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A short-term contrarian strategy in the Swedish Stock Exchange

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Master´s Thesis

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"For many years the following question has been a source of continuing controversy in both academic and business cycles: To what extent can the past history of a common stock's price be used to make meaningful predictions concerning the future price of the stock?"

- Eugene Fama (1965, p.34)

ABSTRACT

One of the most important topics in financial literature is the Efficient Market Hypothesis (EMH). Recent financial research has questioned this hypothesis, and many authors have reached the conclusion that a contrarian strategy creates abnormal positive returns. In other words a strategy profiting buying losers and selling winners. To explain this market behaviour researchers have come up with a numerous of hypothesis. The most widely discussed hypothesis is the so-called overreaction hypothesis. It maintains that stock prices systematically overshoot and therefore reversals can be predicted from past performance.

In this paper we analyze stock price behavior, in the context of the Swedish stock market. We employ data for the period 1995-2005 for stocks listed on A-listan, O-listan, Attract-40 and A-listan övriga. We will investigate the existence of short-term contrarian profits, after a large one-day price change and the sources of these profits. We employ a model following the methods used by De Bondt and Thaler (1985) and a cross-sectional regression model.

Our calculations indicate that contrarian strategies are profitable for SSE stocks and more pronounced for the extreme losers. The profits persist even after adjusting for market frictions, such as transaction costs and bid-ask spread. We believe that the main source behind the contrarian profit is market overreaction. Our results do, to some extent, agree with previous evidence published in the subject. This evidence of contrarian profits implies return predictability and possible rejection of EMH in its weakest form.

Keywords: overreaction, reversal, contrarian strategy, De Bondt and Thaler

1 Introduction

In the first chapter the reader is introduced to the subject of the thesis. Background, problem discussion, our purpose of the study followed by restrictions and target group are presented. The chapter closes with an outline.

1.1 Background

The topic price behavior of the financial markets has generated much research interest. The question of interest is whether the financial markets violate the Efficient Market Hypothesis. This is a very important question to ask because violations of the hypothesis can lead to the conclusion that financial markets are irrational – which is a contradiction to the foundation of financial theory.

In the first half of the 20^{th} century financial economists were mostly believers of the Efficient Market Hypothesis and the idea of a “random walk”. The idea behind the random walk hypothesis is that stock prices react immediately to new information and that tomorrow’s change in prices will reflect only tomorrow’s news and will be independent of price changes today. The theory of the Efficient Market Hypothesis is commonly used as a theoretical basis for current monetary and financial economics theories. According to the hypothesis, the price of a stock reflects all the information that is available to the public. Stocks were believed to be extremely efficient in reflecting information without delay.

1.2 Problem discussion

Benjamin Graham (1949) was a pioneer of security analysis and he was one of the first to discuss mean reversion. He advocated the purchase of stocks whose prices seem low compared to their fundamental value.

Graham based his contrarian advice on the premise that such low prices are expected to bounce back in the future. Therefore a “contrarian strategy” that consists of buying stocks with price declines and selling stocks short with large price increases can result in abnormal profit. Since then literature, on the winner-loser pattern and related subjects, has rapidly been growing. One explanation to this pattern comes from psychologists, economics and analysts who have shown that individuals tend to overreact to new information. De Bondt and Thaler (1985) used the extension of this view and suggested that stock prices also overreact to information through the behavior of overreacting individuals (De Bondt and Thaler, 1985). Given these presumably predictable variations in stock return following prices changes, we found it interesting to investigate whether a contrarian investment strategy can yield profits and if so, why it yields a profit.

Most contrarian studies have been conducted on the US-market. We have not found any research on short-term contrarian strategies in the Swedish stock market and we will contribute to existing research.

1.3 Purpose

The purpose of this paper is to investigate if short-term reversals exist in the Swedish Stock Exchange, and if a short-term contrarian strategy leads to an economically significant profit. If so, we will also attempt to address the causes behind a contrarian profit.

1.4 Restrictions

We have restricted the time horizon to January 1995 through January 2005, which is a large time span and a large number of quotes to give reliability to the calculations. The study is limited to data from the Swedish Stock Exchange (SSE, hereafter) from which we only include the A-listan, Attract-40, O-listan and A-listan Övriga. We can not include stocks from other lists because of lack of liquidity.

Because of the vast time horizon of the data sample we only included 400 randomly selected days to simplify calculations.

We do not attempt to calculate the true amount of market frictions since it is not possible. We will estimate a total percentage cost instead of trying to calculate all costs appearing when trading stocks.

1.5 Target group

The target group should possess good knowledge of finance, risk management and statistics. This mainly includes students of finance at a higher level and people active on the financial market.

1.6 Outline

Chapter 2
This chapter accounts for the theoretical foundations of the paper and will give the reader knowledge about different portfolio strategies.

Chapter 3
Chapter 3 covers what data used and how it was used. We described the used method and the procedure. Furthermore we account for two models used calculating reversals. Finally we criticize the used method.

Chapter 4
Chapter four presents the results from the computational work. We discuss and comment on the results.

Chapter 5
In this chapter we summarize the study and draw our final conclusion and discuss other important findings.

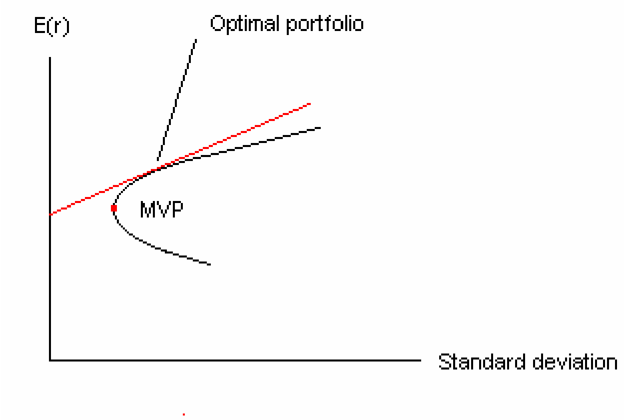
Chapter 6
In the final chapter we discuss alternative ways of conducting contrarian studies

2 Theory

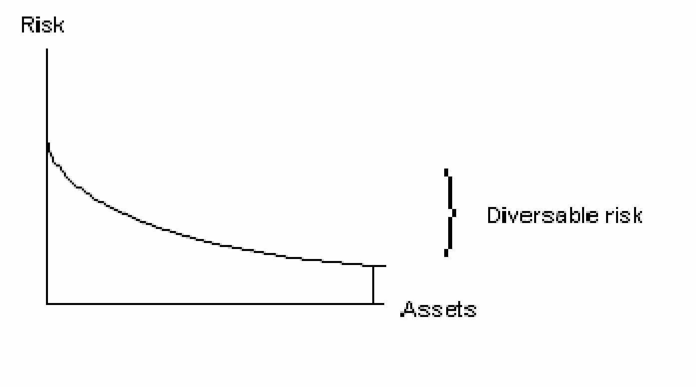
In this chapter we present the relevant economic theories to this Master's thesis. We also account for a number of hypotheses, developed to explain stock price behaviour.

2.1 Mean- variance portfolio

The goal of portfolio theory is to allocate the investments between different assets in an optimal way. In 1952, Harry Markowitz revolutionized portfolio theories when his paper "Portfolio Selection" was published. Markowitz proposed that all securities could be characterized by two variables, risk and expected return (Haugen, 2001). The most efficient portfolios were demonstrated by minimizing the variance for a given expected return. By plotting all the securities or portfolios with the lowest variance in a coordination system, you get the portfolio frontier. The portfolio with the lowest variance in this coordination system is called the Mean-Variance portfolio (hereafter MVP), and all the frontier portfolios with an expected return greater or equal to the MVP are efficient portfolios (Hansson, Lundtofte, 2005)



It is, by diversifying, possible to eliminate the unsystematic risk, which is one of the two basic types of investment risk. A diversified portfolio does not concentrate in one or two investment categories. Instead of "putting all the eggs in one basket" diversifying is a portfolio strategy designed to minimize the risk by combining a variety of investments. Since the unsystematic risk is diversable, the market does not reward investors for taking it. A diversified portfolio is therefore less risky than single securities.



2.2 Capital asset pricing model

The most common risk measure used in finance is the CAPM beta. Markowitz laid the foundation of CAPM in 1952, by showing how increasing the diversification lowers portfolio's variance. His idea was based on the assumption that stock returns are normally distributed and that all investors hold efficient portfolios according to the mean-variance criteria, and that the market portfolio also should be an efficient portfolio since it is a convex combination of all individual's portfolios.
Assumptions of the standard CAPM:

- Investors have homogenous expectations.
- Investors are rational mean-variance optimizers.
- The existence of a riskfree asset.
- The market is in equilibrium at all times.

Later Sharpe and Lintner further developed the model assuming that a riskfree rate of return exists and that investors can borrow and lend at this rate unlimitedly. They showed that no investors would hold any portfolio with an expected return below the riskfree rate of return. But if the riskfree return is lower than the return on the market portfolio, the tangent point on the portfolio frontier will be on the efficient part of the frontier. In this case, the tangent point will be the market portfolio of all risky assets in equilibrium. The positively sloped efficient frontier is called the Capital Market Line (CML) and the equation defines as:

$$E[r_p] = r_f + \frac{\left(E[r_m] - r_f\right)}{\sigma_m}\sigma_p$$

where p is any portfolio on the CML and m is the tangency portfolio.

Since Beta is the measure of sensibility and defines as:

$$\beta_{pm} = \frac{Cov(r_p, r_m)}{Var(r_m)}$$

it is possible to write the equation of CAPM as:

$$E\lfloor r_q \rfloor - r_f = \beta_{qm}\left(E[r_m] - r_f\right)$$

For cases with no riskfree asset this is only true when short sales not are allowed. In the absence of the riskfree asset, Black (1972) derived a more general version of the CAPM where the market portfolio and its zero-covariance portfolio are used. The equation is expressed as:

$$E\lfloor r_j \rfloor = E\lfloor r_{zc(m)} \rfloor + \beta_{jm}\left(E[r_m] - E\lfloor r_{zc(m)} \rfloor\right)$$

This line is the Security Market Line (SML). The slope of SML $\left(E[r_m] - E\lfloor r_{zc(m)} \rfloor\right)$ must be positive since the market portfolio is an efficient portfolio (Haugen, 2001).

2.3 The Efficient Market Hypothesis

"The Efficient Markets Hypothesis is the proposition that an asset's current price fully reflects all publicly available information about future economic fundamentals affecting the asset's value" (Bodie and Merton 2000, p. 206).

The above quote, more or less, concludes the general view that all public information is incorporated in the market price. The assumption of stock prices reflecting new information immediately is of main focus in the theory of efficient markets and in our study.

Harry Roberts laid the foundation to the theory behind the Efficient Market Hypothesis (EMH hereafter) in 1959. He was the first to make the distinction between weak and strong market efficiency. However, according to Fama, the term "Efficient Market Hypothesis" was developed by Fama, Fisher, Jensen and Roll in 1969. They make distinction between three different degrees of efficiency depending on how much information is incorporated in the stock prices (De Silva, 2004):

- **The weak form of market efficiency** claims that all historical information is reflected in today's stock price. If this is true then it cannot be possible to predict future stock returns by analyzing historical stock returns. Many studies have shown that stocks follow a "random walk" which implies that price changes do not follow any systematical pattern, and today's stock price is uncorrelated with historical prices. In the world of finance there exists a consensus that stock prices follow a random walk and that financial markets are at least efficient according to the weak form. This is intuitive due to the fact that historical stock price data are easily obtained and if there were profit opportunities to be extracted then everyone would seek to identify these price patterns and thereby exhausting the profits. Hence technical analysis should not be able to generate abnormal returns.

- **The semi-strong form of efficiency** is fulfilled if all public available information and all historical information are incorporated in the price of securities. When public information arrives in the market, it should immediately impound into its stock price. Investors are, as a result, incapable of predicting movements through studying financial data, news etc. Neither fundamental – nor technical analysis is thought to be able to generate abnormal profit.

Several other studies have been undertaken with the purpose of investigating how stock prices react to other news releases besides those concerning takeovers. These studies imply that most of the information gets incorporated into the prices relatively quickly. This means that a potential investor cannot obtain abnormal returns when the announcement has occurred by trading on the news in question. These findings support the hypothesis stating that markets are at least semi-strong efficient.

- **The strong form of efficiency** states that stock prices reflect all relevant information, both public and private. Thus, according to this level of market condition, people with inside information are not able to make abnormal profits based on their unique knowledge or information. As insider receives new information, the market has already reacted to the information and the stock price is adjusted to its new equilibrium level. Hence, this form of efficiency implies that there is no set of information that allows investors to achieve abnormal profit.

We find the strong efficiency unrealistic for the majority of the world of market. Only in the extremely well developed markets, such as NYSE, DAX and LSE, may such efficiency exist. One can also question this form of efficiency because it implies that stock prices are equal to their intrinsic values and for this to be true stocks prices must reflect a rational forecast of future dividends, which is hard to say is true.

After the IT-boom in 1999 another argument against the strong efficiency came up. The bubble convinced some academics and professionals that it must be possible to outperform the market if you avoid the psychological traps. They further argue that stock tendency to overreact during the boom make stock prices partly predictable.

2.4 The Martingale hypothesis

There are a number of models that predict stock prices. The Martingale hypothesis implies that the best estimate of future value is the current value. The hypothesis can be used when explaining stock price behavior. The conditional expected value of the next observation, given all of the past observations, is equal to the last observation. The equation is as follows:

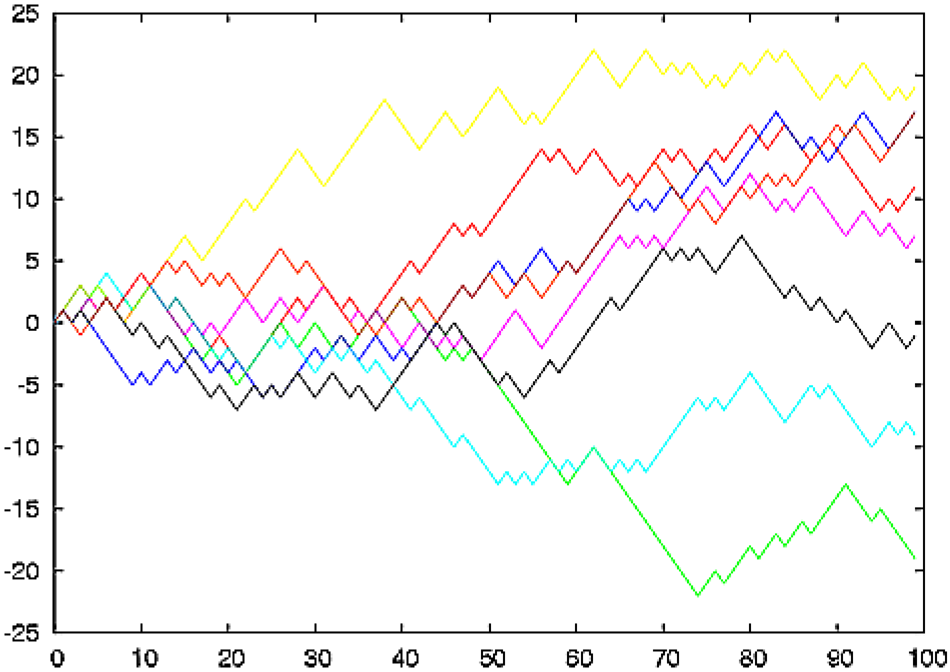
$$E(X_{n+1} \mid X_1, ..., X_n) = X_n$$

The hypothesis has it’s origin in betting strategies such as for the game “heads or tails”. If the coin comes heads up you win and double up and if the coin comes up tail you loose your stake. The Martingale betting strategy had the gambler double his bet after every loss and many gamblers thought the strategy gave safe money which is only true if you have an enormous amount of money. Otherwise you will soon be bankrupt if you experience bad luck and lose *xx* games in a row (www.en.wikipedia.org).

2.5 The random walk

Another stock price behaviour model used within economics is the random walk. It implies that stock price changes have the same distribution and are independent of each other, so the past movement of a stock price or market cannot be used to predict its future movement. In other words, this is the idea that stocks take a random and unpredictable path.

This theory raised a lot questions in 1973 when author Burton Malkiel wrote "A Random Walk Down Wall Street”. His followers believe that it's impossible to outperform the market without assuming additional risk. However, critics of the theory, recognize that stocks maintain an upward/downward trends over time and also point out the existence of anomalies (http://en.wikipedia.org/wiki/Random_walk)



http://en.wikipedia.org/wiki/Random_walk#Example

This graph displays 8 random walks during 100 time steps. At each time step, they either go one step up or one step down. As one can see, while the lines remain clustered around their common origin, their average distance to the origin does indeed increase, but more slowly than linearly.

2.6 Overreaction hypothesis

Many of the early financial marketers believed that security prices could diverge from their fundamental values. As early as in 1936 Keynes observed *"…day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and nonsignificant character, tend to have an altogether excessive, and even absurd, influence on the market"* (Keynes, 1936, p. 153-154).

The first empirical evidence supporting the overreaction hypothesis and documented in the literature is by Rosenberg & Rudd (1982). However De Bondt and Thalers (1985) research, which provided the confirmation of a prices reversal, are the most influential in the ongoing research. These authors base their theories on the findings of Kahneman and Tversky in 1982 whose studies within the field of cognitive psychology suggests that investors tend to over-weight recent information and underweight past information (Forner and Marhuenda, 2001). De bondt and Thaler define the overreaction hypothesis as an over-response to information. They mean that extreme movements in stock price are followed by a “correction” in the opposite direction. The magnitude of the initial price change is closely connected to the magnitude of the “correction”, or the “reversal” (De Bondt and Thaler, 1985). The study was a serious challenge to the EMH and a number of financial theories since they documented an “overreaction effect”, which implies that stock price may be predictable from past price information.

In our study we will focus on stocks experiencing extreme price changes. This because we believe that this will show on more clearly overreaction effect.

2.6.1 Causes behind overreaction

The idea behind overreaction hypothesis is the possibility that security prices swing away from their fundamental values due to waves of optimism and pessimism. This means that prices are not determined by the “true” forces of supply and demand and prices are not in equilibrium at all times, especially when new information arrive or extreme events occur. Stock prices have a tendency to adjust themselves back to equilibrium in the subsequent period.

In the short run we believe price reversals are most likely due to overreaction. In the long run price reversals patterns might be due to slightly different factors, such as stocks experiencing large losses might be considered very risky because the risk of bankruptcy is overestimated. Also, suppose that investors have a tendency to overreact to recent earning trends and other news. The excess risk premium and the overreaction effect will together give a negative momentum force to the losers. Later on when new information (i.e. next quarterly announcement) comes in and investors discover that their fear of bankruptcy were exaggerated and earning forecasts too pessimistic, prices reverse. For winners, however, there might be a fear of “downside potential”. This, in combination with the overreaction effect, should result in a smaller or nonexistent reversal for winners since the effects work in opposite directions. It is also empirically documented that asymmetry in returns to winners and losers exist.

De Bondt and Thaler mean that investors are irrational explained by cognitive psychology, and they denote that this is one reason to overreaction. Below we will discuss some of these psychology aspects.

2.6.2 Noise traders

The definition of a noise trader is a trader who does not have any particular information, but trades for exogenous reasons. Psychologists have found that there is a social cooperation in case of attention and events. People tend to observe events that other people observe which lead to affection in their trading decisions.

According to Shefrin and Statman (1994) noise traders could be seen as driver steering the market away from efficiency. The shock that is generated by these traders is general to all security markets and is partly reflected in the risk premium.

2.6.3 Overconfidence

Another reason to overreaction could be overconfidence. A number of psychology and experimental economics studies indicate that investor tend to believe that they are more skillful than they truly are and overconfident about their own abilities. People also tend to over-value their skill of analysis in situations like stock-trading, more than they do in e.g. horseracing. It is easy for an investor to overestimate his role in an up going portfolio, which could lead to overconfidence. It is also common that the trading volume becomes higher when the investors experience this level of confidence. This increased trading volume and overconfidence could be a contributing source to the overreaction effect (Hvide, 2000).

2.7 The contrarian strategy

We define a contrarian strategy as: selling short conditional upon an increase in the market on the previous day, and going long after a market downturn.

When you, within the subject, look at time-horizons you talk about long-term and short-term returns. Long-term is commonly suggested to be returns on a monthly or yearly basis, and short-term is returns on a daily or weekly basis.

We anticipate that stock prices to some extent follow a reversal pattern that can be predicted on beforehand. If this is true, we should be able to exploit the predictable reversals by acting as a contrarian investor. A contrarian investor (negative feedback trader) buys after a drop in the market and sells after a rise. In this respect they behave like profit takers – a term commonly used in financial papers to characterize investors who sell after a rise. A contrarian strategy would be to study the profit from a costless (i.e., zero net investment) portfolio which includes negative weights of recent winners and vice versa. If stock prices tend to overreact the portfolio will profit from the reversals.

Our contrarian strategy will consist of a number of winners and losers forming a zero-investment portfolio. These stocks are randomly selected from a large time-span and they are to represent a usable short-term contrarian strategy. We mean to prove our strategy profitable to verify the profitability of a contrarian strategy consisting of going long and short in winners and losers on a daily basis.

In the case of a large daily stock increase we anticipate to find some short-term reversals due to overreaction and profit-taking. A large stock loss we anticipate will lead to greater reversals due to overreaction. We expect that the reversals from losers will be more pronounced in line with similar studies.

2.8 The momentum strategy

The momentum strategy contradicts the contrarian strategy and is therefore of interest to us. A momentum investor (positive feedback trader) buys stocks after a period of positive returns and sells stocks that experience a negative trend. The strategy has become popular especially amongst institutional investors.

In 1993 Jegadeesh and Titman add a new insight by documenting “return continuation”, using a sample of NYSE-AMEX stocks over the period 1965-1989. They find that a strategy that buys past six-month winners and sells past losers earns approximately one percent per month over the subsequent six months. This existence of a “momentum” in stock returns does not seem to be too controversial but it is much less clear what might be driving it. A number of authors e.g. Barberis, Shleifer and

Vishny (1998) have presented behavioral models that are based on the idea that momentum profits arise because of inherent biases in the way that investors interpret information. Others have argued that profitability of momentum strategies may simply be compensation for risk. Conrad and Kaul (1998) argue that profitability of momentum strategies could be entirely due to cross-sectional variation in expected returns rather than to any predictable time-series variation in stock returns (Conrad and Kaul, 1998).

According to EMH, investors can not yield extra return by using historical data quotes without bearing extra risk. Therefore both momentum and contrarian strategies presents a challenge to the EMH by providing abnormal retuns without bearing extra risk.

In a study by Goetzmann and Massa (2001) they show that investors using the contrarian strategy beat investors using the momentum strategy. Conrad and Kaul (1998) find that usually momentum strategies are profitable at the medium (3-12 months) horizon. We believe that in the short-run the stocks listed on the SSE market will show a reversal pattern rather than a positive/negative trend pattern and that conrarian profits do exist.

2.9 Alternative and complementary hypothesis

Much research has been conducted on whether reversal patterns reflect an irrational market response to information, or whether they can be explained by other factors. Apart from the overreaction effect, more recent studies have offered alternative and/or complementary explanations for the successful performance of the contrarian strategy.

There are also a number of studies that attempt to explain return predictability within an overreaction and/or underreaction context employing behavioral models (Forner, Marhuenda, 2001).

2.9.1 Size and volume

Some researchers explain the reversal phenomenon with trading volume. For example, Blume, Mackinlay, and Terker (1989) analyze stock return behavior after the stock market crash in October 1987 and find that stocks that experienced higher trading volume on the day of the crash also experienced higher subsequent recoveries. This suggests that the selling pressure moved stock prices under their fundamental values which lead to a subsequent reversal effect. Also Stoll and Whaley (1990) show that prices established on high volume days tend to be reversed at the open of the next trading session. Similarly, Campbell, Grossman, and Wang (1993) find that high volume day returns are likely to revert (Campbell, Grossman and Wang, 1993).

Zarowin (1990) argues that the tendency of losers outperforming winners in the forthcoming period in the USA may be due to the tendency of losers to be smaller sized firms than winners, i.e. an explanation based on the size-effect anomaly. Cox and Peterson (1994) find evidence that larger firms with large capitalizations experience weaker reversals, and they attribute this finding to liquidity. The magnitude of the reversal might be affected by the elasticity of liquidity indicating greater reversals in a bull market.

Reversals can also be explained by the phenomenon that suppliers of liquidity may take position in a stock victim of selling pressure because of the anticipation of reversal returns. Especially smaller investors seem to be attracted by extreme negative returns which contribute to short-term reversal for small cap.

In the light of these findings, we expect that the degree of overreaction will be less pronounced for larger firms. We anticipate that during bullish periods firms with high event day trading activity and lower capitalization will likely show the biggest reversals.

2.9.2 The bid-ask spread

In some studies researchers argue that the explanation to reversals lies in market frictions such as bid-ask biases and infrequent trading which are not properly accounted for (Conrad and Kaul, 1993).

The bid-ask spread is the gap between the stock bid price and the ask price. The bid price represents the highest price that an investor will pay for a security at a particular point in time and the ask price refers to the lowest price at which an investor will sell a security. The difference between bid and ask is simply the “spread”. Market makers seek to buy shares at a lower price and sell at higher price and the bid-ask spread could be seen as a compensation for the risk that is taken by the market makers.

There are three identified main components of the bid-ask spread.

- Order-processing costs
- Adverse selection costs
- Inventory holding costs

The first component is the cost of standing ready to trade and to process the actual transaction. The adverse selection costs, refers to the impact of asymmetric information. The last component is the cost of holding portfolio that is less than fully diversified. The market makers are compensated by adding a premium into the bid ask spread because they cannot distinguish an informed investor from an uninformed investor. Empirically adverse information costs and order processing costs appear to be more important than inventory costs (Asgharian, 2005).

The bid-ask spread is related to security characteristics such as the stock price, volume of trading, market cap and the risk of the security. Generally stocks with low trading volume, small market cap and few shareholders will show relatively large bid-ask spreads. The size of the spread also depends on market regulations. There are spread limits for certain stock price intervals to making trading smooth. For example, say that stock X is a small cap stock with low trading activity. According to the market regulations where X is listed, stocks trading between 0,1 and 1 SEK have minimum spreads of 0,01 SEK. Below are simulated quotes for stock X.

Stock	Buy	Sell	Open	Close	Nr trades
X	0,10	0,12	0,10	0,12	1

The smallest possible spread for X amounts to:

0,01 / 0,12 = 8,33%,

and the actual bid-ask spread for X is:

Buy – Sell = 0,12 – 0,10 = 0,02   0,02 / 0,10 = 20%

Stock X opened at 0,10 SEK and because of illiquidity and regulations one trade made the stock jump up 20 % to 0,12 SEK. In the next period of trading it is quite possible that a trade comes through at 0,11 SEK. In that case, stock X will show an oscillating price pattern indicating price reversals. As noted by Bremer and Sweeney (1991) it is possible that very low priced stocks show signs of reversals, that actually only reflect oscillation between bid and ask prices. Spurious reversals do most likely exist in the collected data but we do not have to take low priced stocks into consideration when putting restrictions on the data sample. In some markets low priced stocks are synonymous with large bid-ask spreads which is not necessarily the case on the SSE, since we not only trade in kronor but also in ören. We must although deal with potential bias from illiquid stocks experiencing oscillating patterns. Otherwise we might draw the wrong conclusion about the reversal effect.

2.9.3 Correlation and nonsynchronous trading

Correlation refers to whether or not securities will move at the same time for the same reason and in the same direction. If they do, they have a correlation of plus 1. However, if they were to move in exactly opposite direction they would have a negative correlation of minus 1. If security movements are unrelated, the correlation is 0. Serial correlations measure the degree to which the return at time *t* correlates to the return in *t+1*. High positive serial correlations denote trends which mean that historical data can be used for future estimates. High negative serial correlations suggest cyclical behaviour, and low serial correlating suggests randomness in returns (www.efmoody.com).

Nonsynchronous trading on short-term is a common phenomenon at stock exchanges. This is very important to account for when using daily data for empirical studies. Ignoring this nonsynchronicity can result in substantially-biased inferences for the behaviour of stock price. To see how this occurs, suppose that the returns to assets A and B are temporally independent, but A trades less frequently than B. Assume that new economic information affects the market at time t. Asset B trades at time t and the price will reflect this information immediately, while asset A not will be traded until time t + 1. The fact that A responds with a lag, causes spurious cross-autocorrelation between the returns on A and B (Asgharian, 2005).

In an early study by Fama (1965) he investigated if there was any serial correlation in day-to-day stock price changes of 30 stocks of the Dow Jones Industrial Average for the period 1957-62. He concluded that the correlations were too small to be of any significance. However, French and Roll (1986) repeated Fama´s test for a greater number of stocks and over a longer period of time and now a new pattern emerged. They found evidence of significant negative serial correlation in daily returns. Evidence that short horizon stock returns exhibit negative serial correlations attracted a lot of attention since there was evidence suggesting that contrarian strategies exploit negative serial correlation to achieve abnormal returns.

In a short-term study by Lo and MacKinlay (1990) they calculate that cross-serial correlations (in terms of a systematic lead-lag relationship between large and small cap stock weekly returns) account for about 50 percent of expected contrarian profits and 50 percent may be attributed to overreaction. Lo and MacKinlay find large positive covariances between the returns of small cap stocks and lagged returns of large cap stocks, but virtually no correlation between returns of large cap stocks and lagged small cap stock returns. The lead-lag effect arises when some stocks react more quickly to information than others do. So even if individual stock returns are serially independent, selling winners and buying losers might be profitable purely as a result of positive cross-serial correlation. However, if the positive cross-serial correlation is induced by nonsynchronous trading the profit can not be realized.

2.10 Anomalies

An anomaly can be explained as diverge from what is normal. Return reversals and stock momentum are two of many anomalies that have been uncovered. Researchers have also found that firm specific characteristics and season variation can partly explain stock price behavior. These empirical findings are associated with excess return which contradicts EMH.

For an anomaly to be rooted, the excess return must be consistent on long-term. Since we analyze stock price behavior we need to consider the fact that anomalies might exist on the SSE and also how (or if) they can affect our results.

The most relevant anomalies for our study are those who can interfere with results based on daily price behavior. The well documented Monday-Friday effect should influence our results. The anomaly has a long record with various results but the main consensus is that stocks have good performance on Fridays and bad performance on Mondays.

There is a positive stock price trend at the end of each month called the month effect. It occurs due to new cash flows (salary payments, interest payments, fund) that pushes prices up. Our results may be influenced by the month effect but this will not be visible in our results since we use a daily perspective.

The January effect suggests that the month of January creates abnormal returns. This is commonly explained by a tax-loss selling effect, where private investors seek to realize capital losses at the year-end to reduce income tax. This creates a selling pressure before year-end which subsequently leads to repurchases. One can question the cause of the January effect. For example, the anomaly was observed by Kato and Schallheim (1985) on the Japanese market where no capital gains by tax-loss exists (Forsgren, 2003). An alternative explanation is that institutional investors prior to the year-end sell losers and buy winners to be able to present a respectable portfolio when being evaluated at year-end.

It is well documented that small firms yield greater returns than larger firms. This size effect is valid after adjusting for higher risk associated with small firms. The effect can partly be explained by lack of liquidity that can lead to abnormal returns. The effect might be visible in our results.

2.11 Hypothesis testing

The purpose of hypothesis testing is to make a decision in the face of uncertainty. A null hypothesis (H_0) is stated and gives a parameter a value, usually zero. Zero means nothing and the null hypothesis is that nothing is present. The null hypothesis is like a presumption of innocence. Further, the null hypothesis is always tested against the alternative hypothesis H_1.

By comparing the test statistic to a critical value, you either reject or fail to reject the null hypothesis. If data are inconsistent with the null hypothesis, H_0 is rejected and no significance could be shown. Even if H_0 is accepted, it does not prove that the null hypothesis is true. There is always a risk of Type 1 – the risk of wrongly rejecting the null hypothesis when it is true. This is depending on the level of significance. On the other hand, the risk of Type 2 is defined as the acceptance of the null hypothesis when it is false.

When comparing the test statistic to the critical value, we will use the p-value. The p-value is the probability that the sample could have been drawn from the population being tested given the assumption that the null hypothesis is true. A p-value close to zero, or less than 0,05 indicates that the null hypothesis is false and should therefore be rejected (Körner, Wahlgren, 2000). We will use the level of five percent when we evaluate our results.

2.12 Literature review

There has been a lot of research within the subject of stock price overreaction and we will present the most influential research. There are also a few studies on other securities than stocks. White and Okunev (2001) find momentum strategies profitable for currencies during the 1980s and the 1990s. Chen (1998) investigates the future markets but finds little evidence to support the overreaction hypothesis. Saitta (1997) concludes that a contrarian strategy for T-bond futures has no great success and that the average profit per trade is negative (Bildik and Gulay, 2002).

2.12.1 Long-term studies

Some believe that in a long-term perspective, stock prices overreact to consistent patterns of information indicating in the same direction. In other words, stocks which have long records of positive news tend to become overpriced and have low average returns in the long-term perspective.

One of the most influential studies is done by De Bondt and Thaler (1985), who finds evidence of long-term price reversals due to overreaction over long time intervals. The more extreme overreaction, the more extreme the reversals tend to be. Using NYSE firms monthly stock returns from 1926 to 1982, the stock returns were ranked in the formation period based on performance classifying the top deciles as “winners”' and the bottom deciles as “losers”. They find that extreme prior losers tend to outperform prior winners during the following years by about 25 % and argue that this is evidence of systematic overreaction due to excessive investor optimism and pessimism. They report that the stock market appears to be highly efficient in rapidly incorporating information that affects prices in the short run, but systematically fails to process more complex and longer-term information in an efficient manner.

The De Bondt and Thaler’s (1985) study is a starting point for many financial researchers and their model have been further developed over the years. De Bondt and Thaler (1987) revisit their prior work and incorporate a time-varying risk coefficient. Their findings reveal a strong correlation between price reversal patterns and the month of January, i.e. the January effect (Mun, Vasconcellos and Kish, 2000).

Campbell and Limmack (1997) study long-term reversals for the UK market for the period 1979-1990. They show that in the 12 months following the portfolio formation, losers persisted in generating abnormal returns, thus appearing to support the overreaction hypothesis. It was also found that the very smallest loser companies did experience a reversal in their abnormal returns over the following 12 months, but that no such reversal existed for the smallest winner companies.

Chopra, Lakonishok and Ritter (1992) find an economically significant overreaction effect. In portfolios formed on the basis of prior 5-year returns, extreme prior losers outperform extreme prior winners by 5-10% per year during the subsequent 5 years. Although the January effect is present, the evidence suggests that the overreaction effect is distinct from tax-loss selling effects. In addition, the results show evidence of significantly stronger overreaction effect for small firms than for large firms. They also observe return reversals for short windows around quarterly earnings announcements, consistent with the overreaction hypothesis (Bildik and Gulay, 2002).

2.12.2 Short-term studies

In the table below we show a summery of the early contrarian strategy studies.

Author	*Sample*	*Methods*	*Result*
Rosenberg, Reid & Lanstein 1985	monthly returns 1981-1984 NYSE companies	buy stock with negative residuals (relative to multi-Factor model) and sell short stock with positive residuals over the previous month	arbitrage portfolio earns 1,36% per month; profit mostly generated by prior Losers
Howe 1986	weekly returns 1963-1981 NYSE and AMEX	all returns that rise or fall more than 50 percent within one week	next 10 weeks winner: -13,0% losers: +13,8%
Dyl & Maxfield 1987	daily returns 1974-1984 Nyse and AMEX	buy/sell 3 stocks with largest 1-day price loss/gain on 200 trading days selected at random all one-day (absolute) returns in excess of 7,5 10 or 15 percent	next 10 trading days winners: -1,8% losers: +3,6%
Jegadeesh 1987	monthly returns 1945-1980 NYSE	regression relating Sharpe-Lintner residual returns to raw returns of previous month and returns in earlier years	extreme decile portfolios: difference in residual returns is 2,5% per month
Bremer & Sweeney 1988	daily returns 1962-1986 fortune 500	all one-day returns in excess of 7,5 10 or 15 percent	next 5 trading days winners: -0,004% losers: +3,95%
Brown, Harlow & Tinic 1988	daily returns 1963-1985 S&P 500 200 largest companies	all one-day (market model) residual returns in excess of (absolute) 2,5%	next 10 trading days winners: +0,003% losers: +0,37%
Lehmann 1988	weekly returns 1962-1986 NYSE and AMEX	buy all stocks that lag the market during the previous week (losers) and sell short the equivalent "winners"	for $1 long in zero-investment arbitrage portfolio,+ 39 cents every 6 months; 2/3 of profit generated by prior losers
Brown & Harlow 1988	1 to 6 month returns 1946-1983 NYSE	study stocks with residual returns that gain/lose (between absolute) 20 and 65 percent between 1 to 6 months	large rebounds for losers; no decline for winners except in the first month

(De Bondt and Thaler, 1985)

In 1988 Brown, Harlow and Tinic developed a theory for investor behaviour under condition of uncertain information which suggests that price changes following positive or negative news should be positive on average. The reversal phenomenon's positive price changes following bad news are consistent with this theory. They use a -2,5% trigger on residuals from daily market model regressions and find that the losers on average rebound 0,045% on the first day, a cumulative rebound of 0,112% on second day increasing to 0,532% by the 60^{th} day. They find that the reversal phenomenon is complete by the second day (Bremer and Sweeney, 1991).

In a study by Dyl and Maxfield (1987) on NYSE and AMEX, 200 trading days in the period January 1974 to January 1984 were randomly selected. On each day the three stocks with the greatest percentage price loss (on average -12%) were noted. Over the next 10 trading days, the noted losers earn a risk-adjusted return of 3.6 percent. Similarly the three highest gainers lost an average 1.8% over the next 10 days (De Bondt and Thaler, 1987).

A study by Zarowin (1989) examine whether size and seasonality could account for short-term price reversals. The results indicate that losers significantly outperform winners over all months, regardless of which group is smaller. Thus he concludes short-term overreaction effect to be a separate anomaly. Using different control, Albert and Glenston (1995) also found an overreaction effect that is distinct from the size-effect (Bildik, 2002).

Jegadeesh (1990) and Lehmann (1990) provide evidence of return reversals at monthly and weekly intervals. Profitability of the contrarian strategy is explained by short-term price pressure or a lack of liquidity in the market rather than overreaction. Jegadeesh and Titman (1991) provide evidence, on the relationship between short-term return reversals and bid-ask spreads that supports this interpretation (Jegaadesh and Titman, 1995).

Bremer and Sweeney (1991) studied a three-day price recovery for Fortune 500 stocks using a trigger of daily price declines of 10 percent or more. They suggest that market illiquidity may partially explain their findings. Similarly, Cox and Peterson (1994) examine returns following large stock price declines and find that the bid-ask spread and the degree of liquidity explain short-term (1-3 days) price reversals (Park, 1995). The impact of the bid-ask spread is also investigated by Kaul and Nimalendran

(1990). They documents two important findings: firstly, the main source of reversals for NASDAQ stocks is the bid-ask spread and a lead-lag effect. Secondly, there is little evidence of market overreaction. The results suggests that the positive profits earned by contrarian strategies could largely be due to a combination of the asymmetric lead lag relations in returns and price reversals due to the bid-ask effect. Kaul and Nimalendran conclude that the bid-ask spread and closing price bias is severe and when calculating returns from successive bid prices, short-term contrarian profits largely disappear (Kaul and Nimalendran, 1990).

In more recent research, Chang, McLeavey, and Rhee (1995) examines short-term abnormal returns of the contrarian investment strategy in the Japanese stock market. They found empirical evidence showing that: a) the short-term contrarian strategy remains profitable after systematic risk and firm size are taken into account, b) the seasonality effect does not explain the contrarian profits, c) abnormal profits are reported regardless of whether losers are smaller or greater than winners and the magnitude of the profits does not differ after an adjustment for firm size, and d) contrary to documented evidence for the US market, a strong asymmetry exists between the performance of the two extreme portfolios (Bildik and Gulay, 2002).

In general, the empirical evidence suggests that contrarian strategies are profitable at short horizons. However, researchers obviously disagree to the causes behind the anomaly.

3 Data and methodology

In this chapter we will account for the methodology and present the data sample. We also describe the used models.

Our study investigates whether stocks that show low/high returns during the previous day will have abnormal returns during the following days, i.e. a reversal phenomenon, and what causes the reversals. If we find reversals, we can use a contrarian strategy to yield significant positive returns.

The main reason to why we have chosen to analyse stock behaviour on a daily basis is intuitive. In short-term new information obviously affect stock movements e.g. unanticipated news of reduced profit makes a stock plunge. When examining price behaviour on long-term it is no longer so obvious what the sources behind stock movement is. For example, say that Ericsson announces that revenues will not meet up with market expectations and the stock plunges 15% in a day. We believe that the market possesses an overreaction characteristic to news (especially negative news) and this will show in the coming days of trading, if no other big news interrupts the scene. The other reason for choosing a daily short-term perspective is the fact that the majority of studies have employed long-terms examining contrarian strategies and few short-term studies have employed daily observations.

We can conclude from the previous studies that the predictability of short-term returns is stronger and more consistent than long-term returns through time. Long term reversals seem to us more difficult to predict and understand because of the obvious problem; the longer the time frame, the more events affecting the result. Therefore, we think, the short-term perspective is more sensible to analyse.

We will analyze stocks during the time period *t-3*, i.e. 3 days before the extreme event (at day *t*), to *t+10*. We chose to include three days before the extreme event due to the possibility of bias from insider trading. We chose a post-window of 10 days which we believe is long enough to capture the effect we are looking for.

We are going to investigate stock performance following a one-day price increase/decline of 10 percent but not more/less than 30 percent. We chose a trigger value of 10 percent because it is large enough to give the sought effect, and it is in line with previous studies for example Bremer and Sweeny (1998). These extreme events can be caused by for example unexpected earnings releases, unanticipated government decisions or bad (good) luck.

We chose to conduct the study on the SSE because there was lack of evidence in the literature regarding SSE contrarian profits and their decomposition. We had on beforehand noticed SSE stocks tendency to reverse and our interest in stock market behaviour lead to this study.

3.1 Data

For the stocks listed on A-listan, A-listan övriga, O-listan and Attract 40 we collected data from SIX Trust via the LINC group. We have chosen not to include data from other listings due to their lack of liquidity. To avoid survivorship bias we also include delisted stocks. This gave us a selection of 108 firms. The stock variables of interest are close price, market cap and AFGX index close price. Daily data is collected for the period 1995.01.02 – 2005.05.09 which gives us daily observations from t = 1,...,2593. In most studies done with the daily aspect time periods of 10-20 years are used. The time period stretches over many business cycles to minimize potential bias from, for example, a positive trend.

3.1.1 Restrictions

Restriction 1

When analyzing the data in Microsoft Excel we found that daily stock prices were, to some extent, missing for all 108 stocks indicating that there might be different reasons for nontrading. Ericsson, for example, is a very liquid stock and trades every day if nothing exceptionable happens. A reason for the "nontrading" in Ericsson might be a trade stop, stock market sytem failiure or SIX Trust are missing some data. To simplify this problem we treat all missing stock price quotes as nontrading since it is the most probable cause for missing data. We decided to accept a maximum level of five percent nontrading of total number of observations to reduce the potential of the nontrading problem. This will exclude the most illiquid stocks and allow a majority of the stocks to be included. Stocks with low liquidity through time are likely to be small cap firms.

Out of a total of 108 stocks, 18 were excluded due to the five percent nontrading limit which means that the data sample consists of 90 observations. The next step is to calculate net returns for each day, defined as:

$$R_{i,t} = \left(\frac{P_{i.t}}{P_{i,t-1}} \right) - 1$$

Were $R_{i,t}$ is the net return, $P_{i.t}$ is stock i´s close price at time t and $P_{i,t-1}$ is stock i´s close price at time t-1. The data sample consists of 199.724 observations with stock returns out of which 87.220 are negative and 112.504 are positive. Hence, during the 10 year period, stocks have had more gains than losses. The sample also includes each stocks market cap (2593*90=233.370 observations) on a daily basis and daily returns for the AFGX index (2592 observations).

Restriction 2

Because of the massive data sample we decided not to analyze every extreme price change. We chose to randomize at an early stage because we could not adopt every restriction on the 2593 days due to too time-demanding Excel-calculations. To simplify excel work we decided to randomly select X trading days that would result in about 50 extreme price change observations, which we considered to be a large enough sample. This was done by using the random function in excel:

$$= SLUMP(\ ) * (2593 - 1) + 1$$

which randomly selects X numbers between 1 and 2593 (1995.01.02 – 2005.05.09). If two equal integers came up, we included that day plus the day after. We found that X=400 gave a satisfying result with 71 winners and 55 losers.

Restriction 3

To minimize across-sample correlation only one event per day is allowed, in accordance to Cox and Petersen (1994). If there were more than one event for a given day, the stock with the greatest change was included. The sample now consisted of 66 winners and 52 losers.

Restriction 4

As Friedman and Laibson (1989) points out that extremely large movement is of little importance and may obscure simple patterns in the data (Park, 1995). We will therefore adjust for movements of more than +/- 30 percent. This number was chosen after analyzing extreme outliers. We excluded 1 stock whose return (-36,8%) exceeded this limit and the sample was now down to 66 winners and 51 losers.

Restriction 5

To deal with the potential bid-ask bias we will set a minimum market cap limit of 100 million SEK. We define small cap as <100 million SEK which can be considered a small number. We set this limit because the number of stocks (N) will dramatically drop if we would have defined small cap as e.g. <1000 million SEK. The market cap used as limit is picked 10 days prior to day *t* so that the possibility of an effect from inside trading is minimized. Small cap are most likely stocks experiencing large spreads and by excluding them from the data sample we hope to minimize the potential spread problem. Also, illiquid stocks experience less trading and we cannot be guaranteed that trade is possible for a certain day. Nonsynchronous trading is also more frequent for less liquid stocks, which might result in biased results. Due to this restriction another 5 winners and 4 losers were excluded.

Restriction 6

The last step is to make the two groups equally sized which is needed for further calculations. We reduce the group of winners by randomly selecting and removing 14 stocks from the sample so that both groups consist of 47 observations.

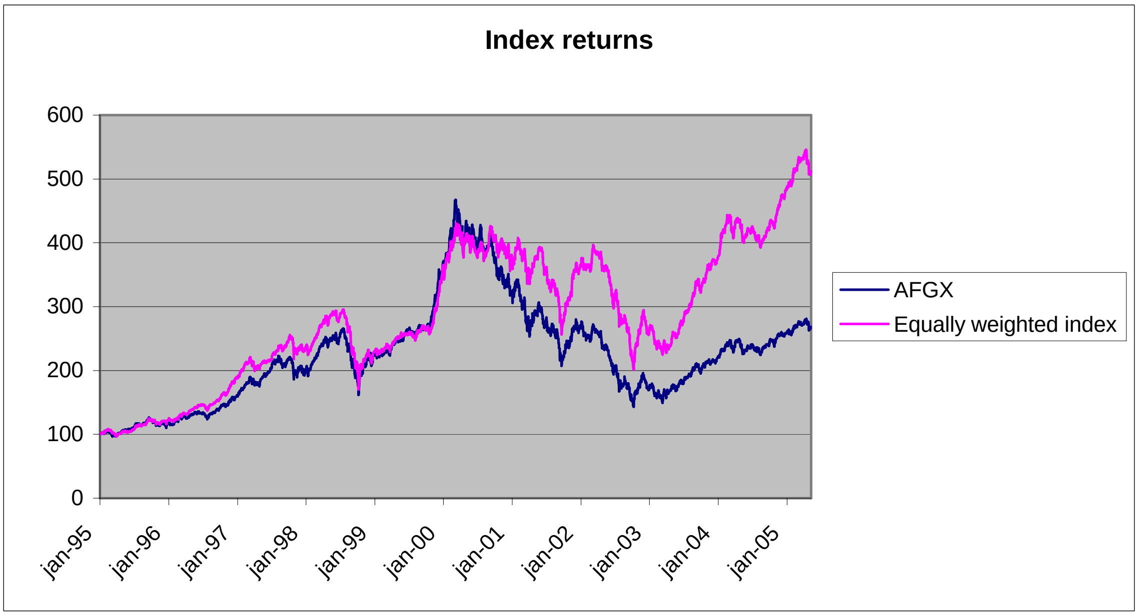
3.1.2 Indexes

As a proxy for the market portfolio we use Affärsvärldens generalindex (AFGX) which is a value weighted index including the majority of companies listed on the SSE.

We will use daily quotes for two different indexes: the AFGX and an equally-weighted index. We created an equally-weighted index that contains the 90 stocks in the data sample after "limitation 1" (which excludes nontrading/small cap stocks). The index was created for the time period by giving all stocks in the sample equal weights.

The performance of the equally-weighted index and the AFGX value-weighted index differ as one can see in the graph below. We can se that the indexes right after the IT-bubble went separate ways. Obviously the equally weighted index outperformed the AFGX. Small companies seems to have performed better which shows in the comparison between the indexes.

Graph 1



3.2 Residual models

We aim to test whether or not Swedish stocks overreact in the short run. This is done by measuring the extent to which a systematic residual return after a given reference day is associated with a systematic residual return in the opposite direction during the previous day. First we must choose a model for calculating residuals. There are three general methods to measure residuals described in financial literature:

1. **Constant mean return model**
2. **Market adjusted model**
3. **Market model**

We have, in consensus with the majority of studies published on the overreaction effect, chosen to employ the market adjusted model and the market model (Forner, 2000).

1. Constant mean return model

The constant mean model is seldom employed in similar research. The model does not account for risk as well as the two other models. It accounts for risk by subtracting the average market return from an estimation window from the stock returns.

$$R_{i.t} = \mu_i + \varsigma_{i.t}$$

$$E(\varsigma_{i,t}) = 0 \qquad\qquad Var(\varsigma_{i,t}) = \sigma^2_{\varsigma,i}$$

Where $\varsigma_{i.t}$ is the estimated residual and μ_i is a constant return calculated from historical data (Ibid).

2. Market adjusted model

The market adjusted model assumes that ex ante expected returns are equal across securities but not necessarily constant for a given security. The model estimates *alpha* to be zero and *beta* to be one for all stocks and the residuals $\varsigma_{i,t}$ are estimated as the difference between observed stock return at *t* and a market index at *t*:

$$\varsigma_{i,t} = R_{i,t} - R_{m,t}$$

$$E(\varsigma_{i,t}) = 0 \qquad Var(\varsigma_{i,t}) = \sigma^2_{\varsigma,i}$$

The only risk adjustments included is for movements of the market as a whole and the adjustment is identical for all stocks. Calculating residuals is easy and they can be measured against different kinds of indexes (Ibid).

3. Market model

The market model is more sophisticated and takes both market movement and stock's systematic risk into account when measuring abnormal performance. The model assumes a stable linear relationship between a stock's return and the return on a relevant market portfolio. Historical data are therefore used with the purpose of estimating expected returns for stocks (MacKinlay, 1997). The residuals $\varsigma_{i,t}$ are calculated as:

$$R_{i,t} = \alpha_i + \beta_i * R_{m,t} + \varsigma_{i,t}$$

$$E(\varsigma_{i,t}) = 0 \qquad Var(\varsigma_{i,t}) = \sigma^2_{\varsigma,i}$$

This model removes the portion of return that is related to variation in the market's return, so that the variance of the abnormal return is reduced. Compared to the other models the market model increases the possibility of detecting the extreme event's effect on return (Asgharian, 2005). When calculating the residuals we first needed estimates of alpha and beta for each stock. For this we used a window of 50 days prior to the event day. Alpha and beta are estimates following OLS regression equation.

3.3 Reversal models

To verify the effectiveness of the contrarian strategy we use the CAR-model employed by De Bondt and Thaler (1985). The De Bondt and Thaler (1985) method is the one that has most extensively used within the topic. The second model used is a cross-sectional regression which also account for the cause of reversals.

3.3.1 The CAR model

The CAR model is a statistical procedure to calculate the validity of the overreaction hypothesis and the effectiveness of the contrarian strategy. This model is popular because of its simplicity and is widely used when analyzing stock price behavior based on historical returns. From the model we can calculate the profit from our contrarian strategy.

For every stock we compute the abnormal returns (ARs) by calculating residuals from the market model and market adjusted model.

The ARs are aggregated in time series to form cumulative abnormal returns (CARs). The average cumulative abnormal returns are computed for the two groups as:

$$ACAR_{W,i,t} = 1/N * \sum CAR_{W,i,t} \qquad \text{(Winners)}$$

$$ACAR_{L,i,t} = 1/N * \sum CAR_{L,i,t} \qquad \text{(Losers)}$$

The overreaction hypothesis predicts that $ACAR_{W,i,t} < 0$ and $ACAR_{L,i,t} > 0$ when $t > 0$, which can be rewritten $ACAR_{W,t} - ACAR_{L,t} > 0$. If $ACAR_{W,t} - ACAR_{L,t} > 0$ is statistically certain, it indicates that the contrarian strategy yields abnormal returns. In order to test if there is a statistically significant difference between the two groups we need an estimate of population variance in CAR_t,

$$S_t^2 = \left(\sum_{n=1}^{N}(CAR_{W,n,t} - ACAR_{W,t})^2 + \sum_{n=1}^{N}(CAR_{L,n,t} - ACAR_{L,t})^2\right)/\,2(N-1)$$

With the sample of equal size *N*, the variance of the difference of sample means equals $2S_t^2 / N$ and the t-statistics is therefore

$$T_t = (ACAR_{L,t} - ACAR_{W,t}) / \sqrt{2S_t^2 / N}.$$

(De Bondt and Thaler, 1985)

3.3.2 The cross-sectional regression

One important question arises if there is evidence of reversal. What is the source of the reversal effect? If an investor knows the impact of different factors he can construct the most efficient contrarian strategy. In order to test possible sources to the reversals we employ a cross-sectional regression including firm specific factors. The factors must be measurable and comparable in the sense that historic data exist and that the variable can be interpreted as a number. We have identified three variables of interest that will be included in the regression:

1. **Size**
2. **Leakage**
3. **Initial price change**

1. Size

There is evidence of larger firms with large capitalizations experience weaker reversals. This can be attributed to liquidity. Also, the documented size effect, states that small firms yield greater returns than larger firms. We therefore expect to find that the degree of reversal will be less pronounced for large cap.

The size index variable is based on the market cap five days prior to the event day. This to make sure there is no bias from possible insider trading. By using Dummy-variables, we divided the size variable into two groups according to their mean market cap.

2. Leakage

A study by Daniel, Hirshleifer and Subrahmanyam (1998) states that leakage is hypothesized to be positively related to the level of overreaction. We have therefore used a pre event window of three days to capture any information leakage. We believe that it is hard to measure this information leakage (if there is one) since insider traders usually trade in small amounts but it is still an interesting variable to investigate.

3. Initial price change

The last variable included in the regression is the initial price change (hereafter IPC) which we predict to be the most possible source of reversal. According to the overreaction hypothesis a large price change will be followed by a price change in the opposite direction. The more extreme the initial change the greater the reversal.

Our cross-sectional model is expressed as:

$$CAR_{i,t} = \delta_0 + \delta_1 * IPC_{i,t} + \delta_2 * SIZE_{i,t} + \delta_3 * LEAK_{i,t} + \varepsilon_{i,t}\,.$$

Were

$CAR_{i,t}$ = the post drop cumulative abnormal return for security i,

$IPC_{i,t}$ = the event day abnormal return for security i,

$SIZE_{i,t}$ = the size variable for security i,

$LEAK_{i,t}$ = the leakage variable for security i,

δ = parameters to be estimated, and

$\varepsilon_{i,t}$ = error term for security i

3.5 Criticism

Qualitative material is mostly gathered from trusted financial journals as Journal of Banking and Finance, and some more general material is gathered from reliable sources from internet (e.g. www.en.wikipedia.org). Quantitative material is collected from SIX Trust which is a very reliable source. The insecurity of the collected information should therefore be very low.

Conrad and Kaul (1993) suggest an explanation of the overreaction hypothesis that rests on computational and other biases (Amir and Ganzach, 1998). We do not believe this to be a big problem for us. We use reliable sources and the Excel work is extensive and as accurate as possible. It is though possible that the human error factor have to some extent distorted the results since a numerous amount of calculations were made in Excel. We have critically reviewed the results to detect any obvious mistakes, which, of course were corrected

To be able to correctly answer our main questions, we have employed recognized methods and models within the relevant area.

One important question is if the conclusions will be different using a larger time period? As we can see in graph 1 in chapter 3.1.2 there has been some dramatic price changes in both directions during our chosen time period. It is possible that these turbulent cycles affect our results. It is also hard to say if the result would be different using a larger data period since the data needed for such analysis is not available for the SSE.

4 Empirical results and analysis

In this chapter we present empirical results from our models and the possible sources behind an eventual contrarian profit.

4.1 The residuals

When calculating residuals we must compare it to a relevant benchmark. We use two different benchmarks: the AFGX and an equally-weighted index. This will give differences in residuals because of the difference in index performance. Also, Brown and Warner showed that using value weighted indexes might result in a higher beta value for a randomly selected sample of stocks, if securities with low cap weights in the index have relatively high betas and vice versa (Atkins and Dyl, 1990).

We calculated the market-adjusted residual returns, as follows:

$$\varsigma_{i,t} = R_{i,t} - R_{m,t}\,,\quad i = 1,...47 \quad t = 1,...2593$$

Where $\varsigma_{i,t}$ is the market-adjusted residual return on the stock i for the day t, $R_{i,t}$ is the return on stock i for the day t and $R_{m,t}$ is the returns on the AFGX index and the equally- weighted index.

The market model residuals were estimated by first calculating alpha and beta from a post window of 50 days from the regression below

$$R_{i,t} = \alpha_i + \beta_i * R_{m,t} + \varsigma_{i,t}$$

where alpha and beta for all 94 (47+47) observations were estimated

Then the residuals where given by:

$$\varsigma_{i,t} = R_{i,t} - \alpha_i - \beta_i * R_{m,t}$$

In table 1 (2) we show results for both the market model residuals and for the market adjusted residuals for the final sample of the 47 losers (winners) stocks. The results can be compared against the two benchmarks.

Table1

	Losers, equally weighted		**Losers, AFGX**	
	Market adjusted	Market model	Market adjusted	Market model
Mean	-0,135	-0,128	-0,126	-0,126
Std deviation	0,033	0,038	0,038	0,043
Variance	0,001	0,001	0,001	0,002
Minimum	-0,221	-0,205	-0,210	-0,226
Maximum	-0,101	-0,065	-0,066	-0,047
Quantity	47	47	47	47

As we can see losers have lost on average approximately 13 percent on the event day. Generally, there seems to be small differences in results between the two models when measuring residuals and also small differences comparing against different benchmarks.

Table 2

	Winners, equally weighted		**Winners, AFGX**	
	Market adjusted	Market model	Market adjusted	Market model
Mean	0,149	0,142	0,147	0,144
Std deviation	0,052	0,054	0,053	0,057
Variance	0,003	0,003	0,003	0,003
Minimum	0,086	0,042	0,072	0,048
Maximum	0,285	0,303	0,307	0,328
Quantity	47	47	47	47

The average price change for the event day is larger for winners compared to the losers. We can also see that winners have larger standard deviation and more extreme outliers.

Since the comparisons between the two indexes not differ a lot, we have chosen to show results only from the equally weighted index.

In table 3 we look at the results from the market model regressions.

Table 3

Market model	**Losers**		**Winners**	
	Alpha	Beta	Alpha	Beta
Mean	-0,002	1,840	-0,001	1,460
Std deviation	0,006	1,036	0,006	0,971
Variance	0,000	1,073	0,000	0,943
Minimum	-0,017	-0,051	-0,014	-0,013
Maximum	0,016	4,041	0,012	5,595
Quantity	47	47	47	47

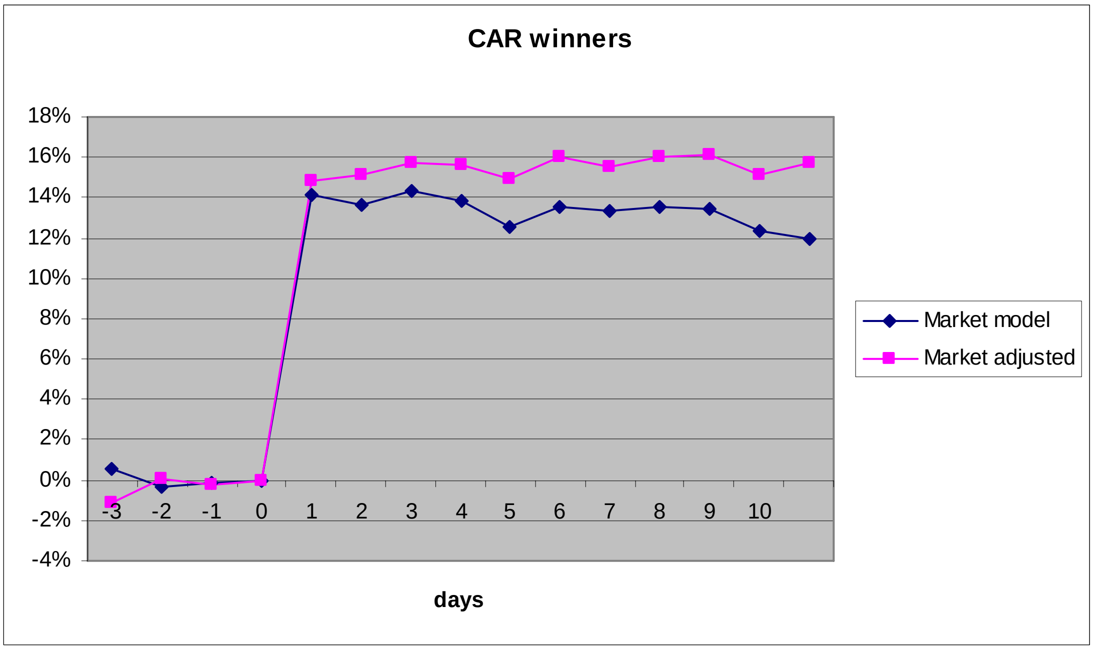
When looking at the losers we found that all the p-values were >0,05 for the alpha variables and six p-values for beta were >0,05. For the winners the alpha p-value is the same and eleven beta p-value were >0,05. Even if several alpha values are non-significant it is not negative since the alpha is very small and will therefore not affect the residuals. However, the betas, are clustered around a 95 percent level of significance. Since beta will have a large impact (see mean value in table 3) on the residuals a high level of significance is desired.

Difference in risk (beta) between losers and winners are possible explanations for asymmetry in reversals of losers over winners. If, for example, losers appear to have higher betas than winners the asymmetry can be partly explained.

4.2 Is there an overreaction effect?

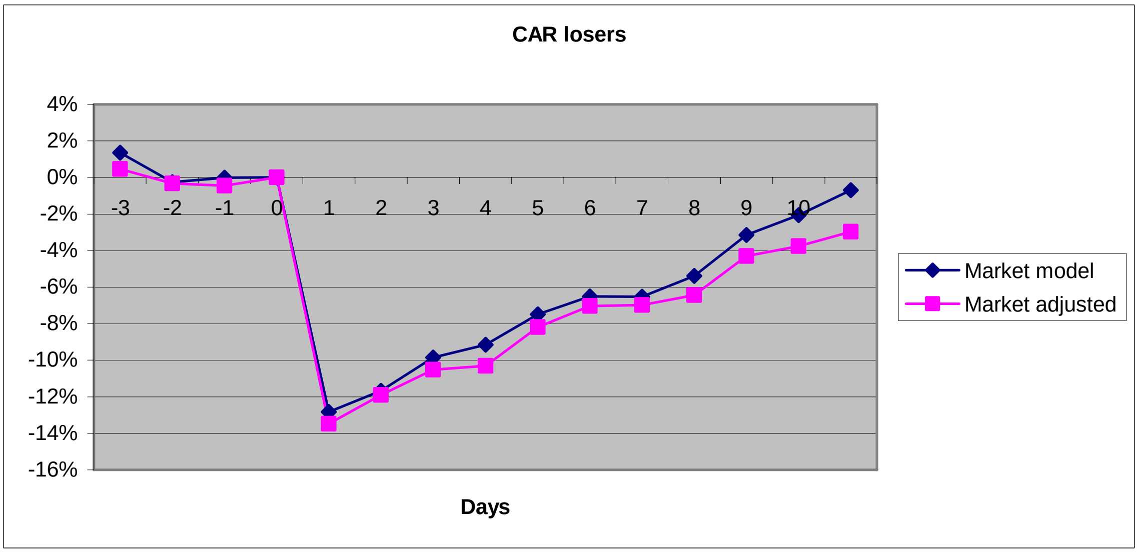
In graph 2 we examine the movement after the event day for the 47 winners. Winners virtually show no reversal effect in the 10 day period following the event, thus the overreaction effect is non-existent. The returns are stabile and do not show any price trend. Similar patterns have been found by previous research and the results are in line with our expectations

Graph 2



Graph 3 shows the cumulative average daily percent return for losers at t-3 and t+10. The average initial drop at t was about 13 percent and trading prior to the event is rather flat. As we can see large negative daily rates of return tend to be followed by positive rebounds. We can see that for a –10 % trigger, the average reversal is about 1% for day one, and by day 2 the cumulative average return is approximately 3 % for the market model.

Graph 3



4.4 Contrarian profit?

Results from De Bondt and Thaler's model with cumulated average abnormal returns are shown in table 4. The null hypothesis implies that there is no overreaction (Forner, Marhuenda, 2001). Hence, the rejection of the null hypothesis in the majority of the CARs in the market model shows that there is an overreaction effect. Results from the market adjusted model are quite similar from the 6th day, except from the 7th day which is significant.

Table 4

Market Model

CAR	1	2	3	4	5	6	7	8	9	10
S^2	0,007	0,007	0,011	0,017	0,022	0,025	0,036	0,036	0,047	0,062
t-stat	-0,863	1,521	1,519	2,221	2,023	1,984	1,956	2,497	2,583	2,571

Market Adjusted

CAR	1	2	3	4	5	6	7	8	9	10
S^2	0,006	0,008	0,012	0,018	0,021	0,022	0,034	0,034	0,045	0,063
t-stat	0,925	1,149	1,066	1,935	1,874	1,980	1,583	2,123	2,144	1,844

Table 5

Day	Market Model	Market Adjusted Model
1	0,017	0,013
2	0,028	0,021
3	0,041	0,024
4	0,069	0,053
5	0,070	0,053
6	0,071	0,059
7	0,080	0,059
8	0,105	0,080
9	0,126	0,094
10	0,144	0,097

From table 4 and 5 we can document statistically significant profit for the contrarian strategy approximately from the 5^{th} day according to t-statistics. The positive trend is not broken during the period but it is not certain throughout the whole period as mentioned when reviewing the market adjusted model.

We can see that the market model yields greater contrarian profits. Both models show that the profit increases from day to day without exception. The size of the profits is in line with previous short term studies.

4.5 The variables behind price reversals

We calculated the regression,

$$CAR_{i,t} = \delta_0 + \delta_1 * SIZE_{i,t} + \delta_2 * IPC_{i,t} + \delta_3 * LEAK_{i,t} + \varepsilon_{i,t},$$

for all 94 stocks which gives us a total of 40 regressions. Below we show the results from the regressions for the CAR 1, 5 and 10 from both models.

Market Adjusted			
Winners	Size	IPC	Leakage
CAR 1	0,027	-0,266	0,333
tstat	1,236	-1,383	0,822
CAR 5	0,030	0,251	-0,968
tstat	0,688	0,638	-1,169
CAR 10	0,064	1,279	-0,767
tstat	1,011	2,264	-0,646
Losers			
CAR 1	0,016	0,068	0,395
tstat	0,665	0,217	1,575
CAR 5	-0,020	0,518	-0,474
tstat	-0,436	0,895	-1,021
CAR 10	-0,072	1,589	-1,639
tstat	-0,823	1,421	-1,830

Market Model			
Winners	Size	IPC	Leakage
CAR 1	0,013	-0,208	0,130
tstat	0,669	-1,216	0,362
CAR 5	0,009	0,216	-1,138
tstat	0,187	0,522	-1,311
CAR 10	0,059	1,177	-1,533
tstat	0,971	2,177	-1,349
Losers			
CAR 1	0,006	0,230	0,467
tstat	0,251	0,733	1,858
CAR 5	-0,033	0,138	-0,416
tstat	-0,775	0,254	-0,958
CAR 10	-0,137	0,546	-1,368
tstat	-1,550	0,481	-1,506

The coefficient (delta) of each independent variable tells us what relation that variable has with CAR_i, the dependent variable, with all the other variables held constant. If there is an overreaction effect for the losers the coefficient of IPC (delta 2) will be large and negative. If market cap or leakage is related to abnormal returns, delta 3 and delta 1 will differ from zero. Surprisingly, a vast majority do not show any significance for the coefficients. Only two observations of significance for the variable IPC were found for winners at t=10 and they had the expected positive sign. Due to the lack of significance we can not make any conclusive comment based on empirical evidence about the presumable sources behind the contrarian profits.

4.6 Adjusting for market frictions

The final test is to investigate if the contrarian profit persists after adjusting for market frictions.

Our contrarian strategies result in buying stocks, that have experienced a large daily loss, at the end of the trading session and selling them after a holding period of x days. Transaction and information costs occur when buying or selling stock. Cohen et al. (1980) and Mech (1993) discuss the effect of these costs. They argue that these costs create market frictions which hold back trades aimed at exploiting cross-security price errors, thus slowing prices reaction to new cross-security information. In other words, the contrarian profit might not be exploitable because of market friction. Mech further analyses a market where stocks are driven by private information. When spreads are positive, informed traders will only trade when the expected profit from private information exceeds the costs for a trade. Thus when “small” events (private information) occur there will be a delayed reaction because of the trade cost, while “large” events (market information) will be efficiently reflected in stock prices (Säfvenblad, 1997).

When adjusting for market frictions we have not included the actual bid-ask price since it is not possible to say at what price the stocks would have been bought. Instead we have assumed that it would have been possible to buy at the close-prices, collected for the data sample. This is not a probable assumption but the general conclusions should not be affected. We only know that a trade was made at closing price but we do not know if it would have been possible buying/selling more stocks without changing the price.

Taking into account various costs of trading such as commission, trading impact costs, bid-ask spread, taxes, risk free rate of return, short-sale costs, and holding period risks, the estimates of average round-trip transaction costs are, according to most studies, generally at about 2 %. The trading costs can differ depending on the investors position (stockbroker, private trade, manager), the size of the investments and vary with time and security characteristics but in general the one-way cost is about 1% of asset value (Kodjovi, 2003).

The contrarian profits are adjusted for these frictions by subtracting 2 %. The results are:

Day	Market Model	Market Adjusted Model
1	-0,003	-0,007
2	0,008	0,001
3	0,021	0,004
4	0,049	0,033
5	0,050	0,033
6	0,051	0,039
7	0,060	0,039
8	0,085	0,060
9	0,106	0,074
10	0,124	0,077

After adjusting for market frictions the profits are at first slightly negative but increases to 12 respectively 8 percent on the 10^{th} day of trading.

5 Summary and conclusions

In chapter five we summarize the results from the calculations and draw our final conclusions.

This study employs data for stocks listed in the SSE in order to investigate existence of short-term reversals. We construct a contrarian strategy and seek the sources of possible contrarian profits.

It is important to question whether the previous studies are reliable because of the fact that researchers have documented a momentum in stocks. Is it possible that both strategies can coexist or are they only profitable at different time horizons? We have not found any documented evidence of a short-term momentum and believe that the reversal phenomenon has its strongest impact at short time horizons.

De Bondt and Thaler (1985) explain the contrarian profit with the overreaction hypothesis. If this hypothesis is correct, De Bondt and Thaler (1985) suggest that two fundamental consequences should be observed:

i. Any extreme change in the price of a given stock should be followed by a subsequent change in the opposite direction; and,
ii. The greater the initial change from the original price in one direction, the greater the subsequent re-adjustment in the opposite direction should be.

Our study provides further evidence of reversals that supports the validity of the overreaction hypothesis. According to CAR-results losers show greater reversals than winners and at an earlier stage.

On beforehand when we discussed the possible results of a contrarian strategy, we were quite certain of finding evidence of profit from buying “losers” but not so sure about going short in “winners”, according to other similar studies. Our CAR-analysis show statistically significant profits from approximately the 5th day where the majority of the profits come from losers.

The results from the empirical analysis indicates that the contrarian strategy produce significant profits. Even after subtracting for market frictions, we could still see mostly positive profits.

The second important question we attempt to address is the source of a reversal phenomenon. Unfortunately our statistical analysis shows that none of the chosen variables are non-significant, and therefore we fail to identify the possible sources of the reversals. We expected to find that larger price changes lead to larger reversals in line with De Bondt and Thaler’s hypothesis. However, our deltas for IPC are neither of the correct sign nor significant. Also the variables, size and leakage, show deltas that are non-significant and signs not in line with our expectations.

The main reason for our unsatisfactory results we believe to be large variations in the residuals. Using a p-value of 5 percent these variations will not give us acceptable results. By for example using the CAR-model we can identify a reversal tendency because the model is based on averages instead of individual stock-variations. One explanation for not finding the size effect might be that the SSE small cap move differently from other small caps on international markets. We also believe that a leakage effect could have been found using only small caps in our data sample. Since leakage effect do not usually appear in price movements of large caps, it is probably not possible to statistically prove this variable using our data sample.

We should consider the fact that calendar seasonality does exist to some extent. A daily contrarian strategy may be biased due to the fact that the largest negative price changes occur most often on Mondays and the opposite goes for Fridays. To avoid this anomaly, one should not e.g. go long in winners on Mondays. The January effect might also affect contrarian results, but could in reality be avoided with the same solution as with the Monday-Friday effect.

It is possible that the asymmetry in reversals are affected by "stop-loss" strategies e.g. a strategy that sells stocks losing more than five percent on a daily basis. The result from such strategies might push stock prices away from their fundamental values.

A successive contrarian strategy presents a challenge to the EMH by providing abnormal returns by taking advantage of underreaction or overreaction without bearing extra risk. In the EMH chapter we discuss whether it is possible or not to retrieve abnormal returns by looking at historical data. According to the weak form of efficiency all historic events are fully reflected in today's price. But due to the fact that we generate abnormal returns by using historic data we contradict the weak form of EMH. We believe that this is because people tend to overreact, rather than information not being reflected in price.

Our results indicate that the Swedish stock market is efficient. In reality, markets cannot be absolutely efficient or wholly inefficient. It is reasonable to see markets as a mixture of both, wherein daily decisions and events cannot always be reflected immediately into a market. If all participants were to believe that the market is efficient, strategies as the momentum and contrarian would not be profitable.

In modern time, markets all over the world are gaining efficiency. Information technology (IT) allows for a more effective, faster means to spread information, and electronic trading allows for prices to adjust more quickly to news entering the market. However, while the pace at which we receive information and make transactions quickens, IT also restricts the time it takes to verify the information used to make a trade. Thus, IT may accidentally result in less efficiency if the quality of the available information is poor.

We can conclude that a reversal phenomenon exists in the SSE and that it is only visible for prior losers. Our contrarian strategy yields significant profits in short-term and positive profits remain after adjusting for market frictions. Regrettably we were not able to locate the sources behind the reversals. We believe in the profitability of a short-term contrarian strategy and that an overreaction phenomenon is the main source to this profit.

6 Research suggestions

It would be interesting to base the analysis on “real quotes” which eliminates the bid-ask bounce and mitigates the nonsynchronity problems. This could be done by actually implementing a contrarian strategy, i.e. by putting money into the strategy.

Since a extremely high percentage of contrarian investment strategy studies is centred on developed markets, an exploration on a less-developed stock market, in for example Africa, would be interesting. The effects from less efficient market could be studied and compared to existing results.

We have not found any studies using hourly perspective. It would be interesting to scale down a reversal phenomenon into hours instead of days and weeks. The analysis would require much data which can only be found on large markets.

It would also be interesting using another approach when defining extreme events. If the cause of the event can be found one can categorize and analyze effects from different type of news.

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All tables and graphs are, if nothing else said, made in Microsoft Excel from our collected data sample.