbb{N}, t \in \mathbb{Z}

where \( P_i(t) \) is the price of security \( i \) at time \( t \) and \( E[R_i(t+1) \mid \Omega(t)] \) is the one period change in expected return conditional on the information set \( \Omega(t) \). The conditional expectation represents dependency on the information which is utilized fully on the expectations, and equals to say that all information is incorporated "fully" [Fama (1970)]. Moreover, the empirical consequence is that no trading strategy can be constructed such that it achieves abnormal periodic returns above expectations. To illustrate, let

\[ AR_i(t+1) = R_i(t+1) - E[R_i(t+1)], \]
then the market represents a fair game if and only if
\[ \mathbb{E}[AR_i(t + 1) \mid \Omega(t)] = 0. \]

The Fair Game Model is only attainable under two specific assumptions, that is (1) market equilibrium can be expressed as expectations, and (2) the equilibrium reflects all available information from set \( \Omega(t) \) into current prices.

...to Random Walk Theory

While the Fair Game Theory assumes that all information is incorporated in expectations, the Random Walk Model is a somewhat extreme variant of the Efficient Market Hypothesis. Here, all prices \( P(t) \) and returns \( R(t) \) are treated as sequences of independent and identically distributed random variables. As a result, the economical interpretation is that all successive prices and returns departure randomly from their previous states. Put in mathematical terms, the return generating process is a random walk having a martingale property such that

\[ \mathbb{E}[R_i(t + 1) \mid \Omega(t)] = \mathbb{E}[R_i(t + 1)], \quad (1.1) \]

where \( R_i(t+1) \) is the random return one period forward, which is independent of the information set. In an economical sence the historical information gives no insight into future returns, instead the only information that can be drawn from a return sequence with independent and identically distributed random variables is these variables’ empirical distribution while the order in which they appear is irrelevant. If

\[ AR_i(t + 1) = R_i(t + 1) - \mathbb{E}[R_i(t + 1)] \]

is the difference between the actual- and expected return, the Efficient Market Hypothesis holds for

\[ \mathbb{E}[AR_i(t + 1) \mid \Omega_i] = \mathbb{E}[AR_i(t + 1)] = 0. \quad (1.2) \]

The conditional expectation based on \( \Omega(t) \) in Equation (1.1) and Equation (1.2) has a very important empirical interpretation. It ensures that no trading strategy or portfolio can be constructed such that, based on the information, there can be expected returns in excess of market expectations [Fama (1970)].

**Remark 1!** In Equation (1.1) and Equation (1.2) the conditional expectation of the abnormal return is zero. In fact, the random walk model usually carries a deterministic drift term and a stochastic diffusion term. When taking expectations of a random walk model, and specifically in financial applications, the model reduces to a constant drift which is non-zero.

**Weak Form Efficiency**

The degree of market efficiency is separated into three forms, where the weak form efficiency assumes that no abnormal returns can be gained by studying the information contained in historical prices [Fama (1970)]. If there are abnormal returns in historical prices, this form of efficiency fails. In more recent literature, the concept of weak form has been extended to additionally include elements of return predictability [Fama (1991)]. These elements are dividend forecasts, interest rates forecasts and seasonal patterns such as the January effect as well as any kind of momentum or contrarian strategy that base the allocation decision on historical returns.
Tests of weak form efficiency are in fact tests of return predictability. There is a rich body of literature that find statistically significant repeating return patterns which can be exploited to make abnormal returns. This literature has proven a great challenge to the Efficient Market Hypothesis from the 1990’s to the time being. Jonsson & Radeschnig (2014) gives a solid review of literature testing for weak form efficiency. Unfortunately such strategies have had its share criticism as well, because those studies are usually made in the absence of transaction costs. The critics point out that a trading strategy using historical discrepancies from equilibrium will have its abnormal returns perish in a real market environment, where costs associated with trading are present.

The literature covering weak form efficiency on the Swedish Stock Exchange is relatively narrow compared to the U.S. markets, and the most contributing work found by the authors is given by Jennergren & Korsvold (1974). By examining serial correlations and runs tests\footnote{Runs tests consider only the sign of successive return changes. The deviation from the expected number of runs during the sample period measures the level of deficiency.} for the 30 most traded stocks on the Swedish exchange from 1967 to 1971, they found that there were serial correlations in the examined price series, and thereby the assumption of the stock market being a random walk with independent random variables must be rejected. Moreover, Jennergren (1975) tested filter rules\footnote{Filter rules are a trading strategy based on filtering the period return by deviations. A filter size can be anything from 1% to 25% depending on strategy, but when the asset deviates from its origin through the filter, a trade is made.} on the same data sample. The conclusion made was that an excess return can be made, if the investor can evade capital related taxes\footnote{Elton et al (2010) imply that the Swedish King is relieved from taxes on capital gains, and based on Jennergren’s study they suggest him to profit under a filter strategy. The authors of this thesis however find no evidence of the King being relieved from such taxes.}

As an endnote, there seems to be mechanical trading strategies that one way or another tend to beat the average return. However most researchers conclude that the final unconditional evidence against weak form efficiency is yet to be found.

**Semi-Strong Form Efficiency**

The second degree of market efficiency tests whether information known to the public is incorporated into stock prices or not. Tests at this level, are more in line with an economic equilibrium, that is, market participants trade until all public information is priced correctly. Fama (1970) defined this level strictly as semi-strong, however after reviewing the literature from twenty years of research in this field, he changed the suggested name to event studies \[Fama (1991)\]. Event studies is a more descriptive name since the tests on this level include studying the impact of announcements which companies listed on a stock exchange releases. It is important to point out that such information should have simultaneous release for all market participants, and moreover be free of charge. Any information that carries cost is seen as private information and thus, does not apply for semi-strong efficiency. A throughout survey of event studies and their main findings was made in the introductory section of this thesis.

**Strong Form Efficiency**

The strongest form of market efficiency is when all information, public and private, is incorporated into security prices. The first declared term for this level of efficiency was strong form \[Fama (1970)\], which later was redefined just as the previous level in order to be more descriptive. The name suggested instead was tests for private information \[Fama (1991)\]. This extreme view is tested by seeing whether some market participants have exclusive information
not available to the general public, where such participants might be hedge funds, mutual funds, managers or other insider related entities with monopolistic sources of information. Seyhun (1985) concludes that insider trading made by fund managers and board members of companies yields abnormal returns, which should not be a surprise. However, outsider trading on public SEC\textsuperscript{9} information regarding insider trades could not benefit from abnormal returns net of trading costs.

Another study concerning insider information was performed by Bhattacharya \textit{et al} (2000) which investigated equity on Bolsa Mexicana de Valores in Mexico, where insider trading was not legally restricted. The selected announcements were several, which created a sample of 119 series (49 firms) between July 1994 to June 1997. The market was further separated into two groups, A-listed securities and B-listed ones, where the prior were only available for Mexican citizens while B-stocks were obtainable for foreigners as well. The drawn conclusion by Bhattacharya \textit{et al} (2000) was that the absence of restricted insider trading drives stock prices to fully reflect the information before the public announcement is made.

Studies on analysts’ information also has an extensive body of literature. The beliefs that security analysts’ posit greater knowledge about market movements is a common thought among casual investors. It is however hard to test this hypothesis because of analyst’ sample bias. Analysts who did well historically gladly share their track record\textsuperscript{10} while those who did worse seldom share it for obvious reasons. Elton \textit{et al} (2010) provide a good summary including a few unbiased studies as well as guiding literature for the curious reader. The conclusion was that no single analyst had informational advantage, thus an investor would be equally rewarded for following analysts’ consensus\textsuperscript{11}.

\textbf{Final Remark 2!}

Pondering on the empirical meaning of market efficiency means that if the markets truly are weakly efficient any form of portfolio construction endeavour, based on historical return patterns, are a waste of time to managers and analysts. If the markets are semi-strong efficient there is no meaning in basing a portfolio strategy on informational announcements nor surprises. It does however not imply that forecasting is a waste of time. If an analyst constantly do a better job than consensus, abnormal returns should come naturally. Finally, if the market is strongly efficient, not even the insider would be to extract abnormal returns, which in turn implies that investing in anything else rather than a well diversified stock portfolio or an index replicating portfolio is a waste of time. A higher form of efficiency also implies that the lower forms hold as well. That is, if the market is strong or semi-strong form efficient (efficient to all public information), it also includes being weak form efficient since historical prices are part of public information.

\textsuperscript{9}SEC stands for Securities and Exchange Commission, and is the United States financial regulatory authority.
\textsuperscript{10}A track record is the historical performance of an individual or entity.
\textsuperscript{11}The consensus estimate is an average value of estimates from professional analysts.
Chapter 2

The Methodology of Event Studies

The process of performing an event study might at first glance seem overwhelming since the procedure involves several different steps, which all can be taken in different directions. The full literature of event studies is however daunting and to explain every possible approach seems nearly impossible. For this reason, the methodology description of this chapter is biased towards short-term event studies, and towards the characteristics of the empirical study in Chapter 3. In addition to all different approaches, the task is even more cumbersome though each step also provide for sources of bias in the statistical estimates.

MacKenley (1997) constitutes a clear and compact guide through the methodology of event studies, although not explaining the different sources and solutions of bias in a perfectly satisfactory manner. Another guide of event studies is found in Brown & Warner (1980), where they rather than only describe the different approaches to take in each step, additionally illuminate the impact of bias for the different approaches. They investigated these possible sources in a study of simulated samples using monthly data, and the study was later extended to the use of daily data by Brown & Warner (1985). In addition, Bartholdy et al. (2006) investigated the event study methodology on smaller stock exchanges where thinly traded stocks may cause methodological problems. The study was performed over the interval 1990 to 2001, using daily data from the Copenhagen Stock Exchange. They found that event studies performed on smaller exchanges can be successfully made if some adjustments are made due to thin trading. Other examples of literature which respective focus lies upon different statistical property issues are Binder (1998), Corrado (2011), and S.V.D. Nageswara Rao & Sreejith (2014), while Lo & MacKenley (1990), Shalit & Yitzhaki (2002), and Saadi et al. (2006) focus upon one specific source of bias within their respective papers.

2.1 Collect Data of Events

The absolute first step in the event study process comes naturally as deciding what kind of event that is of interest. With this done, one has to specify a selection criteria which is supposed to determine whether a certain stock should be included in the sample of investigation or not. Dyckman et al. (1984) claim that abnormal performance of returns should be easier detected when using large portfolios of stocks since the influences from firm-specific factors tend to be diversified for these. However, there may be several reasons for the selection criteria of inclusion, where for example Dyckman et al. (1984), pp. 23-24, in addition to firm-specific risk
also investigated industry classifications. MacKinley \cite{MacKinley1997} further gives examples regarding limitation of data access and market capitalization as potential sources of selection criteria. Nevertheless, any selection criteria may cause biases in the study, which all should be identified as due to the selection. As an example of this, Dyckman et al \cite{Dyckman1984} excluded thinly traded stocks in their simulation study of comparing event study methodologies, which caused a reduction of impact within the sample from firms which stocks were less frequently traded.

In the case when one wish to study the effect of earnings surprises, one must additionally define what announcements in the collected data that actually constitute surprises. There exist several methods of doing so, where the most common is to compare the announcement with the consensus and investigate if there are significant differences between announcements and estimates. All positive differences are then sorted into one group while negative differences are sorted into another. Elton et al \cite{Elton2010} argue that the original event studies investigated announcements at a monthly basis whereas daily data has been the standard in more recent research. The advantageous differences are quite logic in the prospects of daily studies since there may occur several events except the one under study if the time interval is longer, hence, the smaller interval is the more desirable when testing for event effects. Intra-day data may also be used in order to shrink the interval even further, which means that the event effect can for example be studied hourly after the occurrence of the announcement. However, Saadi et al \cite{Saadi2006} states a backside effect of higher frequency data in the form of spurious autocorrelation, a result of non-synchronous trading\footnote{Non-synchronous trading could result in thinly traded stocks, and will be explained within Section 2.4}, which this kind of data is more sensitive against.

Remark 3! The authors of this thesis strongly believe that for any estimation model of normal returns\footnote{In order to calculate an abnormal return an estimation of the normal return must be made. More details concerning this issue is given in Section 2.4}, it would be difficult to estimate a precise number for higher frequency data. Firstly because the sample size would be extremely large if for instance the data concerns estimates per minute, and secondly, if one still desires to estimate for these short intervals, the procedure would be very time consuming. When using daily data the estimated abnormal return acts like a one day average effect, which potentially could smooth the announcement impact enough to be undetectable. This phenomena would be even more substantial if several news\footnote{"News" here refers to any kind of information that may affect stock prices. That is, firm specific announcements from the current company or others, as well as any macro event like for instance inflation-announcements or increases in interest rates.} are released with small intervals, and particular at the event day.

2.2 Identify the Event Day and the Event Window

The next step in the procedure is to identify the actual day of the event. This may at first sight seem ridiculously simple through defining the date of the announcement as the event day but the truth is somewhat different. A reason for this is that the opening hours of the stock exchange are not synchronized with the start and the end of the day. In other words, the announcement may for example be made after the stock exchange has closed and the effect of the event is not measurable until the next-coming day at which the market is open. Moreover, some securities may also be registered in multiple stock exchanges (that is, in other countries as well), causing the effect of an announcement made when the domestic exchange was closed to potentially be captured in an international exchange if open. Thus, defining the day of the
announcement as an event if it occurs before the domestic exchange opens, or the day after if the announcement occurs after the closure is neither a sufficient solution in order to identify the real event day. Problematic or not, Dyckman et al. (1984) argue that the improvement of specifying an exact date of the event and the likelihood of observing an abnormal performance are positively correlated, which this report’s authors from the above discussion assume to be a time consuming task.

In addition, one must also decide the total time interval of relevance, that is, one has to specify the event window. When the event study covers earnings surprises, MacKinley (1997) describes the customary event window, in the case of daily data, to involve at least the day of the announcement as well as the next-coming day, in order to capture those effects that occur after the closure of the stock market at the event day. However, Elton et al. (2010) and Brown & Warner (1985) describe that there exists a possibility that information is absorbed in the market prior to the event which causes the period ahead of the announcement to be of interest, as well as the period succeeding the event may be of interest for interpreting how fast the market stabilizes from the announcement.

A more mathematical description of the event window is made by defining the interval

\[ \text{Event Window} = \{t \in \mathbb{Z} | T_1 < t \leq T_2 \}, \]  

where \( T_1 \) denotes the start of the window, and \( T_2 \) denotes the end of it. \(^3\) The index \( t \) represents intermediate time-steps, where \( t = 0 \) is the day of the informational announcement. Moreover, due to data being discrete, \( t \) must be an integer number, that is why \( t \in \mathbb{Z} \). The properties of the time index will remain throughout the whole report but will for convenience and simplicity not be explicitly written.

Furthermore, the mathematical definition of the event window’s length, \( L_{Ev} \), is given by

\[ L_{Ev} = T_2 - T_1, \]

which there however do exist some problematic issues when determining though. Hypothesize the scenario of earnings events described above, it suggests a desire of extending the window prior to the event in order to analyse the effects of prior information. Another reason of concern for this desire is described in MacKinley (1997) as if specifying the event window interval as to be too narrow. This would cause the estimation window and the real event window to overlap, and bias arise in the sense that the event is affecting the estimation of the normal return, which should be the return in absence of the event.

The other side of the stake is when the event window is set to be too long, then there is an increased probability of clustering. Clustering occurs when two or more securities have overlapping event windows which general consequence is described in Brown & Warner (1980) as decreasing the number of independent events in the sample. In other words, when the event is not isolated, there is a potential risk that the effect on the return is partially due to another firm’s announcement of equal character causing performance between returns to be correlated. In the presence of clustering, a test of no abnormal returns will be rejected too often even in the absence of such abnormal returns. The problem with this kind of clustering in Brown & Warner (1980) did not seem to be very problematic since the degree of clustering was relatively

\(^2\) If the announcement occurs between opening hours, the event day must be "rounded" in any direction (if international data is not obtainable). This obviously causes bias since the actual moment of the event is outside the range for which the effect is to be tested upon.

\(^3\) Elton et al. (2010) suggest that \( T_1 \) and \( T_2 \) should have a negative and positive sign respectively but that they should equal in absolute value.

\(^4\) The estimation window will be discussed in Section 2.3.
small. This was partially due to that the inclusion of events within the sample were randomly generated, independently uniformly distributed over more than 300 candidate events, where they all were based on monthly data \cite{Brown:1980:pp233-234}.

In addition to the issue of event window clustering, \cite{S.V.D.Nageswara:2014} describe another form of clustering when events of other characteristics may influence the event rather than the one under study, and describe a part of the solution as to shrink the event window in order to raise the probability of controlling these confounding events. It can be read that

"It is a challenge before the researchers to eliminate the effect of a different event that happening in the same time along with the incident of interest. Due to these simultaneous occurrences of the events, it is difficult to ascertain the impact of one event on stock returns. Hence it is the task of a researcher to eliminate the presence of confounding events around the event date and event window." \cite{S.V.D.Nageswara:2014:p44}.

The writers of the quoted article suggest to collect firm specific news data in order to discover these nearby confounding events and adjust the resulting impact on the return of the corresponding stock. \cite{Dyckman:1984} further argue that, at least when the selection criteria groups the securities by industry or industries, the combination of a grouped sample and clustering will reduce the power of statistical tests since the two forces exaggerate each other.

\textbf{Remark 4!} The authors of this thesis suspect the time consumption to increase with the sample size, and if ignoring rather than exploring the firm specific news data, the solution of decreasing the event window would not exclude other events when released simultaneously. Shrinking the event window as a solution could also result in estimation bias of normal returns, as described earlier in this section. On the other hand, if an attempt to sort some events out while keeping others is being made, a source of selection bias arises and the question of whether bias due to selection or bias due to clustering distorts the results’ accuracy the most.

### 2.3 Compute Abnormal Returns

The impact of an event on stock returns must somehow be measured, and the measurement is the abnormal portion of the stock return. This measure is simply the difference between the ex-post return and the normal return over the time period. Put different, let \( P_i(t) \) be the closing price of stock \( i \) at time \( t \), then

\[
R_i(t) = \frac{P_i(t) - P_i(t-m)}{P_i(t-m)}, \quad m < t,
\]

is the formula for calculating the \textit{lumped} return (the ex-post return) of security \( i \) over the time period of length \( m \), and

\[
AR_i(t) = R_i(t) - \mathbb{E}[R_i(t) \mid \Omega(t)] \tag{2.2}
\]

\cite{Dyckman:1984} made this statement after investigating securities selected from the industries Aerospace, Building, Machinery, and Oil & Gas.
is the formula for the abnormal return of the same security. The expression in the last term of Equation (2.2) denotes the normal return and it translates from mathematics into being the ex-ante expected return of the security conditional on some information contained in $\Omega(t)$ and in absence of the event. Through modelling the expected return using this information, an estimate of the expected return can be found.

There exist several possible techniques in order to perform the task of modelling, where MacKinley (1997) reports statistical models in the forms of the Constant Mean Return Model\(^7\), Factor models\(^8\), and the Market Model\(^9\). In addition, CAPM and the Arbitrage Pricing Theory\(^{10}\) (APT) are two examples of economic models which are described in Elton et al (2010) and Hillier et al (2010).

So which model should one adopt when estimating the normal return in an event study? MacKinley (1997) leads a discussion of the use and benefits from all above mentioned models and defines CAPM to be the popular model of event studies during the 1970’s, but that the popularity has decreased due to that deviations from CAPM have been detected. MacKinley (1997) also argues that there exist a limit to the gains of employing a multi-factor model in event studies. For factors in addition to the market return the marginal explanatory power is small, causing the variance of the abnormal return to not be very different from if using the market model instead. Similar reasons are also given for the APT. However, one argument adds that caution must be taken if the selection criteria only allows stocks within a certain industry or if they all belong to the same group of market capitalization. To sum this discussion up, the two models that MacKinley (1997) actually promotes as "common choices" are the Constant Mean Return Model and the Market Model.

**The Market Model**

From the previous discussion it follows that a popular and very widely used model for calculating the normal return is the market model. This model is described in a wide range of literature, where Hillier et al (2010) and Elton et al (2010) are two specific examples, but the model is however described in more or less all of the references given to this report.

The market model originates from the single index model, a more general approach in which under certain criteria equals the market model. The return $R_i(t)$ on security $i$ at time $t$, according to the market model, is given by

$$R_i(t) = \alpha_i + \beta_i R_m(t) + \varepsilon_i(t), \quad (2.3)$$

in which $R_m(t)$ is a factor represented by the unknown return on the market, while $\beta_i$ is a constant that measures the asset return’s sensitivity to the factor. Moreover, $\alpha_i$ represents the

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\(^6\)A problem when calculating the return is that trades are not occurring at all days (non-synchronous trading) and may thereby be thinly traded. Small exchanges generally list the last transaction price as the security price at days in absence of trading, and as a result, the return on these days will equal zero while returns are relatively large at days when trading occur. A series containing a large number of zeroes will underestimate the variance and thus, bias the hypothesis test. Bartholdy et al (2006) report four different ways of calculating the actual return, where they find the trade to trade method (which adjusts for thin trading) to be the better option. They moreover argue it to be quite complicated and time consuming to calculate and refer the lumped return to perform nearly as well and to act as a good alternative when the event study must be done more quickly.

\(^7\)The Constant Mean Return Model is a model assuming that the mean return of a security is constant over time and that deviations are due to an error term alone.

\(^8\)Factor models seeks to reduce the variance of the normal return through adding more explanations behind the variance of the normal return.

\(^9\)The Market Model is actually a special case of a factor model when only one factor is included, that is, the market return.

\(^{10}\)The Arbitrage Pricing Theory is a multi-factor regression model where the stock price is assumed to be linearly influenced by some set of factors with different sensitivity.
expected return on the security independent of the performance of the factor while \( \varepsilon_i(t) \) is a random error term which causes the model to be probabilistic rather than deterministic [Wackerly et al (2007), p. 565]. The error term is moreover assumed to be normally distributed\(^{11}\) with zero mean and variance \( \sigma^2_\varepsilon \), and also uncorrelated with \( R_m(t) \), that is, \[
\operatorname{cov}[\varepsilon_i(t), R_m(t)] = 0.
\]

Given these properties of the error term, one can estimate the constants in Equation (2.3) through historical averages of returns using

\[
\bar{R}_i = \frac{1}{T} \sum_{t=1}^{T} R_i(t),
\]

which also holds for the market return. Using this formula and through using ordinary least squares\(^{12}\) (OLS) for estimation, Shalit & Yitzhaki (2002), p. 99, gives the constant \( \beta_i \) in Equation (2.3) to be estimated by

\[
\hat{\beta}_i = \frac{\hat{\sigma}_{im}}{\hat{\sigma}_m^2},
\]

which is confirmed by Elton et al (2010) and Hillier et al (2010). Moreover, the numerator in Equation (2.4) is given by

\[
\hat{\sigma}_{im} = \sum_{t=1}^{T} \left[ (R_i(t) - \bar{R}_i) (R_m(t) - \bar{R}_m) \right],
\]

which represents the covariance between security \( i \) and the market, while the denominator is given by

\[
\hat{\sigma}_m^2 = \sum_{t=1}^{T} (R_m(t) - \bar{R}_m)^2,
\]

which is defined as the variance of the market.

Using the estimated beta, one can now solve for the estimated alpha in Equation (2.3) by

\[
\hat{\alpha}_i = \bar{R}_i - \hat{\beta}_i \bar{R}_m,
\]

\(^{11}\)The normality property of \( \varepsilon_i \sim N(0, \sigma^2_\varepsilon) \) assures that \( E[\varepsilon_i(t)] = 0 \).

\(^{12}\)The relationship between the security and market returns under the OLS framework is illustrated in Figure 2.1. For OLS to be the "best" estimator of existing regression models, there exist seven classical assumptions that are required to hold. These assumptions are given literary in Studenmund (2010) p. 94:

1. The regression model is linear, is correctly specified, and has an additive error term.
2. The error term has a zero population mean.
3. All explanatory variables are uncorrelated with the error term.
4. Observations of the error term are uncorrelated with each other (no serial correlation).
5. The error term has a constant variance (no heteroskedasticity).
6. No explanatory variable is a perfect linear function of any other explanatory variable(s) (no perfect multicollinearity).
7. The error term is normally distributed (this assumption is optional but usually is invoked)."

If one or more of these assumptions are not met by the reality conditions, there may exist another estimation technique that outperforms the OLS. There exist several techniques of testing whether the assumptions are reasonable or not, these procedures are however beyond the scope of this thesis but the curious reader can find them in Studenmund (2010).
and the remaining thing is now to substitute all the unknown variables in Equation (2.3) with their respective historical average. The conditional expected return can now be described by

$$E[R_i(t) \mid \Omega(t)] = \hat{\alpha}_i + \hat{\beta}_i R_m(t).$$

(2.5)

Notice that the market return is not exchanged with its historical average though. In a predictive use of the model this return must be estimated as well, in event studies however, the market model is used to evaluate ex-post measures when the actual return is known, hence, no estimation of the market return is necessary.

**Remark 5**! A possible source of bias again arises, this time due to the non-estimated market return. The OLS generates an output of the security return when the market daily average is being used as input, but inferences are that the market return is non-constant through time and hence, deviations from the average will occur. This obviously cause the estimator in the market model to be biased but the authors appreciate this deviation though. This is because the OLS only provides an approximate value where the true rate of returns are spread around the average (see Figure 2.1). The first scenario that may occur is when the true security return equals its expectation. Then a higher or lower value of the adopted market return, ceteris paribus, shifts the expected security return in the direction of the true normal return value. In other words, contradictions between the market daily average and the actual market daily return would be the market response to some released information and hence, should not be taken into account when estimating the normal rate of security return. Rather the error term will adjust according to the available information in all possible circumstances but one, which leads to the second scenario. If there is a deviation between the actual security return and its expectation, and
the deviation lies in the same direction as the market’s deviation from average, at worse the error term will remain unchanged compared with using the market daily average. Thus, the authors claim this bias to be a positive phenomenon since it at worse do not affect the performance of the estimation.

Shalit & Yitzhaki (2002) argue that OLS is not the best way of estimating \( \hat{\beta}_i \). They claim that the beta, which is showed to be a function of utility, may be sensitive to extreme observations, and they further suggest alternative methods of estimating a more "robust" beta. These procedures will however not be investigated within this report, the authors rather accept the OLS to be a sufficiently appropriate technique of estimation.

In order to perform the OLS regression and find the estimates, one has to define an estimation window which MacKinley (1997) describes will serve as the time period under which data is collected in order to estimate the return in the event window. The estimation window is mostly set as not to overlap with the event window because the estimate should represent the return in the absence of the announcement, thus the effect from the event would bias the results [MacKinley (1997)]. The estimation window can mathematically be described by the interval,

\[
\text{Estimation Window} = \{ t \in \mathbb{Z} \mid T_0 < t \leq T_1 \},
\]  

wheras the length of this window is given by

\[
L_{Es} = T_1 - T_0.
\]

The relationship between the event window in Equation (2.1) and the estimation window in Equation (2.6) is illustrated in Figure 2.2. When the estimation window is set, historical data of returns must be collected and sorted in order to use as input for the market model return. The use of daily returns brings some possible sources of bias in the procedure though. A criteria for many hypothesis tests is that the samples should be normally distributed. Fama (1965) investigated the distribution of daily log prices of 30 stocks at the Dow Jones Industrial Average over an approximate time period from 1956 to 1957, where returns were found to be leptokurtic and fat tailed [Fama (1965), p. 21]. In a study based on the 30 and 15 most actively traded stocks in Sweden and Norway respectively, Jennergren & Korsvold (1974) found similar results.

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13 One could say that the authors assume OLS being the Best Linear Unbiased Estimator (BLUE).
14 This description of the distribution means that there are more amount of samples in the start and the end of the curve relative to the normal distribution (fat tailed), and that the curve is more peaked in the center (leptokurtic).
for the 17 most traded stocks in Sweden, while they found a distribution even more leptokurtic for the 13 remaining Swedish stocks as well as all the Norwegian. In addition, with returns and event dates selected randomly, Brown & Warner (1985) confirmed this pattern even in the case of abnormal returns, but they however also argue that non-normality of returns or abnormal returns does not have a large impact on event studies because the mean abnormal return of a cross-sectional regression, \( \text{as expected under the Central Limit Theorem (CLT),} \) does \text{asymptotically converge} to normality.\footnote{The CLT infers that probability conditions of a function involving some independent and identically distributed variables which are drawn from a sample with a finite variance can be closely approximated to the normal distribution properties, that is, the limiting probability distribution of the function converges to the normal distribution. This is equal as saying that the function is asymptotically normally distributed. A more mathematical definition of the CLT is available in Wackerly et al. (2007) p. 372.} Even though the assumptions underlying the CLT were not empirically met, the study showed it to apply when the sample size equalled 50 but for samples of 20 and less the results were somewhat different. The writers moreover conclude that "the characteristics of daily data generally present few difficulties in the context of event study procedures" \[\text{Brown & Warner (1985), p. 25}\].

In addition, as was the case with event window clustering for normal returns, clustering could be a source of bias for abnormal returns as well. Brown & Warner (1985) pp. 15-16 however showed that when the event day by random construction is equal for all events over the window \((-6, 5]\), the goodness of fit tests generally do not indicate misspecification of the hypothesis test of abnormal performance when using the market model.\footnote{Brown & Warner (1985) constructed 250 samples including 50 securities each from July 1962 to December 1979. The included stocks were randomly selected with uniform probability, for which an hypothetical event was constructed.} The collected data is further used to regress Equation (2.5), which substitution in Equation (2.2) gives the abnormal return as

\[
AR_i(t) = R_i(t) - \hat{\alpha}_i - \hat{\beta}_i R_m(t), \quad t_1 < t \leq T_2, \tag{2.7}
\]

where \(t_1 = T_1 + 1\). Notice that this is nothing else but saying that the actual error term of the market model, rather than the expected, represents the abnormal return.

The properties of the error term in the market model causes the abnormal return to be normally distributed with zero mean, and variance

\[
\sigma^2_{AR_i} = \sigma^2_{\varepsilon_i} + \frac{1}{L_{Es}} \left[ 1 + \frac{(R_m(t) - R_m)^2}{\hat{\sigma}^2_m} \right], \quad t_1 < t \leq T_2,
\]

where \(\sigma^2_{\varepsilon_i}\) is given by

\[
\sigma^2_{\varepsilon_i} = \frac{1}{\tau} \sum_{t=t_1}^{T_2} (\varepsilon_i(t) - \bar{\varepsilon}_i)^2, \quad \tau = T_2 - t_1.
\]
The fact that the abnormal return has more variance than the error term arises from that
alpha and beta are estimates, which variance must be added since Equation (2.3) includes the
true values. Since this additional variance is market related and thus, equal for all securities,
this will be a source of spurious serial correlation for the estimated abnormal returns, even
though they should be independent in reality. However, through extending the length of the
estimation window this source of bias will asymptotically decrease, or put mathematically,
\[ \lim_{L_{E_s} \to \infty} \left( \sigma^2_{\epsilon_i} + \frac{1}{L_{E_s}} \left[ 1 + \frac{(R_m(t) - \bar{R}_m)^2}{\sigma^2_m} \right] \right) = \sigma^2_{\epsilon_i}. \] (2.8)

In other words, if the estimation window is set sufficiently large, the variance of the abnormal
return will converge to the variance of the error term in the market model, and hence, the
variances of the error terms will not be autocorrelated\(^{19}\) causing them to be independent
through time.

### 2.4 Aggregation of Abnormal Returns

So far, the methodology in the event study procedure has involved the abnormal return of an
individual stock at one point in time (that is, one day in this report). Since the event window
is an interval spanning over multiple days, aggregation must be made in order to find a single
measurement of the abnormal return across shares, over the entire event window. However, in
order to test a sample for statistical evidence though, which is the aim of an event study, a single
sample will not yield much of an answer, implying a second aggregation to be a necessity. This
involves a cross-sectional procedure which purpose is to aggregate all the time-series aggregated
individual returns.

#### Time-Series Aggregation

The cumulative abnormal return is a function of time within the event window, which is the
sum of all the daily abnormal gains, and represents the time-series aggregation of abnormal
returns. In the mathematical language, this term is given by
\[
CAR_i(t_1, T_2) = \sum_{t=t_1}^{T_2} AR_i(t).
\]

With the same concept as for the variance of the abnormal returns, MacKinley (1997) denotes
the asymptotic variance of the cumulative abnormal return for large sample estimates as
\[ \widehat{\sigma}^2_{CAR_i(t_1, T_2)} = \sigma^2_{\epsilon_i}(T_2 - t_1 + 1). \]

If however the sample size is not reasonably large (as for the limiting function in Equation
(2.8) to eliminate the term in square brackets), this given variance will have estimation bias in
the same form as the abnormal return variance.

#### Cross-Sectional Aggregation

With the time-series aggregation being complete the next step involves aggregating these cu-
mulative abnormal returns over the entire sample of events. Some assumptions are however

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\(^{19}\)Autocorrelation refers to when there is correlation between estimates of the same sample in different time
periods, that is, the correlation is lagged. This is in fact the same thing as serial correlation.
necessary in order for independence across securities’ abnormal and cumulative abnormal returns. These assumptions involve that the abnormal returns are normally distributed and that there are no event window clusterings.

The procedure is similar to the prior in sense of a summation, where the average cumulative abnormal return (CAR) is given by the arithmetic mean of all CARs, that is, the sum of all CARs divided by number of samples $n$.

$$\overline{CAR(t_1, T_2)} = \frac{1}{n} \sum_{i=1}^{n} CAR_i(t_1, T_2),$$

the function’s expected appearance in an efficient market is illustrated in Figure 2.3 while the sample variance estimator is given by

$$\hat{\sigma}^2_{CAR(t_1, T_2)} = \frac{1}{n^2} \sum_{i=1}^{n} (CAR_i(t_1, T_2) - \overline{CAR(t_1, T_2)})^2.$$

MacKinley (1997) moreover suggests this large sample estimator to be simplified when an assumption of no clustering is made. The covariance term between individual returns in the expression after the summation will then equal zero, which implicitly requires that covariances between cumulative abnormal returns to equal zero. If one on the other hand wish to allow for cross-sectional correlation, the covariance cannot be set to follow this assumption.

A problem with both time-series and cross-sectional aggregation is when the abnormal returns are correlated. Lo & MacKinley (1990) describe a possible source of autocorrelation as "non-synchronicity" (earlier described slightly as thinly traded stocks). This problem arises when time-series data for different securities are assumed to be collected at equal time periods while the truth is rather different, and could cause a false autocorrelation between securities only because they might be traded at different time periods. Brown & Warner (1985) addi-

![Figure 2.3: The Cumulative Abnormal Return](image)

In a semi-strong efficient market, the cumulative abnormal return is expected to increase during the time prior of the announcement while level off from the event an forwards. The graph illustrates the case for the positive portion of the sample while a vertical mirror reflection would be the negative correspondent.

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20 This measure is equivalent with the double sum, $\frac{1}{n} \sum_{t_1}^{T_2} \sum_{t}^{n} AR_i(t)$. 

22
tionally report that cross-sectional dependency would lead to systematic underestimation of variances and in turn, the null hypothesis of no abnormal returns will be rejected too often.

Brown & Warner (1985) continued the discussion with that if the degree of dependence due to non-synchronous trading is small, non-clustering conditions would be enough for ignoring the cross-sectional correlation. Non-clustering is also verified by MacKinley (1997) as sufficient for absence of cross-sectional correlation.

2.5 Statistical Testing

When the process finally reaches the hypothesis testing there exist numerous different tests to choose from, all providing benefits as well as disadvantages in the form of correctness. Which one to choose depends on the characteristics of the study as well as the data sample. First to mention comes naturally as standard statistical t-tests of the aggregated measures derived in Section 2.4. These tests are normally referred to as parametric tests within the literature [see for example Corrado & Truong (2008), MacKinley (1997) and S.V.D.Nageswara Rao & Sreejith (2014)], which also argue that parametric tests are heavily dependent on normally distributed returns, causing non-parametric tests to yield more accurate results.

One particular non-parametric test is the rank test, which many authors refers to originate in Corrado (1989) [see for example Cowan (1992), Campbell & Wasley (1993), and Bartholdy et al. (2006)], and is suggested to under certain conditions give the most accurate results. However, the test has been refined since its origin in order to account for the experienced limitations, and Luoma (2011) explains the procedure in a quite clear manner.

Based on Corrado (1989) and Corrado & Zivney (1992), Luoma (2011) describes the rank test in detail, where firstly one have to standardize the abnormal return given in Equation (2.7). Let \( SaR_t(t) \) be this standardized abnormal return, which is defined as the abnormal return divided by its standard deviation,

\[
SaR_t(t) = \frac{AR_t(t)}{\hat{\sigma}_{AR_t}}, \quad \forall t \in \mathbb{Z},
\]

where \( \hat{\sigma}_{AR_t} \) is calculated as in Equation (2.8), for large samples. One of the conditions for the rank test to be superior in the testing procedure is the absence of event induced volatility. Event induced volatility refers to that the volatility may increase around the actual event while it is estimated during a period in absence of this increased volatility. It may however be hard to ensure homoskedasticity within a sample, which leads to a measure robust to this kind of bias. Boehmer et al. (1991) and Corrado & Zivney (1992), cited in Luoma (2011), refined the standardized abnormal return to be such a robust measure, defined as

\[
SAR_t(t) = \begin{cases} 
SaR_t(t), & \text{for } t_1 \leq t \leq T_2 \\
SaR_t(t), & \text{elsewhere},
\end{cases}
\]

where

\[
\hat{\sigma}_{SaR(t)} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (SaR_i(t) - SaR(t))^2}
\]

Under conditions of homoskedasticity, the variances of the samples are constant, as oppose to heteroskedasticity where they fluctuate with time.
is the cross-sectional standard deviation of $SaR_i(t)$ in which

$$\overline{SaR}(t) = \frac{1}{n} \sum_{i=1}^{n} SaR_i(t).$$

Equation (2.9) is valid for $t$ values outside the event window because the test requires more SAR values than produced within this interval. Now let the length of the SAR window be denoted by $L_{SAR}$, then the rank of the standardized abnormal return is given by

$$r_i(t) = \text{rank}(SAR_i(t)), \quad r_i(t) \in \{1, \ldots, L_{SAR}\},$$

where the security with the lowest standardized abnormal return is assigned rank one. The rank is further scaled through letting

$$K_i(t) = \frac{r_i(t)}{L_{SAR} + 1},$$

and the average scaled rank is found by

$$\overline{K}(t) = \frac{1}{n} \sum_{i=1}^{n} K_i(t),$$

caus[ing the sum of scaled ranks to equal the SAR window length divided by two.]

Time-series aggregation of the cumulative scaled ranks for the set as a whole as well as the subset alone gives

$$U_i(t) = \begin{cases} \sum_{t=t_1}^{T_2} K_i(t), & \text{in event window} \\ \sum_{t<t_1}^{T_{SAR}} K_i(t), & \text{in SAR window}, \end{cases}$$

in which $t$ and $T$ are arbitrary integers for any specified SAR window. Furthermore the cross-sectional aggregated scaled rank is defined inside the event window and found through

$$\overline{U}(t_1, T_2) = \frac{1}{n} \sum_{i=1}^{n} U_i(t_1, T_2).$$

In order to test a sample for an event effect, the observed mean and variance of the cumulative scaled rank should be tested to see whether they equal their theoretical values or not. Luoma (2011) states that the sample expectation is uniformly distributed and thus, equals

$$E[\overline{U}(t_1, T_2)] = \frac{1}{2} \tau,$$

(2.10)

where $\tau = T_2 - t_1$, and the variance is given by

$$\text{Var}[\overline{U}(t_1, T_2)] = \frac{\tau (L_{SAR} - \tau)}{12(L_{SAR} + 1)n} \left( 1 + \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij}(t_1, T_2) \right).$$

The SAR window is an extension of the event window, that is, the event window is a subset of the SAR window.

Luoma (2011) tested SAR windows of length 25, 50, 100, and 239 (excluding the event window length itself for which he also tested several lengths), and found the most statistical significance within tests of the shorter SAR window interval.
For a market to be efficient at semi-strong degree, Equation (2.10) must hold for any $\tau$ with length shorter than $L_{SAR}$. By assuming that the cross-sectional correlation of cumulative ranks equals the cross-sectional correlation of returns, which previously mentioned is reasonable to equal zero in absence of clustering, the second term within brackets in the variance formula equals zero. This reduces the null hypothesis to only cover if the mean value, $\mu(t_1, T_2)$, equals its expectation, hence, the statistical test is constructed as follows:

$$H_0 : \mu(t_1, T_2) = \frac{1}{2} \tau \quad \text{(The market is semi-strong efficient)}$$

$$H_a : \mu(t_1, T_2) \neq \frac{1}{2} \tau \quad \text{(The market is semi-strong inefficient)}.$$

Luoma (2011) additionally compared different versions of the proper test-statistic to test the null hypothesis against the alternative, starting from the one derived by Corrado & Truong (2008), following the version by Campbell & Wasley (1993). He further modified their test-statistics to be robust against cross-sectional correlation and proposed

$$t = \frac{\bar{U}(t_1, T_2) - (1/2)\tau}{\sigma_{\bar{K}(t)}} \left( \frac{L_{SAR} - 2}{L_{SAR} - 1 - \left( \bar{U}(t_1, T_2) - (1/2)\tau \right) \sigma_{\bar{K}(t)}^{-2}} \right)^{1/2} \quad (2.11)$$

to perform the task. The volatility term is given by

$$\sigma_{\bar{K}(t)} = \sqrt{\frac{\tau (L_{SAR} - \tau) \sum_{t=1}^{L_{SAR}} k(t) \left( \bar{K}(t) - \frac{1}{2} \right)^2}{L_{SAR} (L_{SAR} - 1) \sum_{t=1}^{L_{SAR}} k(t) \left( \bar{K}(t) - \frac{1}{2} \right)^2}},$$

where $k(t)$ is the total amount of sampled securities at time $t$. The test-statistic in Equation (2.11) has a minor tendency to under-reject the null hypothesis for an event window of $(-6, 5]$, but is still argued to be the best alternative among the ones studied. Luoma (2011) however argues that the small loss in power of the test when modifying to account for the cross-sectional correlation turns out to be small.

**Remark 6**! The developed test-statistic aims to test a portfolio of stocks for abnormal performance rather than individual securities, and a modification of the test would be appropriate if the latter is the desired hypothesis. Hence, one cannot exchange the cross-sectional aggregated scaled rank with the time-series aggregated in order to test for individual performance.

The test-statistic should now be measured against a critical value, $t_{\frac{0.05}{2}}$, d.f., with $L_{SAR} - 2$ degrees of freedom and a desired $\alpha$-level. This value can be approximately read from a t-table while several software programs can provide a more precise number. If $|t| > t_{\frac{0.05}{2}}$, d.f.

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24At first glance one automatically would think that $k(t)$ should equal $n$. If different sample sizes however are used to measure the cross-sectional standardized rank at different points in time (that is, an average value of $K(t)$, which hypothetically can be calculated for different sample sizes in different time-points), then $k(t) \neq n$. Usually the sample size does not differ in magnitude through time though.

25The degrees of freedom measures the amount of explanatory variables within a set in a way that the set can be fully explained. For example in the sample variance, d.f. is given by $n - 1$ where the $n^{th}$ component is represented by the sample mean and thus, a dependent variable. [Box (1978)]

26The $\alpha$-level is the level of significance at which a researcher would like to test the hypothesis. For instance, an $\alpha$-value of 0.05 indicates that the test would be reliable at 95%. [Wackerly et al. (2007)]

27A t-table is available in for example Wackerly et al. (2007), while Microsoft Excel is an example of a software providing statistical tools.
in a two-tailed test, the null hypothesis is rejected, otherwise there is now statistical evidence of the desired significance level suggesting that the null hypothesis should be false.

As previously mentioned, the rank test has been showed to outperform other tests under certain conditions. The conditions that have been taken into account through modification of the rank test are return induced volatility as well as cross-sectional correlation. Bartholdy et al. (2006) moreover stress that when the event day is unknown, parametric tests tend to outperform non-parametric tests. Cowan (1992) conclude that if the sample contain thinly traded stocks, a non-parametric sign test would outperform the rank test, while Campbell & Wasley (1993) argue that in presence of clustering the rank test loses substantial power.

**Final Remark 7!**

As stated in the introductory section of this chapter, the methodology of event studies may seem daunting due to the statistical issues related to all different steps. However, all of these individual sources posit a respective solution or may in practice be of a minor importance and hence, might be ignored without a significant loss in power. Nevertheless the bottom line is that event studies provide a good financial tool for investigating if the eternal search for abnormal returns is praised for its effort.

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28 The previously discussed studies indicating that the rank test is superior contra other tests has evaluated the rank test when not accounting for cross-sectional correlation. The test allowing for such bias was firstly developed, as far as the authors of this thesis can verify, by Luoma (2011).
CHAPTER 3

EARNINGS SURPRISES AT NASDAQ OMX STOCKHOLM

This chapter empirically examines abnormal stock returns around earnings surprises on Nasdaq OMX Stockholm. All companies listed on a stock exchange release earnings-announcements at each firm quarter. When reported earnings deviate from the consensus, the share is expected to trade upward or downward in relation to its equilibrium. However, earnings per se does not give enough information about the amplitude on share prices, and therefore earnings are divided by the number of shares outstanding to be put in relation to the stock price. The resulting measurement is consistent and easily compared between shares as earnings per share (EPS), and its estimated counterpart, the consensus EPS, is an average analyst estimate compiled by the research company SME Direkt and released in financial news.

3.1 Construction of the Data Sample

The selection criteria requires the stock’s actual- as well as consensus EPS to be listed in the SME Direkt database under the relevant study period and that the security has been listed on Nasdaq OMX Stockholm for at least the four closest full quarters prior to the announcement quarter. The retrieved sample comprised 72 such stocks where the presence involves representatives from Large Cap and Mid Cap, but the authors however found specific firm-types to be excluded from the sample where investment companies such as Investor, Ratos, Kinnevik, Industrivärden and Svolder are some examples while real estate companies such as Fabeg and Klövern are others. The authors suspect that the reason for these exclusions may be that the concerned stocks are evaluated by substantial value of asset portfolios rather than EPS

The full sample however provided 1058 quarterly EPS estimates released ahead of their respective earnings event. This set was narrowed down from a much larger database, where firstly all yearly EPS estimates were removed since the fourth quarter- and yearly EPS usually

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are announced simultaneously. Secondly, the time period chosen was the most consistent period with samples of both actual data and estimates. The database originally contained more actual earnings data before 2009 but in absence of corresponding estimates, whereas there were more estimates after 2012, but irregular series of actual data, thus, the full study investigates earnings surprises for all firm quarters during the financial years 2009 to 2012.

The earnings events were then scaled by their level of surprise, measured by absolute deviation in actual earnings from consensus. The minimum deviation was set at 5% in order to have as good as possible trade-off between the surprise-size and number of sampled events. The final sample comprised 808 earnings surprises spanning from April 1st 2009 to February 15th 2013. 463 of these surprises were positive with deviations between 5.19% and 2221.52%, while 345 were negative with deviation between −5.39% and −883.22%. The positive sample was then divided in half such that one panel constituted large surprises while the other represented small ones, and the cut-off between them was around 18.20%. Three different study groups were then formed with a respective sample of 50 randomly selected surprises from each sub-sample (large positive surprises, small positive surprises and negative surprises), where the randomness was uniformly distributed without replacement, over the group’s total events.

The authors moreover decided to investigate surprises over the interval (−6, 5], which constituted each security’s event window. All estimation windows were further set independently over the four closest full quarters prior to the announcement quarters. Daily time-series of return data were then collected from \( \text{http://www.nasdaqomxnordic.com/aktier/historiskakurser} \) between April 1st 2008 to February 20th 2013. This also accounts for the market proxy, which was chosen to be the broad Nasdaq OMX Stockholm Gross Index. The collected data was then used within the market model according to theory given in Chapter 2, in order to estimate the abnormal returns in the SAR window, which automatically fills these numbers in the corresponding event window. The interval of this SAR window was set to (−31, 10] which gave a total of 41 SARs where 25 were located prior to the event window and 5 after. This interval was chosen to reflect the window length of highest statistical significance in [Luoma (2011)].

A Pervasive Review of Assumptions and Possible Sources to Bias

As stated in the introductory chapter of this thesis, presence of limitations causes the treatment of all potential biases to be impossible. The introduction also mentioned that access of consensus data was restricted to only account for 72 securities whereas the Swedish main market listed around 250 stocks during the time period. The authors found the full set of stocks listed on Nasdaq OMX Stockholm Small CAP as well as Large/Mid CAP investment and real estate companies, to be fully excluded from the sample (but the sample was not considered grouped as it constituted representatives from many industries/sectors as well as from the two remaining market capitalization groups), causing the study not to account for their influences. As a result however, assuming trading frequency to be positively correlated with firm size the authors could theorise absence of non-synchronous trading within the sample. If there still

\[ \text{While the trade-off itself serves as an argument for the level of surprise at 5%, there is also an economical significance in this number. For a company having a price/earnings ratio at 10, an earnings surprise of 5% would yield a 0.5% impact on share price above expectation, ceteris paribus.} \]

\[ \text{To clarify, the OLS estimation for an event that occurred for example in April 23rd 2009, was estimated using data from April 1st 2008 to March 31st 2009. An event that occurred for example February 22nd 2010 was estimated using data between February 1st 2009 to January 31st 2010.} \]

\[ \text{OMX Stockholm GI consists of 281 components and is thereby the broadest share index on OMX Stockholm. Further, it is a gross index meaning that all dividends paid out by the components are re-invested. The index was deliberately chosen as market proxy, and in line with the security data collected.} \]
would have existed some thinly traded stocks within it, they were expected few in amount. The chosen method of calculating (lumped) returns has also been verified to approximately hold for thinly traded stocks [at the Danish stock market by Bartholdy et al (2006)] and recommended to use when the study needs to be performed quickly, while the rank test should be superior if the exact event day is known and in absence of event induced volatility as well as clustering. The authors have however been utilizing a special version of this hypothesis test that is supposed robust to event induced volatility, while they due to the time limitation had to assume that the exact event day equalled the announcement date. The problems arising with this latter assumption were not expected to be very severe since evaluation of abnormal returns occurred over an interval of days rather than the event day alone, and again, thinly traded stocks were assumed non-present. Thus, under these circumstances biases in the rank test should have been at minimal if no clustering was present. The issue of clustering will be returned to later within this section.

The restriction to daily return data caused the abnormal returns to be measured as daily averages rather than in immediate effects, which excluded the possibility of investigating the response within for example one hour after the earnings reports were released. This circumstance constituted a problem by itself, but the problem would have been exaggerated if clustering in any form occurred during a day in the SAR window and especially in the event window. With this is meant that if one or more events (that is, informational releases from the individual firm, other firms, or from macro sources) occurred in the investigated interval in which a firm reported earnings, the abnormal return may have been reduced or enlarged due to that other event. This would have been particularly cumbersome if the clustering occurred at the exact event day since the immediate market response to earnings-announcements on this day are expected to be more dramatic contra other days within the interval.

Another problem arising with clustering is that abnormal returns may end up with spurious autocorrelation and/or cross-sectional correlation between them. This would violate the core assumption of error terms being uncorrelated and causing the OLS estimation (that the authors according to an earlier statement assumed to be the best estimation procedure although true ex-post values of the market return were used rather than the historical average mean) to no longer be BLUE. Assuming the market model to be correctly specified for its purpose, the estimated constants should not be biased but they would no longer be the minimum variance ones. Any estimate in time would thereby most likely differ from the true value which then was used in order to estimate abnormal returns, thus the hypothesis testing of abnormal returns should have been undeniably unreliable. The bottom line is that the issue of clustering seems to be pervading through more or less all steps of the event study methodology causing the authors to assume no kind of such thing, and that assumption was drawn by construction. In an attempt to replicate the selection process of the study by Brown & Warner (1985), where clustering turned out to be of a minor and unimportant degree, the authors randomly selected events (although without replacements) to be included from a total of 72 firms (232, 231, and 345 events for the large positive, small positive, and the negative panel respectively). The trade-off between no-clustering conditions and enough events included for representing the full population, as well as for asymptotically reduce bias in the statistical estimators of the testing procedure, was judged to be fair in aspect of the prior study. The event window further turned out to be the same in both studies but the two differed in terms of event periods. While the prior study included events spanning over a 17 year interval, the authors of this thesis only

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5 Obviously, this additionally forces the assumption of that all securities could be obtained at the closing price during the entire day.

6 The authors decided that 50 events out of at least 200 would include at maximum one of four events. This seemed reasonable in context of reducing the risk of clustering conditions.
accessed events over a 4 year period. However, all potential actions, based on the study's given conditions and limitations, have by the authors been taken in order to eliminate clustering. Thus, the authors assume a very small degree of this source to bias, if any at all (and recall that non-clustering conditions is enough for ignoring cross-sectional correlation if the degree of dependence due to non-synchronous trading, that is thinly traded stocks, is small). They moreover rely on the utilized rank test developed by Luoma (2011) to be robust against the remaining cross-sectional correlation of returns, if still present, which actually was the purpose for the modification made by that writer.

Time issues additionally limited the market model estimation process of abnormal returns, where the estimation window was set as one year in terms of full quarters prior to the announcement quarter. This lead to all returns in one quarter being estimated under the same time interval, hence, individual windows with meeting estimation and event window edges were not obtainable. Bias could have arose due to return affecting events that potentially occurred between non-synchronous events and hence, may have affected some reactions from earnings-announcements while leaving others alone. The estimation model would then not make any difference between the two cases, which obviously should be made for correctness. However, non-overlapping windows, and particularly when the security is non-thinly traded, should reduce the risk of spurious autocorrelation due to non-clustering conditions. An attempt to reduce spurious autocorrelation was also made through estimating the market model over a full year estimation window, such for the serial-correlation to asymptotically disappear as in Equation (2.8).

The market model moreover requires the market return in order to estimate the constants, alpha and beta. The market portfolio by definition should represent all existing assets having any value, hence, the broader proxy is the better measurement for this portfolio. Therefore Nasdaq OMX Stockholm Gross Index, the broadest index the authors could find at the Swedish equity market, was adopted to act as the market proxy. This index is however far from the definition of the entire market and thereby the critique raised by Roll (1977) also apply to the study of this thesis.

As an endnote, although the econometric properties of the possible biases and their solutions have been investigated by others, it is important to keep in mind that these have been evaluated at other markets in different time, using different sample characteristics (that is, selection criteria, sample size, window lengths etcetera). Based on these isolated studies however, one cannot explicitly draw the same inferences about other samples in other circumstances. The last assumption is therefore stated using a heuristic where the authors are aware of the representativeness. Hence, the final assumption is that all the econometric investigations declared in Chapter 2 of this thesis also holds for the Swedish market in general, and particularly for the sample posited by the authors.

3.2 Results of the Study

As seen within the event study methodology described in Chapter 2 there are several approaches to investigate for market efficiency. Analysing the aggregated cumulative abnormal returns are superior in terms of graphical overviews of the surprise effect while developed tests...
can provide more statistical inferences. On the other hand, the latter one cannot provide a satisfactory graphical representation in order to see how and where the potential effect takes on. The authors of this thesis however thought that one way of investigation must not exclude the other and have therefore been using both methods to capture each respective advantage. The analysis of the cumulative abnormal returns are deemed as economical because no statistical theory was applied in the evaluation process, while the rank test was entrusted to provide the pure statistical evidence of this study.

**Economical Inferences from Abnormal and Cumulative Abnormal Returns**

Theory suggests that an efficient market displays no expected abnormal return around an earnings surprise event. To see whether this expectation equals the theory or not, daily cross-sectional aggregated abnormal returns $\bar{AR}(t)$s were computed. Estimates were investigated both within the event window itself, as well as for the whole SAR window, in order to investigate for persisting deviation from zero. In addition, since daily observations most likely will deviate from the expectation, $\text{CAR}(t_1, T_2)$s were calculated to see the summed effect over the event window interval. For notational convenience, the time indexing will from now on be excluded.

Table 3.1 displays a summary of the behaviour of the $\bar{AR}$s and $\text{CAR}$s inside the event window. In all three panels of surprises, the abnormal deviation generates different signs at different days which is exactly what the Efficient Market Hypothesis predicts. However, the average values over all days are non-equal zero and appears in the same sign as one expects from the direction of the surprise. The two groups comprising positive surprises both have an average $\bar{AR}$ of 0.11% while the negative panel constitutes an absolute deviation of 0.25% from the expected one. Additionally, looking at the small positive and the negative panel, the average $\bar{AR}$ is higher in magnitude within the event window rather than the SAR window, indicating an event related increase of abnormal returns in the $(-6,5]$ interval.

The day which contributed with the highest $\bar{AR}$ in the event window was the same for all three panels of investigation. Not surprisingly, this day was the event day itself, where the effect was 1.47%, 0.71% and $-2.96\%$ for the large positive, small positive and negative panel respectively. These numbers moreover suggest the size of the effect to relate with the size of the surprise. It also seems like investors are most sensitive to negative surprises, which is not unlikely because of investors’ loss aversion.

Turning the focus to the $\text{CAR}$ values, all panels show a cumulative effect in the direction of the surprise around the announcement. From Table 3.1 there seems to be a reverse effect of $\text{CAR}$s prior to the announcement for the small positive and the negative panel respectively, which is verified by the graphs in Figure 3.1. For both of these the trend takes off at day $-4$, but looks more severe for the small positive group since it lasts until the announcement is made, whereas for the negative group it start to flatten (and slightly move in expected direction) after only one day’s duration. The $\text{CAR}$ of the large positive panel however, seems not to provide such an effect since the values increase and decrease alternately prior to the announcement.

One way the authors interpret the reaction in the small positive panel is that investors under-estimate information ahead of the announcement and thereby sell of some securities when only a small increase above previous expectations is expected from the new information (such as for instance the released consensus), while they think that large increases may be enough to not under-perform the expectation. In other words, when investors spot a better investment opportunity through bigger surprises than previously expected, they reallocate their

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9Abnormal returns for the entire SAR window can be obtained if requested from the authors.
<table>
<thead>
<tr>
<th>Event Window Day</th>
<th>Large Positive Surprises</th>
<th>Small Positive Surprises</th>
<th>All Negative Surprises</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$AR(t)$</td>
<td>$CAR(t_1, T_2)$</td>
<td>$AR(t)$</td>
</tr>
<tr>
<td>−5</td>
<td>0.16%</td>
<td>0.03%</td>
<td>−0.11%</td>
</tr>
<tr>
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<td>0.15%</td>
<td>−0.15%</td>
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<td>−0.20%</td>
</tr>
<tr>
<td>0</td>
<td>1.47%</td>
<td>0.12%</td>
<td>−2.96%</td>
</tr>
<tr>
<td>1</td>
<td>−0.24%</td>
<td>0.66%</td>
<td>−0.55%</td>
</tr>
<tr>
<td>2</td>
<td>−0.32%</td>
<td>0.90%</td>
<td>0.01%</td>
</tr>
<tr>
<td>3</td>
<td>−0.11%</td>
<td>1.15%</td>
<td>0.31%</td>
</tr>
<tr>
<td>4</td>
<td>0.27%</td>
<td>1.19%</td>
<td>−0.14%</td>
</tr>
<tr>
<td>5</td>
<td>−0.07%</td>
<td>−0.35%</td>
<td>0.20%</td>
</tr>
<tr>
<td></td>
<td>Average $AR$</td>
<td>0.11%</td>
<td>−0.25%</td>
</tr>
<tr>
<td></td>
<td>Average $AR_{SAR}$</td>
<td>0.11%</td>
<td>−0.07%</td>
</tr>
</tbody>
</table>

Table 3.1: Event Window Time-Series

The table comprises three panels of ARs and CARs computed using the theory of Chapter 2 for an event window of $(-6, 5]$. There are two positive groups divided into large surprises and small surprises, and one group representing negative surprises. For all three panels, the numbers are aggregated values from a uniformly distributed sample of 50 securities each. The average $AR$ and $AR_{SAR}$ denotes arithmetic means over the event window and SAR window respectively, in which the SAR window posits 41 daily observations.

Capital is reallocated to sources where they can earn a higher return.

Under-estimation of information may also be the explanation behind the reaction in the negative panel, where also early optimism may cause the effect to be more severe, but then the fear of losing capital causes a turnover when the investors interpret the information more realistic.

Moreover, the highest CAR value of the large positive panel is achieved on the event day, indicating a sell-off successive to the announcement. The most likely reason is that the supply of shares is in excess of demand as investors bank profits made from the large surprise, causing a price fall due to overreaction. The authors suspect that investors potentially assume that this large surprise is something really abnormal and a "once upon a time event" and thereby expect a contrarian effect to follow in order to balance towards equilibrium. In contrast, for small positive surprises there is a lagged effect of the CAR where its highest value is achieved day 4 after the announcement. A reason might be that investors interpret good news of smaller scale as positive in the longer term (that they signalize a new level of earnings), and thereby

\[\text{Table 3.1: Event Window Time-Series} \]

<table>
<thead>
<tr>
<th>Event Window Day</th>
<th>Large Positive Surprises</th>
<th>Small Positive Surprises</th>
<th>All Negative Surprises</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$AR(t)$</td>
<td>$CAR(t_1, T_2)$</td>
<td>$AR(t)$</td>
</tr>
<tr>
<td>−5</td>
<td>0.16%</td>
<td>0.03%</td>
<td>−0.11%</td>
</tr>
<tr>
<td>−4</td>
<td>−0.16%</td>
<td>0.15%</td>
<td>−0.15%</td>
</tr>
<tr>
<td>−3</td>
<td>0.08%</td>
<td>−0.15%</td>
<td>0.73%</td>
</tr>
<tr>
<td>−2</td>
<td>−0.02%</td>
<td>−0.18%</td>
<td>−0.04%</td>
</tr>
<tr>
<td>−1</td>
<td>0.13%</td>
<td>−0.59%</td>
<td>−0.20%</td>
</tr>
<tr>
<td>0</td>
<td>1.47%</td>
<td>0.12%</td>
<td>−2.96%</td>
</tr>
<tr>
<td>1</td>
<td>−0.24%</td>
<td>0.66%</td>
<td>−0.55%</td>
</tr>
<tr>
<td>2</td>
<td>−0.32%</td>
<td>0.90%</td>
<td>0.01%</td>
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<tr>
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<td>−0.11%</td>
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<td>−0.14%</td>
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<td>−0.07%</td>
<td>−0.35%</td>
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<td></td>
<td>Average $AR_{SAR}$</td>
<td>0.11%</td>
<td>−0.07%</td>
</tr>
</tbody>
</table>

At first sight one could also easily claim this to be the explanation behind the average $AR$ being equal between the two positive panels. If investors always reallocate towards better opportunities (that is, they maximize their expected utility), an equilibrium between the options' respective marginal utilities should arise since it is the aggregate investor that determines the market prices and thereby indirectly the market returns. If the expected marginal utility solemnly was determined by the increase in expected return (and if the increase in this study equaled the average $AR$), the marginal utilities would equal and the two investment opportunities would act as perfect substitutes with a marginal rate of substitution of 1. In reality however, the risk is also a factor affecting the investor’s utility maximization and thereby can no conclusion regarding the equality of equal average $AR$s in the positive panels be made from the study of this thesis.

Moreover, the act of short selling normally carries more risk than entering a long position, causing investors to require a higher expected return for bearing that extra risk. This is partly verified by the negative panel, in which the average $|AR|$ turned up more than twice the size of the same parameter for the positive panels.
The figure illustrates each respective CAR\((t_1, t_2)\) of the three panels studied, and shows how the cumulative abnormal returns stack around the earnings surprise. The measurement points along the x-axis are from the closure of the market at each day, while the solid vertical line indicates the closure at the event day.

Figure 3.1 illustrates these effects of the CARs for the three panels respectively. It is clear that the abnormal returns are significantly large on the interval \([-1, 1]\) with a dispersive effect on the interval \([2, 5]\). Real world data seldom visualize as well as their theoretical counterparts, as seen if comparing the graphs with Figure 2.3. However, statistical inferences about their dissimilarities is needed, which are provided in the next-coming section.

**Statistical Inferences Provided by the Rank Test**

While economical inferences speak their language, statistical tests give a level of confidence at which the studied data is statistically reliable. Recall from Section 2.5 that the null hypothesis is constructed such that all scaled ranks have uniform probability, rendering the market semi-strong efficient if the null hypothesis is accepted. This means that if there exists an interval around the event in which the rank distribution is not uniform for a statistically accepted level, the market is inefficient.

Since the event window interval has length \(\tau = L_{Ev} - 1 = 10\), it follows from Equation (2.10) that the expectancy of uniform ranks within the event window is 5, thus a statistically accepted deviation from this value in the event window is required to infer the market as
inefficient.

Table 3.2 declares the result for each panel respectively. The first and second row shows the empirical cumulative scaled rank inside the event window as well as the differences from their respective expectations. This difference should be inferred zero for a true null hypothesis, or equivalently no event effect.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Large</th>
<th>Small</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{U}(-5,5) )</td>
<td>5.571</td>
<td>5.657</td>
<td>5.841</td>
</tr>
<tr>
<td>( \hat{U}(-5,5) - \hat{E}[\hat{U}(-5,5)] )</td>
<td>0.571</td>
<td>0.657</td>
<td>0.841</td>
</tr>
<tr>
<td>( \hat{\sigma}(\hat{K}) )</td>
<td>0.334</td>
<td>0.353</td>
<td>0.382</td>
</tr>
<tr>
<td>( t )</td>
<td>1.757</td>
<td>1.926</td>
<td>2.317</td>
</tr>
<tr>
<td>( t_{0.05,39} )</td>
<td>1.685</td>
<td>1.685</td>
<td>1.685</td>
</tr>
<tr>
<td>90% C.I.</td>
<td>[5.024, 6.119]</td>
<td>[5.082, 6.232]</td>
<td>[5.229, 6.452]</td>
</tr>
<tr>
<td>( t_{0.025,39} )</td>
<td>2.023</td>
<td>2.023</td>
<td>2.023</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>[4.897, 6.229]</td>
<td>[4.944, 6.347]</td>
<td>[5.107, 6.574]</td>
</tr>
<tr>
<td>( p )-value</td>
<td>0.087</td>
<td>0.061</td>
<td>0.026</td>
</tr>
</tbody>
</table>

**Table 3.2: Statistics of the Rank Test**

The table comprises three panels of metrics for the statistical test. \( \hat{U}(-5,5) \) is the cumulative scaled rank in the event window, whose expected value equal five. \( \hat{\sigma}(\hat{K}) \) is the volatility of scaled ranks, while the \( t \)-value refers to the observed \( t \)-statistic. The critical values of \( t_{2, \alpha, d.f.} \) in rows four and six are \( t \)-distributed two-tailed \( \alpha \)-values with 39 degrees of freedom. The \( p \)-value is the exact minimum \( \alpha \)-level at which the null hypothesis is rejected and C.I. is short for the confidence interval, reported for respective level of significance.

The observed value, calculated by Equation (2.11), is measured against the critical value which follows a \( t \)-distribution with 39 degrees of freedom. At the 10% level of significance, all tests reject the null hypothesis, which means that with 90% level of confidence, the market is inefficient during the event window in all three cases. The corresponding \( p \)-value for the large and small positive surprise panels are 0.087 and 0.061 respectively, meaning that the results are reliable to 91.3% and 94.9%. Furthermore, the highest statistical deviation is found in the negative surprise panel, where the \( p \)-value is as low as 0.026, which translates into a statistical difference from the uniform distribution with 97.4% confidence. The probability that the null hypothesis is true, is thus less than 9% in all cases and only 2.6% for the negative panel.

To sum it all up, the statistical tests suggest to accept the null hypothesis of the two positive panels while reject the null hypothesis of the negative panel, at the desired level of significance (\( \alpha = 0.05 \)). The authors however think that in conjunction with the economical inferences found in Section 3.2, the positive panel provides enough evidence against the Efficient Market Hypothesis, although only statistically with 93.9% confidence. In addition, since this test rather under-rejects the null hypothesis than over-reject it, these arguments are justifiable. Thus, it is thereby statistically rather safe to infer that there are semi-strong inefficiencies in the market, at least when aggregated over individual earnings surprise events.
CONCLUSION

As stated earlier, a study on market efficiency at the semi-strong degree is in fact a study investigating how events in the financial market shift returns from their estimated equilibriums such that an abnormality occurs. It is a misconception that an efficient market would equal a return generating process which is totally random. Rather, researchers try to understand whether market efficiency imperfections can be exploited to gain excess returns.

If the market is efficient, it should include all potential sub-markets or groups within it. For any interval, event, or any magnitude of events, the market is either efficient or inefficient, it simply cannot be both at the same time. The task of proving market efficiency is a life long duty since the variations of event studies are infinitely many and all of them have to show market efficiency. In order to prove the opposite on the other hand, only one circumstance of inefficiency is required to fulfil the task. Hence, it should be enough to show that the market is inefficient in at least one panel of the study within this thesis in order to conclude market semi-strong inefficiency on the Swedish stock market.

In the study covering five days before and five days after an earnings surprise was released, the authors investigated market efficiency using three panels of samples, where all of these gave statistical results with quite low level of significance (the highest had a \( p \)-value of 0.087). Some researchers however argue that for a result to be significant, a test should be accepted at the 5\% \( \alpha \)-level and some even advocate the 1\% level of \( \alpha \). The authors are however willing to follow the prior and thereby accept the negative panel as evidence of market inefficiency at the 2.6\% level of significance for negative surprises, hence, abnormal returns are possible to earn through short-selling equity on negative earnings surprises at the Swedish market \( \pm 5 \) days around an earnings surprise occur.\textsuperscript{11} The majority of this effect though, seems to be intra-day related due to the fact of that the bulk abnormality occurs somewhere between the closing price of day \(-1\) and day 0. Overall, investors seem to be more averse to negative effects since the negative abnormal magnitude was almost twice as the large positive one, even though events were randomly selected and there were more large positive events in absolute magnitude.

With the results in hand, the authors can further conclude that investors may take advantage of the market being semi-strong inefficient. The trading strategy in order to catch some of the average abnormal returns is through take a one day short position in securities which firms surprise with negativity of less than \(-5\%\) of the earnings that were expected. Investors looking for long positions may catch an abnormal return if taking a four day position in companies

\textsuperscript{11}The authors moreover accept the small positive surprises to provide evidence against the Efficient Market Hypothesis with a \( p \)-value at 0.061 in conjunction with the graphical CAR result. They further do not consider the large positive panel to provide sufficient evidence against the null hypothesis. Since one circumstance of inefficiency alone however speaks for the entire population of earnings surprises, semi-strong market efficiency must be rejected.
declaring excess earnings but smaller than 18.20%. Even if the exact day to close a position would deviate from these suggested ones, the peak of the negative and small positive panel’s respective abnormal return is located at the announcement day and seems to remain unreachable in the reminder of the event window. Thus, averaged over each of these two panels an abnormal return should be obtainable, maximized or not. No opportunities of utilizing the earnings-announcement from firms reporting earnings greater than 18.20% were found since no market inefficiency could be verified through this group of events.

It is however important to remember the potential of representativeness since a four year interval seems short in the full horizon perspective, and additionally using techniques developed for other samples on other markets. This automatically leads to potential further research in forms of econometric analysis of the estimation model as well as the hypothesis testing procedure, all using Swedish historical data from a longer time interval. The assumptions made by the authors may additionally be relaxed for further states of correctness and minimized level of bias. A very interesting continuation of this study would in addition be to investigate semi-strong form market efficiency using intra-day data in order to look for further abnormality patterns. Additionally, a study based on more estimates from the SME database could provide enough samples to include three positive and three negative panels respectively. Utilizing this opportunity of examining whether the magnitude of surprise matters, would give the possibility to investigate more profitable occasions taking advantage of the market inefficiency. Lastly, by adding trading volume as a parameter there are other ways of measuring unexpected earnings, which relates to investor attention, firm size and market environment [as did for example].

"According to the proponents of the Efficient Market Hypothesis, stock prices reflect all available information about companies and investors can’t beat the market indexes by stock picking. They say investors trying to find a secret formula are wasting their time because stock prices follow a random walk. Interestingly, this theory also implies that a monkey selecting stocks by throwing darts at a newspaper’s financial pages should perform as well as any star hedge fund manager who may or may not use inside information.

You could guess how this was such a huge relief for millions of stock market investors. Suddenly, one need not worry about timing or stock picking skills. Since all the information is incorporated into stock prices, there’s no need to do any research about the companies, or the macro economic developments, or the regulatory environment. Nothing, nada. Do you want to invest in an internet start-up that sells toys, with $30 million in revenue, $50 million in losses and $6 billion in market cap? Don’t worry. Markets are efficient. Just buy it, as simple as that."

— Warren Buffet (2010)

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12 The authors do not intend to advertise these strategies as "optimum" in a risk-to return context, but rather suggest, based on the results of this study, in what direction one could expect prices/returns to move. In addition, the optimum timing is probably not at the end of a trading day but rather intra-day located. The task of developing an optimal trading strategy is thereby left for the reader to perform.
REFERENCES


