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Market Efficiency Theory and the Earnings Announcement Premium at the Oslo Stock Exchange

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Abstract

Lamont and Frazzini (2007) document that a trading strategy consisting of buying every stock expected to announce within the coming month and selling short every stock not expected to announce the coming month generates a large and statistically significant earnings announcement premium in the U.S. stock market between 1972 and 2004. Lamont and Frazzini (2007) claim that the main explanation for the earnings announcement premium is uninformed or irrational demand by individual investors, coupled with imperfect arbitrage by sophisticated investors. Their results are not in accordance with weak-form market efficiency in the U.S. stock market in the sense that historical information can be used to predict future stock prices. This thesis will test if related trading strategies based on predicted quarterly earnings announcement dates generates an earnings announcement premium at the Oslo Stock Exchange in the period between 1999 and 2007.

Contrasting with the results of Lamont and Frazzini (2007) the results presented in this thesis, that are not statistically significant, show that various versions of the trading strategy based on predicted earnings announcement dates seem to generate negative monthly average excess returns. Further, a L/S portfolio trading strategy based on actual announcement dates does not generate average monthly returns statistically significantly larger than zero. This indicates that improved methods for predicting earnings announcement dates would not assist in forming L/S portfolios generating positive excess returns over the sample period. Consequently, it seems there was no earnings announcement premium at the Oslo Stock Exchange in the sample period between 1999 and 2007. The results presented in this thesis can therefore *not reject* market efficiency at the Oslo Stock Exchange.

The main reasons for the presented results, which are differing from the results of Lamont and Frazzini (2007), are the following: Firstly, there is a possibility that the dataset of earnings announcement dates utilised in this analysis is not representative for the sample period regarding the real coverage of earnings announcement dates. Moreover, there is a possibility that the patterns found by Lamont and Frazzini (2007) are random, and caused by for example data-mining, and that in reality there is no earnings announcement premium.

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1. Introduction

Lamont and Frazzini (2007) found that a trading strategy holding a zero-cost portfolio of expected announcers while selling short a portfolio of expected non-announcers generated yearly excess returns of between 7 and 18 percent. The positive excess returns, they claim, can not be explained by the factors included in the Carhart (1997) four-factor model, and are hence “abnormal”. According to market efficiency theory, it is not possible to earn returns greater than a risk-free rate plus a compensation for the risk related to investing in risky assets. The results of Lamont and Frazzini (2007), which are not in accordance with weak-form market efficiency in the U.S. stock market, are therefore relatively interesting since they are indicating that it is possible for a market participant to earn excess returns without having to take on excess risk. Given that the U.S. stock market is one of the largest in the world, and regarded as relatively efficient, it is interesting to examine if the same earnings announcement premium exists in the much smaller Norwegian stock market.

In this thesis, I test if various trading strategies, similar to the earnings announcement premium strategy of Lamont and Frazzini (2007), generates excess returns over the Norwegian Government three month Treasury bill at the Oslo Stock Exchange over the sample period between 1999 and 2007. At the last day of month t-1, the monthly trading strategy buys a value-weighted portfolio of stocks that are expected to announce their quarterly earnings the coming month and sells short a value-weighted portfolio of stocks that are not expected to announce their quarterly earnings the coming month. Combined, this trading strategy creates a value-weighted zero cost L/S portfolio.

In other words, in this thesis, I test for the existence and the robustness of an eventual earnings announcement premium at the Oslo Stock Exchange between 1999 and 2007. This is tested with the following zero-hypothesis:

A) $\mathbf{H_0}$: Average monthly excess returns L/S portfolio = 0

$\mathbf{H_1}$: Average monthly excess returns L/S portfolio > 0

With zero-hypothesis A, this thesis tests if various versions of the L/S portfolio trading strategy generates positive average monthly excess returns that are statistically significant. Clearly, if the value-weighted portfolio that sells short expected non announcers generates average monthly excess return that are more negative than the value-weighted monthly average excess return of the portfolio that buys expected announcers, the combination of these two portfolios, the zero cost L/S portfolio, would earn positive monthly average excess returns. In this case, one would earn larger returns by only selling short the portfolio of expected non-announcers. I limit my approach to focus on whether or not a trading strategy *combining* the two portfolios each month generates statistically significant positive returns over the Norwegian Government three month Treasury bill.

If zero-hypothesis A is rejected, I further test whether the above zero average excess returns generated by the L/S portfolio strategy are abnormal by regressing the returns on the four risk factors from Carhart (1997) with the following zero hypothesis:

B) **H_0:** Average monthly abnormal returns L/S portfolio = 0

H_1: Average monthly abnormal returns L/S portfolio > 0

If zero-hypothesis B is rejected, this indicates that there is an earnings announcement premium at the Oslo Stock Exchange. This means that a monthly trading strategy taking a long position in portfolios of stocks expected to announce their earnings and a short position in portfolios of stocks not expected to announce their earnings in the following month, generates returns that can not be fully explained by the Carhart (1997) four-factor model. The abnormal returns generated from this trading-strategy is statistically significant. If the Carhart (1997) four-factor model describes the risk related to following the tested trading strategy, a rejected zero hypothesis is inconsistent with weak form market efficiency at the Oslo Stock Exchange in the sense that historical information can be used to predict future stock prices.

Contrasting with the results of Lamont and Frazzini (2007), the results presented in this thesis, which are not statistically significant, show that various versions of the trading strategy based on predicted earnings announcement dates seem to generate negative monthly average excess returns. There is hence no signs of an earnings announcement premium at the Oslo Stock Exchange in the sample period between 1999 and 2007. I find no results that can reject weak-form market efficiency at the Oslo Stock Exchange.

This thesis is organised as follows. In section 2 an overview of market efficiency theory is presented. Lamont and Frazzini (2007) claim that the main explanation for the earnings announcement premium is uninformed or irrational demand by individual investors, coupled with imperfect arbitrage by sophisticated investors. In order to understand the implications of a found stock price anomaly, market efficiency theory, including behavioural finance theory, is given focus in this section. Section 3 reviews relevant literature covering the earnings announcement premium and its possible explanations. Additionally, section 3 covers previously done empirical studies, with focus on stock price anomalies, which have been conducted on the Oslo Stock Exchange. Section 4 presents the data utilised in the empirical analysis as well as the methodology used for testing the zero hypothesis. In section 5 the results and the analysis of the empirical research are presented, as well as robustness checks of the results. Section 6 presents a discussion of the results found in this thesis, and places the results in the literature presented in sections 2 and 3. Moreover, section 6 contains a discussion of potential reasons till why the presented results are in contrast to the results of Lamont and Frazzini (2007), criticism of the presented results as well as proposals for further studies on the earnings announcement premium at the Oslo Stock Exchange. Section 7 presents conclusions.

2. Market Efficiency Theory

Market efficiency theory is substantial knowledge when analysing stock return series, and its most important implication is that an investor can not obtain returns greater than the corresponding on taken risk. The earnings announcement premium of Lamont and Frazzini (2007) is not in accordance with weak-form efficiency in the U.S. stock market. In order to understand their results and being able to analyse the degree of efficiency in the Norwegian stock market, this first part of this section reviews market efficiency theory and its implications. Further, the relationship between risk and return as well as found stock price anomalies are discussed. This part is relevant for understanding the implications of trading on the basis of stock price anomalies that have been documented. Lamont and Frazzini (2007) offers an explanation in the field of behavioural finance for their found earnings announcement premium. Lamont and Frazzini (2007) claim that the main explanation for the earnings announcement premium is uninformed or irrational demand by individual investors, coupled with imperfect arbitrage by sophisticated investors. The last part of this section is therefore focusing on behavioural finance theory, a field of finance still in its early stage. This section ends with a short discussion of the predictability of stock prices.

2.1 The Random Walk and the Efficient Market Hypothesis

The market efficiency theory can be traced all the way back to the French mathematician Louis Bachelier's dissertation, "The Theory of Speculation" from 1900. Bachelier's "Theory of Speculation" from 1900 was not taken further into examination until the 1950s; Followed by the possibility of using computers for analysing economic time series in the early 1950s, Maurice Kendall examined the assumption that stock prices reflect the past and the future prospects of the firm (Kendall, 1953). He could not identify any predictable patterns in stock prices; stock prices seemed to follow random patterns.

The suggestions of that stock prices are fluctuating randomly imply that changes in stock prices are independent of one another. In other words, it implies that there is no correlation between the change in the stock price at time t and at time t+1. This is known as the random walk hypothesis; stock price changes are random and unpredictable. The logic behind the random walk hypothesis is that if past stock price changes could be used to predict future stock price changes, investors would take advantage of it until the stock prices were adjusted to a level where all the information in the past stock prices would be reflected in today's stock price. Hence price patterns would not exist.

That prices are fluctuating randomly was further demonstrated by Paul Samuelson in his article from 1965. Also Eugene Fama takes the theory of random walks in stock market prices as well as its implications further into examination is in his articles from the same year. It is in these articles that the expression "efficient market" first is used. In the article "Random Walks in Stock Market Prices" Fama (1965a, p. 2) defines the expression "efficient market" as

"a market where there are large numbers of rational, profit-maximisers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value."

Fama argues that the implications of an efficient market are that past history of series of stock prices cannot be used to predict their future behaviour. He claims that *"the future path of the price level of a security is no more predictable than the path of a series of cumulated random numbers."* (Fama 1965a, p. 2). Consequently, it is not possible to achieve above normal returns by using any trading rules or techniques based on the information that is already known in the market, compared to a buy-and-hold policy. This is known as the Efficient Market Hypothesis (EMH).

The EMH states that stock prices fully reflect all available information. It is hence impossible to "beat the market" since stock prices already has all relevant information incorporated. This means that according to the EMH, stocks are always exchanged at their fair, or the fundamental, value. It is therefore not possible for investors to find over or underpriced stocks in the market. The only way to obtain higher returns is to invest in riskier stocks.

The general assumptions made in the EMH are:

1) The market consists of a large number of rational investors who are actively competing with each other in order to maximise profits.
2) The existence of irrational investors will affect stock prices both positively and negatively and the effect of this on stock prices is in total zero; the *markets* are hence assumed to be rational.
3) All investors have access to the same information and they perceive this information in the same way.
4) Information is obtainable for no or low costs.
5) The market makes unbiased forecasts of the future.

Due to that the statement claiming that stock prices in an efficient market fully reflect all available information was relatively general, and in order to make the efficient market model testable, Eugene Fama saw the necessity of specifying the efficient market definition. In his paper from 1970 "Efficient Capital Markets: A Review of Theory and Empirical Work", Eugene Fama classified market efficiency into three forms; weak form efficiency, semi-strong efficiency and strong efficiency:

2.1.1 Weak Form Efficiency

Weak form market efficiency claims that all past prices of a stock are reflected in today's stock price. Historical stock prices cannot be used to predict future stock prices, the stock prices follow a random walk. In other words, technical analysis cannot be used to predict and "beat" the market.

On the other hand, the weak form market efficiency allows for that fundamental analysis can be used for finding under- or overpriced stocks. By using companies' financial statements, not historical stock prices, investors can possibly find under- and overpriced stocks.

2.1.2 Semi-strong Form Efficiency

Semi-strong market efficiency claims that all public information, as well as future expectations, is reflected in a stock's current price. The implication of the semi-strong market efficiency is that neither fundamental nor technical analysis can be used to achieve above normal returns. A passive, diversified buy-and hold strategy will generate the highest returns in a semi-strong form efficiency market since an active strategy; by definition, an active strategy will not be more profitable due to the related transaction costs. Since all publicly known information is baked into the current stock price, an investor needs private information in order to achieve above normal returns.

2.1.3 Strong Form Efficiency

The strong form market efficiency implies that all information in a market, both public and private, is reflected in a stock's price. Profits exceeding normal returns can not be obtained regardless of the amount of research or information an investor has access to. It also implies that above normal returns cannot be achieved by investors with insider information since the market predicts future stock behaviour and therefore has taken all private information into account. This degree of efficiency is by many seen as only theoretical, and there are hence strong regulations against insider information based trading.

2.1.4 The Market Efficiency Paradox

As stated by the EMH, it is impossible to" beat the market" since stock prices reflect all relevant information. It is therefore not possible for investors to find under –or overpriced stocks through analyses and the only way to obtain higher returns for investors is by taking on more risk through buying riskier stocks. In an efficient market no investors will hence have the incentives to perform analysis looking for under – or overpriced stocks since they in theory won't be rewarded for it. On the other hand; available information has to be taken into account somehow, and it is through investors analysing this information and trading on the basis of their analysis that a stock market becomes efficient. In order to be willing to pay the costs related to analysing the available information in a market, investors require compensation. This leads us to the market efficiency paradox; In order to have an efficient stock market, there has to be investors believing that they can make above normal returns by performing additional analyses, hence, believing that the market is inefficient. The stock market is eventually efficient only because there are investors in the market believing that it's not.

2.2 The Relation Between Risk and Return

According to the Efficient Market Hypothesis, an investor has to take on more risk in order to obtain higher returns. This is consistent with the assumption that investors are risk averse in the sense that they are willing to sacrifice some return in order to reduce risk. Thus, an investor will demand higher returns for holding riskier assets.

The standard deviation of returns, or volatility, is a widely accepted measure for risk (Womack and Zhang, 2003). The logic behind this is that the more an asset's return is fluctuating, the less sure an investor holding the asset can be of its value at the time he or she wishes to sell the asset. The total risk of a stock is normally decomposed into two components, namely the market risk and the specific risk. Market risk, also called systematic risk, is the variance that arises from a stock's covariance with the return of the market and can not be diversified away. The specific risk, also called un-systematic or idiosyncratic risk, is the variance that arises from other stock-specific determinants of returns and can be diversified away. Through holding several stocks with as little correlated returns as possible, an investor can hence reduce stock-specific risk, and hence overall portfolio volatility, without lowering return expectations. However, the rate of volatility reduction due to adding more assets into a portfolio is decreasing with the increasing number of assets. Therefore, a general rule of thumb is that a portfolio is well-diversified if it contains 30 or more assets (Womack and Zhang, 2003). Since stock-specific risk can be diversified away, its expected average is zero. In other words, there is no risk premium associated with stock specific risk and an investor can hence only expect compensation for the market risk.

Beta is normally used to measure the degree to which the variation of the return of a stock is correlated with the variation in the return of the market. More specified, a stock's beta is calculated as the covariance between the return of the market and the return of the asset, divided by the variance of the return of the market:

$$\beta_i = \frac{\operatorname{cov}(r_i, r_M)}{\operatorname{var}(r_M)}$$

The market beta is by definition unity. Stocks with a beta higher than unity are in general more sensitive to market movements than stocks with a beta lower than unity. The beta of a portfolio of stocks is normally calculated by taking the weighted average of each stock's beta, on the basis of each stock's market capitalisation.

Various asset pricing models are used for predicting the expected return of a portfolio. The Capital Asset Pricing Model (CAPM), which was introduced by Jack Treynor, William

Sharpe, John Litner and Jan Mossin in the 1960's, is one of them. The CAPM predicts the equilibrium relationship between a portfolio's expected return and its risk:

$$CAPM : E(r_{p,t}) = r_{f,t} + (E(r_{M,t}) - r_{f,t})\beta_p$$

The CAPM implies the equity risk premium of a portfolio, the market return, $E(r_M)$, minus risk free return, r_f, is directly related to the beta of the portfolio. Thus, the CAPM predicts expected return of a portfolio, $E(r_i)$, is equal to the equity risk premium times the portfolio's beta plus risk free return. An investor's compensation for bearing risk by investing in a risky asset is measured by the portfolio's beta. The CAPM is therefore a single factor model.

In order to be able to evaluate a portfolio's performance, one compares its expected return with its actual return. A portfolio's difference between expected return and actual return is normally referred to as alpha, and is under the CAPM by definition expected to be zero in order to avoid arbitrage opportunities. If there is a difference between expected return and actual return on a portfolio, one can hence either draw the conclusion that CAPM is a poor asset pricing model, or that the portfolio has generated abnormal returns, returns that are lower or higher than expected with the level of risk taken on over the investment period.

In order to calculate a portfolio's alpha, it is common to run a regression based on the CAPM-model:

$$R_{p,t} - r_{f,t} = \alpha_p + \beta_p (R_{m,t} - r_{f,t}) + \varepsilon_{p,t}$$

Where $R_{p,t}$ is the portfolio's return, $r_{f,t}$ is the riskfree rate, α_p is the portfolio's alpha, β_p is the portfolio's beta, $R_{m,t}$ is the return of the market while $\varepsilon_{p,t}$ is the error-term.

$$E(R_{m,t}\varepsilon_{p,t}) = 0$$

$$E(\varepsilon_{p,t}) = 0$$

And

$$E(\varepsilon_{p,t}\varepsilon_{p,t}) = 0$$

A positive alpha is indicating that the portfolio has performed better than expected compared to the portfolio's market related risk, namely its beta.

The assumptions behind the CAPM are:

1) Investors are rational, and they only care about expected return and risk. They will therefore always seek to maximise expected return for any given level of risk.
2) All investors have the same perception of the trade-off between risk and expected return.
3) Investors are well-diversified and therefore, they will only get compensated for the systematic market-risk they are bearing.

According to Womack and Zhang (2003), the CAPM normally achieve an R^2 measure around 0.85. The R^2 measure describes how well the model predicts actual returns, and if the CAPM was predicting returns perfectly, its R^2 would have been 1. The predictable power of the CAPM is therefore relatively high. However, many researchers believe that there are other sub-factors of risk that, when added to a model, could predict expected returns more precisely than the CAPM. Fama and French's three-factor model is the most known one:

2.2.1 The Fama and French Three-Factor Model

Fama and French (1993) observed that small capitalisation stocks tend to have higher average returns than large capitalisation stocks, and that stocks with a high book-to-market value tend to have higher average returns than stocks with low book-to-market value. They therefore represented an extended version of the CAPM in 1992, which is referred to as the Fama and French three-factor model. In addition to the overall market factor, they identified a factor related to firm size and a factor related to a firm's book-to-market value, as risk factors in stock returns. In order to represent the risk factors related to firm size and book-to-market value, they constructed a SMB and a HML factor.

SMB stands for "Small Minus Big". The factor is calculated as the average return for the smallest 30 % of stocks minus the average returns of the largest 30 % of stocks that month, and measures the additional return, or the "size premium" related to investing in small capitalisation stocks versus investing large capitalisation stocks. While a positive SMB indicates that small capitalisation stocks outperformed large capitalisation stocks in a given month, a negative SMB indicates the opposite. The logic behind adding SMB as an additional risk factor is, according to Womack and Zhang (2003), that smaller firms' stocks often are less liquid than larger firms' stocks. Also, smaller firms are more sensitive to "*many risk factors*" and they're ability to "*absorb negative financial events*" is lower than for larger firms.

HML stands for "High Minus Low" and is calculated as the average return of the 50 % of stocks with the highest book-to-market ratio minus the average return of the 50 % of stocks with the lowest book-to-market ratio each month. The HML measures to which extent investors are compensated for investing in companies with high book-to-market values, also called the "value-premium". Stocks with high book-to-market ratios are regarded as value-stocks and stocks with small book-to-market values are seen as growth stocks. While a positive HML indicates that value stocks have outperformed growth stocks in a given month, a negative HML indicates the opposite. In order to get listed on a stock-exchange, a firm normally needs to be of a certain size. Thus, according to Womack and Zhang (2003), the logic behind adding HML as a risk factor is that firms with high book-to-market values have most likely been victims of the market's disbelieve of the firms' future earnings. "Since these companies have experienced some sort of difficulty, it seems plausible that they would be exposed to greater risk of bankruptcy or other financial troubles than their more highly valued counterparts".

In order to test if a portfolio is earning abnormal returns, one can therefore run a regression on the following equation:

$$(4)\ R_{p,t} - r_{f,t} = \alpha_p + \beta_p MKT_t + s_p SMB_t + h_p HML_t + e_{p,t}$$

Where $R_{p,t}$ is the portfolio's return, $r_{f,t}$ is the riskfree rate, α_p is the portfolio's alpha, β_p is the portfolio's exposure towards market risk, MKT is the return of the market while $e_{p,t}$ is the error-term. The s_p and h_p are respectively the portfolio's exposure towards SMB and HML. If alpha is significantly larger than zero, the portfolio is earning abnormal returns in the sense that its return is not fully explained by the three risk factors. According to Womack and Zhang (2003), the Fama and French three-factor model often achieve an R^2 measure around 0.95, and is due to its strong explanatory power of returns commonly used. For example, Morningstar, a mutual fund rating company, classifies mutual funds based on the three Fama and French factors. Alpha-values found by performing a regression based on the

CAPM-equation often tend to diminish or turn into zero when regressed on the latter equation. In practise, if one finds abnormal returns by performing the CAPM-based regression, one should therefore execute a robustness check on the same data material by performing a regression based on more risk factors.

2.2.2 The Carhart Four-Factor Model

Mark Carhart (1997) introduced a forth risk-factor to the Fama and French three-factor model, namely the momentum-factor. This factor will, according to Carhart capture the one-year momentum-anomaly discovered by Jegadeesh and Titman (1993)[1].

(5) $R_{p,t} - r_{f,t} = \alpha_p + \beta_p MKT_t + s_p SMB_t + h_p HML_t + p_p PR1YR_t + e_{p,t}$

Where $R_{p,t}$ is the portfolio's return, $r_{f,t}$ is the riskfree rate, α_p is the portfolio's alpha, β_p is the portfolio exposure towards market risk, while $e_{p,t}$ is the error-term. Further, "*SMB, HML and PR1YR are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns*" (p.61). The MKT is the market return. The momentum-factor, PR1YR, is constructed by taking "*the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal weight average of firms with the lowest 30 percent eleven-month returns lagged one month*" (Carhart, 1997, p.61). An alpha-value different from zero indicates that the four factors can not fully explain a portfolio's excess return. Thus, a portfolio earns abnormal returns if alpha is different from zero.

Carhart (1997) claims that the four-factor model, on average, improves the pricing errors of the CAPM and the three-factor model. By examining the returns on portfolios of mutual funds, he finds that the mean absolute pricing errors from the CAPM is 0.35 percent, while it is 0.31 percent for the Fama and French three-factor model and 0.14 percent for the four-factor model. Carhart (1997, p. 62) concludes that the four-factor model "*well describes the cross-sectional variation in average stock returns*".

[1] This anomaly is further discussed in section 2.3.3.

2.3 Oppositians to market efficiency- Market Anomalies

In an efficient market it is not possible for investors to obtain above risk-adjusted market returns; new information is immediately reflected in a stock's price. It is hence necessary to look further into how quickly new information actually is reflected in a stock's price. Fama et al. (1969) examined the process by which stock prices adjust to new information. More specifically, they examined how the stock market is reacting to stock splits and found no particular market-imperfections. Since this, it has been tested through several empirical studies whether different stock markets are efficient or not. In this section I will list a few of the studies that have found anomalies pointing towards market inefficiency.

2.3.1 The Earnings Announcement Drift

According to Brealey and Myers (2003), investors often under-react to earnings announcements and only revise their opinions about the full significance of the earnings announcements when further information arrives.

Ball and Brown (1968) examined the movements of U.S. stock prices around earnings announcement dates between 1946 and 1966, and were amongst the first to provide evidence indicating that there is a drift in stock returns after earnings announcements.

Bernard and Thomas (1990) found that companies with earnings surprises in a current quarter tend to experience positive earnings surprises of the same sign over the subsequent three quarters. This, they claim, is evidence that stock prices fail to reflect the implications of current earnings for future earnings: "*stock prices partially reflect a naive earnings expectation: that future earnings will be equal to earnings for the comparable quarter of the prior year*" (p. 338). In other words, Bernard and Thomas (1990) documented a tendency for stocks to generate positive (negative) abnormal returns during the three quarters following a positive (negative) earnings announcement. The alternative explanations considered, namely problems with risk adjustment and the impact of transaction costs, are by Bernard and Thomas not seen as viable for explaining the found return-pattern.

2.3.2 Standardised Unexpected Earnings (SUE)

Standardised Unexpected Earnings (SUE) is the difference between actual and expected earnings per share divided by the standard deviation of expectations. Latané et al. (1974)

were amongst the first to claim that unexpected earnings forecasts, based on publicly available information, can be used to forecast stock prices and to obtain abnormal returns. In contrary, Reinganum's study from 1981 indicates that abnormal returns can not be earned by using SUE. However, by using a larger sample and claiming to represent a more complete and detailed analysis than Reinganum et al. (1982) again found results opposing to those of Reinganum; namely that there is a SUE effect. A trading strategy taking long positions in stocks with unexpected positive quarterly earnings announcements, while taking short positions in stocks with unexpected negative quarterly earnings announcements, would hence generate abnormal returns. They also found that about one half of the excess returns from stocks occur over the 90 day period after the unexpected earnings are announced. According to Keon et al. (2002), the SUE effect was highly present in the American stock market during the 1980s and the early 1990s. Over the later years, diverse regulations resulting in more companies supplying the market with more accurate information than before has resulted in the market rarely over-estimate earnings any more, meaning that the negative surprise is less frequent today. Keonet al. (2002) claims the SUE effect to be nearly eliminated today, but with the lately developments in the financial markets related to the American sub prime crisis there might be a chance for SUE to revive.

2.3.3 The Momentum Effect

The momentum effect was documented by Jegadeesh and Titman (1993). By examining portfolios of stocks they found that stocks that had performed well (poorly) in the past would continue to perform well (poorly) over the next 3-12 months. A trading strategy taking long position in past winners and short positions in past losers generated significant positive returns over 3-12 months holding periods. They also documented a similar pattern of returns around the earnings announcements; average returns around quarterly earnings announcement dates are significantly positive following a favourable earnings surprise in the previous quarter.

Jegadeesh and Titman (2001) tested their trading-strategy again in 2001 on another dataset and came to the conclusion that the momentum effect was present there too. This is inconsistent with the weak form market efficiency theory.

2.3.4 Mean-Reversion

The mean-reversion effect implies that stocks that have performed well (poorly) over a certain period will reverse and perform worse (better) over the next period. De Bondt and Thaler (1985) examined portfolios consisting of winner stocks over past three years and portfolios consisting of looser stocks over three past years. They found that portfolios consisting of three years loser stocks performed better over the following five years than portfolios consisting of three years winner stocks over the same period. According to De Bondt and Thaler (1985) the mean reversion effect is due to an overreaction in the market to available information; winner stocks are hence overpriced while loser stocks are under priced. This is inconsistent with weak-form market efficiency.

2.3.5 Calendar Effects

A large range of theories are suggesting that certain days, months or seasons of the year are subject to above average stock market price changes.

The Weekend effect, also known as the Monday effect, suggests that stock prices tend to be un-normally high on Fridays while they tend to fall on Mondays. What is puzzling about this effect is that since Monday stock returns are based on three days, one would expect that the higher risk involved with the longer period would be compensated with higher returns compared to the return of other days. A logical explanation may have its roots in behavioural finance theory; investors are in general more positive on Fridays since the weekend is around the corner than on Mondays while they have a whole working week in front of them, making investors more likely to trade on Fridays. This effect was first documented by French in 1980 and has since been further examined by several researchers. The large transaction costs related with trading on this information makes a Weekend effect trading strategy unprofitable in most cases.

Several seasonal effects have been documented, and especially the January effect has received a lot of attention. Keim (1983) found evidence that average abnormal returns are higher in January than in other months of the year. During the first week, and especially during the first day, of trading in January this effect is visible. He also finds that the relation between size and abnormal returns is always negative, and that this relation is more pronounced in January than in any other month. A possible explanation for the January effect is that investors sell past losers in December in order to realise capital losses that can offset eventual capital gains, creating an abnormal selling pressure in December, which is relived in January when investors re-buy these past losers, creating a January premium for past loser stocks. Closely related to the January effect is the December effect; through holding past winner stocks until January investors can postpone capital gain tax payments by a year. This would result in a small selling pressure on past winner stocks in December, which translates into rising prices of past winners in December; the December effect. Chen and Singal (2003) present evidence of the existence of tax-advantage-motivated behaviour causing the December and January effect. They also stress that the December effect is persistent due to limited knowledge amongst investors of its existence. In addition, the January effect they find is mainly for small-cap stocks, and it is persistent due to the difficulties exploiting profits, due to the large transaction costs involved with trading small-cap stocks.

Other examples of calendar effects are the Halloween effect suggesting that the stock market on average has stronger growth in the period from November to April resulting in a trading strategy “Sell in May and go away”, and the Holiday effect suggesting that stocks perform unusually well on days prior to public holidays. There are several other calendar effects which have been discovered and discussed amongst investors, some are documented and some are not. However, many calendar effects have disappeared or even reversed since they were discovered (behaviouralfinance.net, 2008).

2.3.6 The Size Effect

Banz (1981) examined the relationship between market value and return of stocks listed at the New York Stock Exchange (NYSE), and found that smaller firms in average had larger risk adjusted returns than larger firms. This is known as the size-effect; despite the higher (beta-) risk involved with investing in smaller firms versus larger firms, he found that the increased risk itself was not enough for explaining the differences in returns. Even though Banz concluded that it was difficult to say “whether the size per se is responsible for the effect or whether size is just a proxy for one or more true unknown factors correlated with size”, his study indicated that the CAPM is misspecified.

2.3.7 The Value Effect

The price-earnings (P/E) ratio is calculated as the market value of a company’s stocks compared to its earnings per share, and is used by analysts and investors in the belief that it may be an indicator of a stock's future performance. Basu (1977) examined the relationship between investment performance of NYSE-listed stocks and their P/E-ratios and found that low P/E portfolios earned higher risk-adjusted returns than high P/E portfolios. His results were inconsistent with the semi-strong form of the efficient market hypothesis as P/E ratio information proved to not be fully reflected in stock prices. However, Basu (1977) concluded that transaction and search costs, as well as tax effects, taken into account, eliminated the possibilities for investors to earn abnormal returns greater than zero by trading on the P/E-effect over the sample period. Basu (1977) confirmed the existence of the value-effect in his study from 1983, but concluded that the value-effect is not independent of firm size; he found the P/E-effect and the size-effect's effect on expected returns to be more complicated than previously thought and stressed that both variables most likely were "*proxies for more fundamental determinants of expected returns for common stocks*".

Another value-effect is the Book-to-Market (B/M) ratio, a ratio comparing the accounting value of a firm to its market value. A firm with a B/M ratio greater than 1 is said to be undervalued in the market while a firm with a B/M ratio lower than 1 is said to be overvalued in the market. Stattman (1980) examined the B/M ratio and found that average returns on US stocks were positively related to their B/M-ratios. In their study from 1992, Fama and French confirmed that firms with high B/M ratios in average had higher returns than firms with low B/M ratios. Their results also showed that when adjusting beta, a firm's systematic risk, for size and the B/M ratio, the beta can not fully explain average returns. Fama and French (1992) conclude that their results not necessarily indicate market imperfection, but that stock risks may be multidimensional. They suggest that one dimension of risk is proxied by size, while another dimension of risk is proxied by B/M. This was the start of the Fama-French three-factor model that is further explained in section 2.2.1.

2.4 Are These Anomalies Real?

The Efficient Market Hypothesis, which is explained in section 2.1., assumes zero transaction costs and zero information gathering costs. The already mentioned market efficiency paradox states that investors would not participate in the information gathering, unless they would at least earn their research costs back.

In their article from 1993, Fama and French offers evidence that several of the patterns previously found in stock price data are explained with their three-factor model. Fama

(1998) examines the reliability of individual studies having found long-term return anomalies. His findings suggest that long-term market anomalies tend to disappear when the way they are measured changes. However, he cannot find explanations for Jegadeesh and Titman's short term momentum-effect neither the post-earnings-announcement drift mentioned in section 2.3.1.

Today, there are still opposing views regarding whether market anomalies do exist or not. However, it is a common perception that no markets are perfectly efficient. Market events such as the October 1987 stock market crash as well as the 1999-2000 technology, media and telecom bubble, provides evidence that stock prices can defer tremendously from their fundamental value (Ritter, 2003).

Possible explanations for stock price anomalies are further discussed in section 3.3. Section 2.5 focuses on behavioural finance theory, which is a field of finance that tries to explain stock market anomalies by psychology based theories.

2.5 Behavioural Finance

From micro economic theory it is known that prices are set on the basis of supply and demand. Likewise, in the stock market, stock prices at any time are set by matching the highest offered price (demand) with the lowest demanded price (supply). In an efficient market with perfect investor rationality, these prices will reflect the true value, the fundamental value, of a stock. As described in section 2.4, there have been several studies that have documented long-term historical phenomenon in the stock market implicating that the efficient market hypothesis is not perfectly described by models based on rational investor behaviour. Behavioural finance is a field of finance that tries to explain these stock market anomalies by psychology based theories. Martin Sewell (2007) defines behavioural finance as *"the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect in markets"*(p. 1).

2.5.1 From Expected Utility Theory to Prospect Theory

The expected utility hypothesis assumes that the utilities of different outcomes are weighted by their probabilities. An individual's expected utility is calculated by taking into account the individual's utility in each possible outcome. In their book from 1944, "Theory of Games and Economic Behaviour" Neumann and Morgenstern proved that any "normal" preference relation over a finite set of states can be written as an expected utility (Leonid Hurwicz, 1945). Neumann and Morgenstern had by this defined rational economic behaviour of an individual when the rationality of the individual's actions depends on the likely behaviour of other individuals.

Until the 1970's, the Neumann Morgenstein utility model was extensively applied as a descriptive model of economic behaviour and for studies of decision making under risk. In 1979 the two psychologists Tversky and Kahneman represented an alternative model for choice under risk, the prospect theory. In their model, they showed that when individuals are faced with assigning probabilities to uncertain outcomes, they tend to use cognitive heuristics, "rules of thumb-reasoning". They showed that individuals tend to overweight outcomes that are considered certain compared to outcomes that are just probable, a so-called "certainty effect". In other words, they showed that an individual's utility of outcomes is not weighted only by the probability of the different outcomes. The certainty effect proved to lead to risk aversion in choices involving certain gains, and to risk seeking in choices involving certain losses. Tversky and Kahneman also found that choices represented in different forms tend to lead to inconsistent preferences, a so-called "isolation effect". This tendency showed that individuals tend to discard components shared by all options of choices, or prospects, under consideration. Tversky and Kahneman therefore replaced some the terms in the expected utility model; Instead of probabilities of outcomes, their model contains decision weights and instead of the money-value of the outcome of the decision, they refer to value in terms of gains and losses relative to a certain reference point. For example, the difference in value between a gain of 100 and a gain of 200, is perceived to be greater than the difference between a gain of 1100 and 1200. Likewise, the difference of a loss of 100 and a loss of 200, is perceived to be greater than the difference of a loss of 1100 and a loss of 1200. Thus, the value function is in general concave for gains, implying risk aversion, and convex for losses, implying risk seeking. Also, the value function tends to be steeper for losses than for gains, implying loss aversion. Regarding the decision weights, they were found to be lower than the corresponding probabilities, with exception of low-probabilities outcomes that tended to be overweighed. Tversky and Kahneman had proved that decision-making under uncertainty could not be fully explained by the expected utility model due to its non-recognition of psychological principles involved in decision making. Tversky and Kahneman (1986) also suggest a "framing"-theory. They argue that when the same problem is framed in different ways, an individual's perception of the problem and its evaluation of probabilities and outcomes produce foreseeable shifts of preference.

Cognitive psychology refers to the mental process of perception, and is a field of psychology that has been widely used for analysing investors' behaviour in the stock market after the publications of Kahneman and Tversky's first articles. In 1984, Robert Shiller proposed in a model of stock prices that recognises the influence of psychological principles. By studying the history of the U.S. stock market in the post-war period, he finds results indicating that social movements and fashion are likely to have major effects on the aggregate demand for stocks, and hence result in excessive stock market volatility. In other words, his results are indicating that the opinions of individual investors may reflect the opinion of a larger group, resulting in stock price movements that have little rational explanation.

As mentioned in section 2.3.4, De Bondt and Thaler (1985) propose evidence that investors tend to systematically overreact to unexpected and dramatic news events, resulting in weak-form inefficiencies in the stock market. This is the article that is seen as forming the start of what is today known as behavioural finance.

In his book "Market Volatility" from 1991, Shiller examines different stock market data and finds evidence of price volatility that is too large relative to economic fundamentals (Sandmann, 1992). The unexplained stock price volatility that could indicate stock market inefficiency, he claims, may in reality be due to an incomplete description of the market by the efficient market theory. Further, he investigates investor behaviour during the 1987 stock market crash. Through questionnaires answered by market participants during the market crash period, he finds results indicating that investors were trading on the basis of price changes, not on the basis of news and information about fundamentals (Russel, Philip and Torbey, Violet, 2008). He therefore concludes that social psychology is an important factor for understanding price changes in the stock markets.

Several cognitive biases, errors in investors' information processing have been documented. In the following section the most important ones will be presented.

2.5.2 Mental Accounting

Based on the value function of Tversky and Kahneman's prospect theory, Thaler (1985) developed a new model of consumer behaviour called "mental accounting". He stresses that individuals tend to separate their assets into different asset groups, especially current assets tend to be separated from future assets. Further, he claims that individuals tend to allocate different levels of utility to each asset group, affecting their consumption decisions and their attitude towards risk. Thus, instead of rationally viewing each dollar in their “capital-basket” as equal, individuals may split their dollars into portions that they have different risk-attitudes towards. Mental accounting may therefore help explain why many investors divide their capital into “risk capital” and “low-risk capital”. While rational behaviour would be to treat the whole “capital-basket” as unity, they have different risk attitudes to mentally portioned parts of their capital.

2.5.3 Informational Cascades and Herd Behaviour

In 1992, Abhijit Banerjee published the paper “A Simple Model of Herd Behaviour”. By analysing a sequential decision model, he finds that rather than using their own information, individuals rely on decisions made by previous decision makers, causing herd behaviour. Each individual finds it rational to rely on the previous decision-makers decision, rather than using their own information, because previous decision makers may have had some information being important for them too. On an individual basis, most individuals would not necessarily make the same decision. Banerjee showed that herd behaviour may cause a social disequilibrium. An example of herd-behaviour was exhibited in the end of the 1990’s through the dotcom bubble, when large amounts of money were invested in internet-related companies without properly established financial business models. The attention this kind of companies got through the media and in the markets is likely to having provoked investor herd behaviour.

Bikhchandani et al. (1998) stress that the informational cascades theory, or, herd behaviour, may help explain market events such as stock market crashes. The logic behind this is as follows: An informational cascade arises when individuals instead of analysing available options, rely on the decision action of others. Relying on the decision action of others may seem rational for an individual due to the time and money that would be spent if he was to analyse the available options on an individual basis. Bikhchandani et al. stresses that the higher the investigation cost is for an individual, the less incentives he will have to collect information himself, making him likely to rely “more” on the previous decision maker. The higher the investigation costs and the “more” wrong the previous decision maker was, the noisier the next decision maker’s decision is likely to be etc. Bikhchandani et al. also underlines the importance of “fashion leaders”. People tend to imitate the actions of others who *seem* to be better informed. Profiled investors’ decisions may therefore lead to information cascades.

2.5.4 Representativeness

Kahneman and Tversky (1973) observed that intuitive predictions follow a representative heuristic. The representativeness heuristic refers to people’s tendency to evaluate the probability of an event with reference to how closely it resembles a “comparable” event, assuming that the probabilities are similar. According to Kahneman and Tversky, this heuristic may cause that people think they see patterns in random sequences. People predicting by representativeness do often not take into account that a small sample of a population is not as representative as a large sample. As an example, the high stock returns in the U.S and Western Europe between 1982-2000 have caused many people to assume that such high returns are normal (Ritter, 2003). According to Bodie et al. (2005), the representativeness heuristic may cause anomalies such as overreactions as well as corrections. Bodie et al. (2005) mention a study by Chopra et al. (1992) that provide evidence that prior winner stocks are subject to reversals the days around quarterly earnings announcements. This may be interpreted as a correction to too extreme initial investor-beliefs.

2.5.5 The Conservatism Principle

Another cognitive bias that has been discovered by psychologists is the conservatism principle; people are slow to change their opinions and tend to anchor on the way things “always” have been. In 1997, Sudipta Basu finds evidence for the conservatism principle in financial statements. Basu (p.33) characterise conservatism in accounting as *“the more timely recognition in earnings of bad news regarding future cash flows than good news”*. Using firms’ stock returns to measure news, he finds earnings to be more sensitive to negative unexpected returns than positive unexpected returns. Thus, he finds that earnings reflect bad news more quickly than they reflect good news. He also argues that positive earnings changes tend to persist whereas negative earnings changes tend to reverse. As a concluding remark, he stresses that conservatism has increased over time, something he links to auditors’ increased legal liability exposure over the same time period. According to Bodie et al. (2005), investors being too slow in responding to recent information may lead to under-reactions to events in the stock market; stock prices will reflect new information only gradually, which may again lead to momentum in stock market returns.

The conservatism bias and the representativeness bias are contradicting in the sense that the conservatism bias may lead to under-reactions while the latter may lead to over-reactions and corrections. However, Ritter (2003, p. 5) argues that if the pattern is long enough people "*will adjust to it and possibly overreact, underweighting the long-term average*". According to Bodie et al. (2005), combining these two biases patterns of short-to-middle-term momentum followed by long-term reversals can be obtained.

2.5.6 The Disposition Effect

In their article from 1985, Shefrin and Statman predicted a "disposition effect". The disposition effect relates to that people dislike realising losses much more than they enjoy making gains. On the basis of this, Shefrin and Statman (1985) predicted a tendency for investors being more willing to realising gains, and reluctant to realising losses. Terrance Odean (1999) provides evidence for the disposition effect; he finds a tendency for investors to sell stocks whose price is increasing while keeping stocks whose price has fallen relative to their purchase value. According to Odean (1999), this tendency leads to profitable stocks being disposed of too soon and losing stocks being held for too long. Thus, investors tend to be more influenced by the past movements of stock prices than their likely future movements.

2.5.7 Overconfidence

Overconfidence is a cognitive bias that consists of that people tends to overestimate their abilities and the precision of their forecasts (Bodie et al. 2005). Oskamp (1965) found evidence of overconfidence in people's behaviour by conducting an experiment on judges. His findings showed that the judges' confidence shown in answering a question increased steadily with the number of new information that was given. However, the accuracy of their conclusions did not increase significantly with increasing information. He therefore concluded that increased feelings of confidence are not necessarily related to increased predictive accuracy.

Daniel et al. (1998) proposed a theory of securities market over- and under-reactions based on investor overconfidence and biased self-attribution. They define an overconfident investor as “*one who overestimates the precision of his private information signal, but not of information signals publicly received by all*” (p.1841). Daniel et al. argue that an overconfident investor will underestimate his forecast errors. Biased self-attribution is referred to as when “*individuals too strongly attribute events that confirm the validity of their actions to high ability and events that disconfirm the action to external noise and sabotage*” (p. 1842). Based on this, Daniel et al. develop a theory that implies that investors overreact to private information signals while they underreact to public information signals. They also show that momentum returns may be results of continuing overreactions in the stock market, and that these are followed by long-run corrections; short-term momentum returns may therefore be consistent with long-term reversals.

Odean (1998) provides another example of overconfidence in the financial markets. He finds that overconfident investors are expected to trade more than rational investors. Further, he finds that an overconfident investor’s increased trading activity lowers his expected utility. He claims that a markets consisting of many overconfident traders tend to underreact to the information of rational traders. Also, he argues, markets tend to overreact to “*salient, but less relevant, information*” while underreacting to “*abstract, statistical, and highly relevant information*” (p.1916). According to Barber and Odean (2001), psychology literature reveals that men are more overconfident than women in male-dominated areas such as finance. By testing this hypothesis through analysing the trading activities of people with discount brokerage accounts, they document that men trade more actively than women. In accordance with the findings of Odean (1998), the more frequent trading-activity amongst men results in male investors having a poorer predicted investment performance, compared to female investors.

2.5.8 Forecasting errors

This cognitive bias refers to that people, when making forecasts, tend to give recent experience compared to prior beliefs too much attention (Bodie et al. 2005). This may cause forecasts that are too extreme. By examining security analysts’ earnings forecasts, De Bondt and Thaler (1990) found that their earnings expectations were too extreme and too positive to be considered rational, causing patterns of overreactions in the stock market. They claim that excessive optimism (pessimism) may be related to high (low) market-to-book value ratio firms and high (low) growth rate of earnings over the last years firms. However, they found that neither of these variables could explain the *variation* in the forecast errors to a large extent. Given that their paper investigates the behaviour of security analysts which are seen as "*one possible source of rationality in financial markets*" (p.56), De Bondt and Thaler (1990) conclude that a "*generalized overreaction can pervade even the most professional of predictions*" (p. 57).

2.5.9 Limits to Arbitrage

According to Bodie et al. (2005), profiting from "behavioural mispricings" in the stock market is difficult in practise. They list three factors that are limiting rational investors to profit from the mistakes of "behavioural investors", namely fundamental risk, implementation costs and model risk.

As an example of fundamental risk, Bodie et al. (2005) point out buying an underpriced stock. The risk related to this is that the market underpricing may get worse. If the investor exploiting an arbitrage opportunity has a short investment horizon, there is hence a chance that the market value of the stock not yet has converged into its fundamental value when he wishes to sell it. Thus, buying an underpriced stock is not a risk-free profit opportunity. According to Bodie et al. (2005), fundamental risk related to exploiting obvious arbitrage opportunities may therefore limit "*both the activity and the effectiveness*" of potential "*arbitrage traders*".

When it comes to implementation cost related to exploit profit opportunities, it is according to Bodie et al. (2005) related to transaction costs, short selling constraints and management fees. As an example, they mention costs related to short selling. An indirect cost related to that is that an investor borrowing a stock to short sell it may have to return the borrowed stock on short notice, making the short sale horizon uncertain.

Model risk is related to the risk of finding arbitrage opportunities due to poor valuation models. An investor using an unreliable valuation model may find, according to his model, under- or overpriced stocks in the market, while they in reality are correctly priced. Risk related to trading on model-found arbitrage opportunities may therefore, according to Bodie et al., limit apparent arbitrage opportunities trading activity.

2.5.10 Criticism Towards Behavioural Finance Theory and its Future

In the Efficient Market Hypothesis it is assumed that investors behave rationally and that they percept the same information in the same way. However, it has come true in this section that individuals have limited capabilities of processing information and that investors do not always behave rationally. Behavioural finance theory may help explain what is not captured by models based on perfect investor rationality. David Hirshleifer claimed in 2001 that psychology-based asset-pricing theory, although in an early stage, had promise of capturing the reality. Today, the main criticism towards behavioural finance is that many of the theories do not give advice on how to exploit investor irrationality caused market anomalies (Bodie et al., 2005). According to Ritter (2003), many of the behavioural finance theories are accused for only providing possible explanations of market phenomenon *ex post*. Thus, many of the theories are not seen as useful for making *ex ante* predictions of how investor irrationality may affect stock market prices. Finally, Bodie et al. (2005) points out that behavioural finance is still in an early stage, and that it "*is probably still too early to pass judgement on the behavioural approach, specifically, which behaviour models will "stick" and become part of the standard toolkit of financial analysts*" (p. 401).

2.5.11 So Are Stock Returns Predictable?

According to Cochrane (1999), the predominant view amongst financial economists was until the mid 1980's that returns are unpredictable. The view was that stock returns are close to unpredictable and that they follow a random walk. Also, it was believed that apparent predictability was a "*statistical artifact*" caused by too short sample periods or too specific samples. According to Cochrane, short horizon stock returns, such as daily, weekly and monthly, are still seen as nearly unpredictable by financial economists. However, Cochrane argues, a large amount of stock return variation over business cycle horizons, and longer horizons, appears to be predictable by variables such as the dividend/price ratio. Further he suggests that strategies "*such as value and growth, market-timing possibilities generated by return predictability, dynamic bond and foreign strategies, and even a bit of momentum"* (p. 56) may provide investors with substantial premiums for "*holding dimensions of risk unrelated to market movement* . However, he stresses that *"the exact size of the premiums and the economic nature of the underlying risks is still a bit open to question"* (p. 56).

Stamland (2007) claims that the view of Cochrane (1999) is consistent with the current view of many financial economists.

3. Literature Review and Relevant Facts

Section 3 presents and reviews literature that is relevant for understanding the earnings announcement premium documented by Lamont and Frazzini (2007). Further, this section builds a basis for analysing whether or not there is an earnings announcement premium at the Oslo Stock Exchange. The main focus of section 3. is naturally given to the paper of Lamont and Frazzini from 2007, “The Earnings Announcement Premium and Trading Volume”. Moreover, this section presents relevant information about the Oslo Stock Exchange as well as studies of stock prices at the Oslo Stock Exchange. This is relevant for the discussion in Section 6. Finally, possible explanations for stock price anomalies are presented and discussed.

3.1 The Earnings Announcement Premium and Trading Volume

3.1.1 The Earnings Announcement Premium

As already mentioned in section 2.3.1, Ball and Brown (1968) were amongst the first to provide evidence that there is a drift in stock returns after earnings announcements.

Beaver (1968) examined whether investors do react to earnings announcements and how, and observed both a price and a volume reaction. His results indicated an “*above normal price activity when earnings reports are released*” (p. 82). Also, he observed above normal trading activity for about two weeks after an earnings announcement, hence a substantial increase in volume. Beaver concluded that the above normal trading activity in the two weeks following an earnings announcement was consistent with investors evaluating the content of the released reports.

Chari et al. (1998) documented a seasonal pattern in stock returns around quarterly earnings announcement dates. They find that small companies in average have large positive abnormal returns around quarterly earnings announcement dates. Also, they find that the variability of returns increases around quarterly earnings announcements for smaller companies. However, Chari et al. (1998) find that large firms do not seem to generate abnormal returns around quarterly earnings announcements. In addition, they claim that the increase in the variability of returns around quarterly earnings announcements is much smaller for larger companies that for smaller companies.

Ball and Kothari (1991) documented generally positive abnormal risk adjusted returns around earnings announcement dates that were decreasing in firm size. They suggest that an explanation for the abnormal returns may be that they are a compensation for “disclosure risk”. In other words, a compensation for the risk of holding a stock in a period when information that is relevant to the stock’s value is expected to be released.

Cohen et al. (2007) re-examined the earnings announcement premium that was documented by Ball and Kothari (1991). Cohen et al. (2007) stress that the “*disclosure environment*” has become richer after the time period studied by Ball and Kothari (1991). Thus, the motivation behind the re-examination was that the richer disclosure environment should according to Cohen et al. cause a decreased earnings announcement premium. On the other hand, they underline that there has been an increased earnings announcement period variance after the period studied by Ball and Kothari (1991); which in that case, they claim, should have increased the earnings announcement premium. While Ball and Kothari (1991) used actual announcement dates in order to measure the earnings announcement premium, Cohen et al. (2007) use predicted earnings announcement dates. The predicted earnings announcement dates are estimated by using “*the median announcement date for each firm quarter as the proxy for the expected announcement date*” (p. 157). In addition, expected earnings announcement dates are collected from the “Earnings Calendar” published in the Wall Street Journal. Based on their predicted earnings announcements method, Cohen et al. (2007) documents a statistically significant earnings announcement premium beyond the period studied by Ball and Kothari (1991). However, they find that the “*magnitude*” of the earnings announcement premium is smaller than the premium documented in the period studied by Ball and Kothari (1991). Cohen et al.’s evidence is hence consistent with the claim that the earnings announcement premium has decreased with the increased disclosure activity of companies over the later years. They also claim that arbitrage has not completely eliminated the earnings announcement premium over the studied period. Especially, they claim, stocks with “*greater limits to arbitrage*” tend to have a higher earnings announcement premium, indicating that the premium is likely to continue existing.

3.1.2 The Volume Hypothesis

According to the volume-hypothesis, stocks with the largest predicted volume increases in earnings announcement months tend to have a higher subsequent premium.

Odean (1999) documented that the overall trading volume in the U.S. stock market is excessive amongst investors with brokerage accounts. By trading excessively is meant that the investors reduce their average returns through trading additionally. He offers a possible explanation for the excess trading, namely investor overconfidence. Odean(1999) suggests that attention awoken by news-sources such as the financial media, the disposition effect and investors' unwillingness to sell short may explain the return patterns before and after purchases and sales are made by overconfident investors.

Lee and Swaminathan (2000) provided evidence that past trading volume provides an important link between momentum and value strategies. They find that trading volume is unlikely to be an approximation for a stock's liquidity. Contrarily, their results provide evidence that "*the information content of trading volume is related to market misperceptions of firms' future earnings prospects*" (p. 2065). This is backed up by their findings that low volume stocks tend to be under-valued in the market, while high volume stocks tend to be overvalued by the market. Further, Lee and Swaminathan (2000) provide evidence that past trading volume may help predict the timing of the long-term momentum effect reversal. In other words, they find that past trading volume may help predict "*the magnitude and persistence of future price momentum*" (p. 2065). The ability of past trading volume to predict future returns is inconsistent weak form market efficiency. However, Lee and Swaminathan (2000) conclude that:

"*The market is better characterised as being in a constant state of convergence toward intrinsic value. Viewed in this light, intermediate-horizon "underraction" and long-horizon "overreaction" are simply two elements of the same continuous process by which prices impound new information*" (p. 2066).

Barber and Odean (2008) claim that when an individual has many different alternatives, "*options that attract attention are more likely to be considered, hence more likely to be chosen*" (p. 1). This, they argue, is especially true for investors; when buying a stock, there are "*thousands of common stocks from which to choose*" (p. 1). Contrarily, when selling a stock, investors mainly consider stocks they already know. This is particularly expressed for individual investors, who, according to Barber and Odean (2008), rarely sell short, and thus mostly sell stocks they already own. Due to the fact that humans can process only a certain amount of information, humans have *“bounded rationality*” (p. 1). Barber and Odean (2008) test the hypothesis that that attention is a key factor determining which stocks individual investors buy, not the stocks individual investors sell. Also, they test the hypothesis that individual investor buying behaviour is more heavily influenced by attention that the buying behaviour of sophisticated investors. Predicting that individual investors’ buying activity will increase on high attention days, they examine a stock’s abnormal daily trading volume, the stock’s return on the previous day as well as whether or not the company were in the news the day the abnormal trading volume is observed. Barber and Odean (2008) find that individual investor buying behaviour clearly is driven by attention. Also, they find that attention-driven individual investor buying is similar for large capitalisation stocks and small stocks. However, they conclude that the documented “*attention-driven buying patterns…do not generate superior returns*” (p. 25).

3.1.3 The Earnings Announcement Premium and Trading Volume

Lamont and Frazzini (2007) examined U.S. stock returns in the period between 1972 and 2004. They examined the monthly returns of the value weighted portfolio of companies expected to announce as well as the monthly returns for companies not expected to announce. In other words, they test if companies expected to announce tend to have higher returns than companies not expected to announce in a given calendar month. Based on predicted earnings announcement dates, they test a trading strategy consisting of holding a zero-cost portfolio of expected announcers while selling short a portfolio of expected non-announcers. Lamont and Frazzini (2007) document that this trading strategy earns excess returns of between 7 and 18 percent per year. The documented excess returns, they claim, can not be explained by the factors included in the Carhart (1997) four-factor model. The earnings announcement premium they document is large and statistically significant. They also find that the trading strategy gives higher Sharpe-ratios than “*other popular anomalies*”, such as the one-year momentum strategy documented by Jegadeesh and Titman (1993). In other words, their trading-strategy generates higher risk-adjusted returns over the sample period than for example the momentum-strategy.

In addition, Lamont and Frazzini (2007) find that the earnings announcement premium is strong in large capitalisation stocks. This is contradicting the findings of Chari et al. (1988)

and Ball and Kothari (1991), who documented a larger earnings announcement premium for smaller companies[2]. According to Lamont and Frazzini (2007), this is surprising due to the fact that there is higher transaction costs involved with trading smaller companies' stocks. The earnings announcement premium should therefore be higher for smaller companies in order to cover these transaction costs. Also, they stress, there is in general less information available in the markets about smaller companies. Consequently, one would think that earnings announcements should generate larger volatility for smaller companies than for larger companies.

Besides, Lamont and Frazzini (2007) document that stocks with high past earnings announcement premiums tend to have a high subsequent earnings announcement premiums. They also claim that the stock-specific seasonal effect documented by Heston and Sadka (2005) is not driving their results.

The Volume Hypothesis

Moreover, Lamont and Frazzini (2007) tests whether the predictable increase in stock prices around earnings announcements is driven by the predictable rise in volume around earnings announcements. Their results are indicating that the earnings announcement premium is "*strongly related to the concentration of past trading activity around earnings announcement dates*" (p. 1). They find that stocks with predictably high announcement volume have an earnings announcement premium of 1.5 percent per month. Contrastingly, stocks without predictably high announcement volume have, they claim, "*a small earnings announcement premium that is insignificantly different from zero*" (p. 21). Consequently, they construct a long/short portfolio that generates a yearly earnings announcement premium of 18 percent.

Possible Explanations for the Earnings Announcement Premium

Further, Lamont and Frazzini (2007) test whether or not the earnings announcement premium is a compensation for idiosyncratic risk related to the long/short trading strategy. They find that idiosyncratic risk is substantially higher in announcement months. Also, they document that compared to stocks with low volume concentration, stocks with high volume

[2] However, it should be emphasised that both Chari et al. (1998) and Ball and Kothari (1991) used actual earnings announcement dates, not predicted, and daily returns, not monthly.

concentration have higher idiosyncratic volatility increases in announcement months. This proves that "*higher premium stocks have higher earnings-related idiosyncratic risk*" (p. 21). However, they claim that not all of the return earned by high volume stocks can be explained by excess idiosyncratic risk. As an example, they show that stocks with high volume earn average excess returns of 1.9 percent in expected announcement months, and 0.4 percent in other months. For comparison, volatility is 14.5 percent on expected announcement months and 12.6 percent in other months. Lamont and Frazzini (2007) therefore propose that a possible explanation for earnings announcement period returns is that they "*reflect fundamental/permanent innovations in prices*" (p. 22) while they suggest that non-announcement period returns "*reflect sentiment/noise/temporary innovation in prices*" (p. 22). Further, they compare their findings to the framework of Campbell and Shiller (1988) and Campbell and Vuolteenaho (2004), and suggest that earnings announcement returns may "*reflect cash flow news*" (p. 22) while non-announcement returns may "*reflect future return news*" (p.22). On the other hand, Lamont and Frazzini (2007) stress, if fundamental idiosyncratic risk earns a higher premium, while non-fundamental idiosyncratic risk does not, this would be an explanation for high average returns around earnings announcement dates. Lamont and Frazzini (2007) underlines that while the latter explanation may contain some truth, it "*fails to generate predictions about volume*" (p. 22) which they have shown is a "*key element of the story*" (p. 22). Moreover, idiosyncratic risk can be seen as a limit to arbitrage in the way that it prevents rational arbitragers from eliminating the earnings announcement premium. A high idiosyncratic risk around earnings announcements would "*deter attempts to eliminate the anomaly*" (p. 22) for investors that "*for some reason are unable to sufficiently diversify*" (p. 22). However, Lamont and Frazzini (2007) argue that limits to arbitrage do not provide an explanation for the *sign* of the earnings announcement premium.

Besides the volume hypothesis, Lamont and Frazzini (2007) consider other explanations for the earnings announcement premium:

One possible explanation, they argue, is that the earnings announcement premium is a liquidity risk premium: If there are high levels of asymmetric information or low liquidity around earnings announcement dates, investors will require a reward, the earnings announcement premium, for holding stocks during these periods. However, Lamont and Frazzini (2007) stress, this could only be a possible explanation for the few days before an earnings announcement, not for a the premium generated by in average buying stocks two weeks before its expected announcement and selling it two weeks after. They refer to Lee, Mucklow and Ready (1993) who show that bid/ask spreads are "*widening in the hours surrounding the announcement but quickly reverting to normal within a day or two*" (p. 24).

One explanation, Lamont and Frazzini (2007) claim, may be downward analyst forecast biases that "*naive*" investors fail to realise. Naive investors will consequently be systematically positively surprised by actual earnings announcements. If these naive investors affect market prices they will hence consistently push up stock prices on their earnings announcements.

Another similar explanation, they argue, is related to the conservatism principle explained in section 2.5.5. If investors use historical earnings as their benchmark, they will in average end up being consistently surprised due to growing nominal profits caused by either inflation or real growth.

However, Lamont and Frazzini (2007) state that these two closely related latter explanations "*fail to predict the cross-sectional relation between volume and the premium*" (p. 23). Further, these explanations are contradicted by "*two other pieces of evidence*" (p. 23). Firstly, they argue, Barber and Odean (2004) and Hirshleifer et al. (2004) showed that "*individual investors are net buyers in response to either positive surprises (such as extremely high earnings growth) or negative surprises (such as extremely low earnings growth)"* (p. 23). Individual investor buying in response to negative surprises is inconsistent with the conservatism principle. Secondly, Lamont and Frazzini (2007) find that the earnings announcement premium appears in different sub-periods. The premium appears in periods before analyst forecasts were common (prior to the 1970's), in periods with low inflation (1927-1949) and in periods with high inflation (1973-1983). Thus, Lamont and Frazzini (2007) argue that the earnings announcement premium is stable enough over the sub-periods to suggest a "*more general explanation*" (p. 24).

Further, Lamont and Frazzini (2007) test whether individual investor buying is triggered by earnings announcements by calculating imputed order flow from small and large investors. They find that large investors tend to buy stocks in the days and the weeks before earnings announcements. Further, they find that small investor buying tend to soar on announcement days, while large investor buying tend to drop on announcement dates and on the two days subsequent to the earnings announcement. Also they find that large imputed buy orders to peak the day before small imputed buy orders. Thus, like the "fashion leaders" described in section 2.5.3, large investors seem to be "*front-running*" small investors by "*initiating purchases of announcement stocks in the weeks prior to an earnings announcement*" (p. 26-27). An explanation for this may be that large informed investors expect small investor buying, and hence are "*arbitraging away*" the earnings announcement anomaly. This is consistent with efficient market theory: Sophisticated investors are trading to eliminate predictable returns, and hence smoothing stock prices, that are driven by the predictable demand-shock caused by small investors around earnings announcement dates. However, Lamont and Frazzini (2007) claim, since small, uninformed investors are still affecting prices with their increased buying around announcement dates, large informed investors are not "arbitraging enough". A possible explanation for this is according to Lamont and Frazzini (2007) idiosyncratic risk or holding costs: "*If sophisticated traders are unable to fully diversify or face a high daily cost of holding shares, then they will not trade off price appreciation against length of holding period*" (p. 27).

Finally, they show that companies with high past trading volume around earnings announcements have high small investor buying around earnings announcements, while firms with low past announcement volume have "*no discernable announcement effect*" (p. 27). According to Lamont and Frazzini (2007), individual investors are more likely to buy stocks that grab their attention via earnings announcement than large, sophisticated investors. In addition, they claim that individual investors rarely sell short. Lamont and Frazzini (2007) therefore suggest that for "*some stocks*", buying pressure from individuals is causing the price increase around earnings announcements. By "*some stocks*", they refer to stocks that get more media coverage related to their earnings, companies that have more variable earnings or companies that appeal differently to "*inattentive*" investors. Lamont and Frazzini (2007) hence conclude that companies that are getting more attention in general earn higher predictable returns around earnings announcements due to small investor buying. Yet, they emphasise that their found relation between buying pressure from individuals and price increases around earnings announcements is "*primarily suggestive since it relies on a number of assumptions*" (p. 24).

Conclusively, Lamont and Frazzini (2007) documented that predictable increases in volume lead to predictable increases in stock prices around quarterly earnings announcement dates and that "*concepts such as liquidity, information flow, heterogeneous beliefs, and short sale constraints are potentially important in understanding this connection*" (p. 29). Uninformed investor trading activity combined with imperfect arbitrage trading by informed sophisticated investors is suggested as the main explanation for the earnings announcement premium. However, Lamont and Frazzini (2007) call for further future theories connecting volume and stock prices.

3.2 Relevant Information and Studies of Stock Prices at the Oslo Stock Exchange

3.2.1 About Oslo Stock Exchange

The Oslo Stock Exchange was opened for stock trading in 1981. In December 2000, the Oslo Stock Exchange signed a co-operation agreement together with the Stockholm Stock Exchange, the Copenhagen Stock Exchange and the Iceland Stock Exchange, creating NOREX, a "*joint Nordic marketplace for trading in securities*" (Oslo Børs, 2008). The four stock exchanges are using the same surveillance system, the same regulatory framework and the same trading system. The intentions behind this were to make Nordic securities more accessible to international markets, make the marketplace more cost-effective through economies of scale and serving the needs for simplicity and quality to its investors, issuers and members. Oslo Børs claims that the surveillance system used by NOREX is "*one of the most effective surveillance systems in the world*". NOREX' goal for the future is "*to be one of the world's most efficient securities markets*". The companies listed on the Oslo Stock Exchange were required to report their earnings quarterly from 2000 (Dyvik, 2008).

The strongest sectors at the Oslo Stock Exchange are related to Norway's natural resources are energy, shipping and fishery. As a result, many international oil- and shipping-industry related companies are listed on the Oslo Stock Exchange. The daily turnover at the Oslo Stock Exchange has quadrupled over the later years, as an example, the daily turnover went from around 1.3 billion NOK in 1998 to around 14 billion NOK in 2007 (Oslo Stock Exchange, 2008). International investors' ownership at the Oslo Stock Exchange is increasing and currently around one third (Sønnervig, 2007). The Norwegian government's ownership is also around a third, but its ownership is decreasing (Sønnervig, 2007). Sønnervik (2007) points out that the Norwegian government is a typical buy-and-hold investor and that it is international investors that stand for around two thirds of the trading activity at the Oslo Stock Exchange.

The volatility of Norwegian stock prices is seen as relatively high compared to other markets (Eilifsen et al., 1999). Eilifsen et al. (1999) claim that the standard deviation on annual stock returns of 24 percent in Norway in the period between 1983 to1994. As a comparison, the standard deviation of annual stock returns for the same period was 12 percent in the US and 13 percent in the UK. They claim that the volatile stock prices in Norway may have economic and market-structure related explanations. One of those reasons is related to the Norwegian economy which is characterized as small and open. The market prices of Norway's natural resources, such as oil and gas, are hence sensitive to world market prices. They also claim that the commodity price risk sensitivity is increased by the Norwegian industry structure, "*characterized by processing intermediate products rather than final goods*" (p.4). However, they claim that the commodity price risk sensitivity is what makes Norwegian securities attractive investments for international investors. Another point worth mentioning is that the Norwegian stock market is a small one compared to many other stock markets in the world, such as the US and the UK. Also, it is a less mature one seen with the eyes of the world. This, according to Eilifsen et al. results in "*both market structure-related noise and information-related noise, as well as lagged price adjustment to value changes*" (p.4).

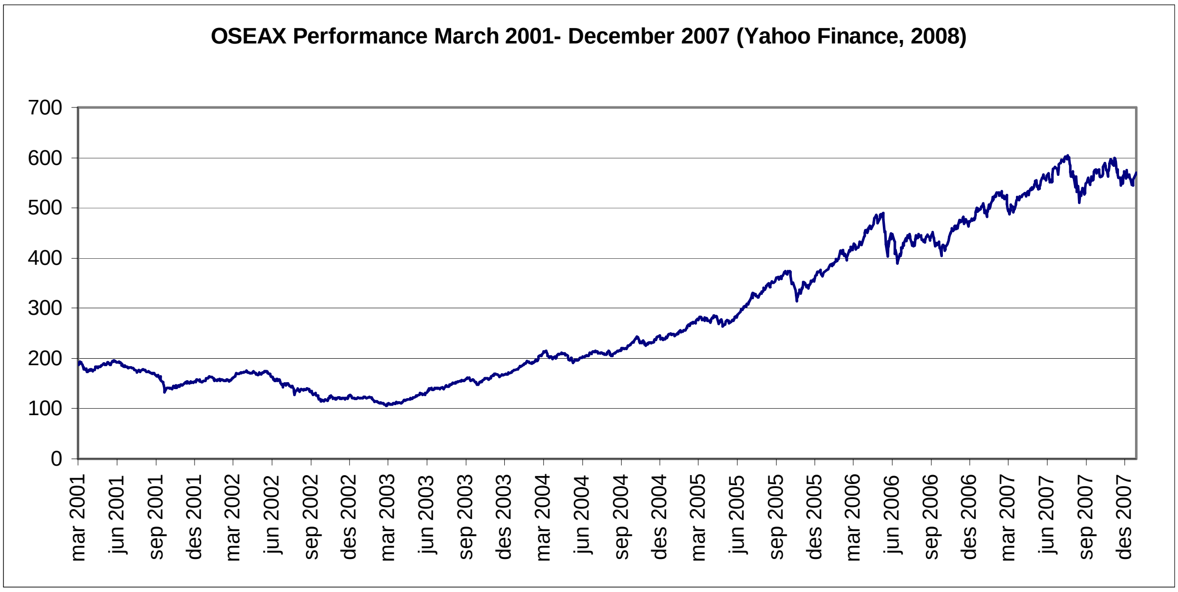

Figure 1: OSEAX Index Performance March 2001 - December 2007

Figure 1 shows the price development of the Oslo Stock Exchange All Share Index (OSEAX) from March 2001 to December 2007. The OSEAX consists of all stocks listed at the Oslo Stock Exchange. The index is adjusted for dividends, corporate actions and the current outstanding numbers of shares on a daily basis. The OSEAX index was introduced on 2nd of February 2001 and Yahoo Finance has data available starting from 7th of February 2001. Figure 1 shows that there has been considerable upwards trend starting from March 2003.

3.2.2 The Value Relevance of Financial Reporting on the Oslo Stock Exchange Over the Period 1964-2003

Gjerde et al. (2005) examined the value relevance, or usefulness, of financial reporting for investors trading on the Oslo Stock Exchange in the period between 1964 and 2003. Their findings indicate that the value relevance has increased significantly over the sample period. This is according to Gjerde et al. (2005) consistent with the general view that "*Norwegian accounting regulators and standard setters have been successful in achieving more relevant financial statements over time*". Over the examined period, Norway has according to Gjerde et al. (2005) moved from a "*tax-based creditor-oriented accounting legislation*" to a "*market-based investor-oriented accounting legislation*". Gjerde et al. (2005) points out that Norwegian accounting rules have been based on an *earnings-oriented conceptual framework*, meaning that the rules have been on revenues and expenses. For comparison, International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) have based their accounting principles on a *balance-oriented conceptual framework*, meaning that the rules have been on assets and liabilities.

It is important to emphasise that Norwegian companies listed at the Oslo Stock Exchange have since 2006/2007 been required to report their earnings under the International Financial Reporting Standards (IFRS) adopted by the IASB. Non-Norwegian companies listed at the Oslo Stock Exchange, but also listed at other stock exchanges with other financial reporting standards have been given the option to report according to their "home"-standards under the convergence period to IFRS. To my knowledge, no literature has empirically studied the usefulness of accounting information on investors trading at the Oslo Stock Exchange after the introduction of the IFRS. It is therefore important to point out that even though IFRS is not based on an earnings-oriented conceptual framework, it is likely that investors' usefulness of financial reporting at the Oslo Stock Exchange have continued increasing with the introduction of the IFRS in 2006/2007. The IASB's intention is to adopt standards that make sure financial reporting meets the informational needs of all stakeholders in a company. Investors being the group of stakeholders with the greatest informational needs, the requirements of financial reporting are often fit to meet their needs. Also, the IFRS, and modified forms of the IFRS, are used as financial reporting standards by stock exchanges located over the whole world, such as in the European Union and European Economic Area membership-countries, Hong Kong, Singapore and India. International investors can in general therefore more easily compare and understand the financial statements of companies listed on stock exchanges with IFRS requirements. Given the previously mentioned increasing ownership of international investors at the Oslo Stock Exchange, the introduction of the IFRS requirements at the Oslo Stock Exchange is unlikely to have decreased investors' usefulness of financial reporting.

3.2.3 Stock Price Volatility at the Oslo Stock Exchange

According to Eilifsen et al. (1999), there is an increased flow of information in the Norwegian stock market before earnings announcement dates. As a consequence, investors are revising their earnings expectations consequently when an earnings announcement date is approaching. Eilifsen et al. (1999) examined stock returns of companies listed at the Oslo Stock Exchange in the period 1990-1995 and found "*a significant reduction in stock price volatility in the post-announcement period relative to the pre-announcement period*" (p.1). By decomposing the found return volatility into three components, namely "*the volatility of the underlying business*", "*the volatility caused by the speed at which information is incorporated into stock prices*" and thirdly, "*the volatility caused by noise in the price process*", they find a significant decline in the latter component after earnings announcements for the largest companies in their sample. Consequently, they claim to have found support for the hypothesis stating that an earnings announcement reduces informational asymmetry amongst investors, which again reduces noise. Further, they find that earnings announcements per se don't have any effect on the first volatility-component. Regarding the second volatility component, they find coefficients "*generally higher than unity*", suggesting that there is a general overreaction to new information in the Norwegian stock market. Eilifsen et al. (1999) suggest that this may provide an explanation for the higher observed stock return volatility at the Oslo Stock Exchange, compared with other markets such as the UK or the US. Nonetheless, they find that earnings announcements per se do not affect the speed of which prices are adjusting to newly released information.

3.2.4 Calendar Effects at the Oslo Stock Exchange

According to Holm (2007), Ingrid Johansen found in her siviløkonomutredning from 1995 significant positive returns on Fridays and significant negative returns on Mondays, providing evidence for a week-end effect at the Oslo Stock Exchange in the period from 1984 to 1995, (Holm, 2007).

In his master-thesis from 2007, Holm examined the OSEBX (Oslo Stock Exchange Benchmark Index), the OSEAX (Oslo Stock Exchange All Share Index) and the OSESX (Oslo Stock Exchange Small Cap Index) at Oslo Stock Exchange, between 1996 and 2005, and claims to have found significant positive returns on Fridays and before Holidays. However, when testing for the existence of week-day effects on individual stocks, Holm (2007) finds that the Friday-effect is non-existent for most of the stocks. Further, Holm (2007) finds that the Friday-effect has diminished at the OSEBX and enlarged at the OSESX over the last half of the examined period compared to the first half of the examined period. His results are indicating that the Friday-effect is stronger for small capitalisation companies. Although he doesn’t find significantly positive returns at the OSEBX on Fridays between 2000 and 2005, he finds that there are in average higher returns on Fridays compared to average treading day returns over this period. Holm (2007) concludes that since the diminished Friday-effect at the OSEBX over the last half of his sample period it may indicate that the Oslo Stock Exchange has become more efficient over the sample period.

Åsland (2006) examined in his siviløkonomutredning a sample of 50 stocks in the period between 1999 and 2004. He did not find evidence of the existence of a December effect in the Norwegian stock market.

3.2.5 Momentum at the Oslo Stock Exchange

Kloster-Jensen (2006) analysed a dataset consisting of 73 stocks listed on the Oslo Stock Exchange between 1996 and 2005 in his master thesis. He finds that a momentum strategy combining long positions in winner portfolios with short positions in loser portfolios generates excess returns. However, he finds that these excess returns are mainly compensation for systematic risk related to trading on a momentum strategy, rather than a momentum premium. Kloster-Jensen (2006) also underlines that transaction costs related to implementing the momentum strategy would eliminate any eventual excess returns.

Also Myklebust (2007) tested whether the momentum effect exists in the Norwegian stock market or not in his master thesis. Analysing a dataset consisting of stock listed at the Oslo Stock Exchange between 1984 and 2006, he finds significant positive returns for the momentum-strategies he is testing, but not for all sub-periods. He claims that the obtained positive returns are not explained by beta, but underlines that other variables explaining risk have not been considered. However, like Kloster-Jensen (2006), Myklebust (2007) has not taken into account transaction costs related to trading on the momentum strategies. In addition, he underlines that it may be difficult to trade on the momentum-strategy in reality. As an example, it may be difficult in reality to take short positions in small and relatively illiquid stocks at the Oslo Stock Exchange.

3.2.6 Overreaction at the Oslo Stock Exchange

In his siviløkonomutredning from 2006, Mamelund tests the Oslo Stock Exchange for weak-form market efficiency in the period between 1989 and 2005. Mamelund (2006) claims to find a tendency for past winner-stocks consisting of that prices in average continue to increase the following day after a price increase greater than 5 percent, indicating that the market is reacting slowly to new information having caused the original greater than 5 percent decrease. For past loser stocks, he claims to find that days with price decreases greater than 5 percent in average tend to be followed with a price-increase the following day. His results indicate that there is an overreaction for past loser stocks at the Oslo Stock Exchange. Mamelunds findings are hence inconsistent with weak-form market efficiency.

3.2.7 The Speed of which Information is Incorporated in Stock Prices after the Release of Yearly Earnings Announcements

In their Siviløkonomutredning from 2000, Åkre and Røsdal tested how quickly and efficiently new information was incorporated in stock prices at the Oslo Stock Exchange after companies had released their yearly results in the time period between 1993 and 1997. They find a tendency for the market to overreact on surprisingly good earnings results. The overreaction, they claim, is being followed by a correction. However, Åkre and Røsdal (2000) concludes that the Oslo Stock Exchange can not be regarded as inefficient.

3.3 Possible Explanations for Stock Price Anomalies

According to Stamland (2007), patterns that at first gaze look like market anomalies may have other explanations. Firstly, the “abnormal” returns may in reality be compensation for increased risk related to trading on the above mentioned effects. An example of this is the so-called peso-effect: If the market expects an event that may happen and which may affect the firm, and hence its stock price, in the future with a very small probability, “abnormal” returns may in reality therefore be compensation related to the risk for holding the stock. Also, several empirical models are assuming constant parameters, and does hence not allow for time-varying systematic risk. This may also be an explanation for “abnormal” returns that in reality are compensation for higher risk than the model-measured risk

Secondly, it is important to remember the limits to arbitrage mentioned in section 2.5.9, such as large transaction costs involved with the trading strategies utilised for taking advantage of these effects. Further, investors may have tax incentives behind their trading decisions; something that should be taken into consideration in the various models utilised for testing for market anomalies.

Data-mining and data-snooping may also cause patterns that are not real to appear in a dataset. Often, researchers independently test various trading strategies in the same dataset, causing data-mining problems: When several tests are made in one dataset, it is quite likely that some of these tests will give significant results. Most often, only the studies giving significant results are published. The statistical power of a result, its p-value, tells us how likely it is that we’re wrongly rejecting the zero-hypothesis being tested. However, it is important to take into consideration the p-values of other tests run in the same dataset. With N tests run in one dataset, the true p-value of the test is equal to 1- (1-p)^N. When N grows big enough, the p-value of the test goes towards 1, or in other words, the more tests that are run in one dataset, the more likely it becomes that significant results are noise. While published studies often only take into consideration their own p-value, not the p-values of unpublished studies of strategies tested in the same datasets without significant results, it is a large possibility that the published results are found due to randomness; noise. Data-snooping on the other hand, is when a zero-hypothesis is formed knowing the dataset. If a researcher has looked at the dataset aimed for testing before forming his zero-hypothesis, it is likely that his data-knowledge will affect him when forming the zero-hypothesis, which again makes it more likely for him to get significant results.

Like explained in section 2.5, behavioural finance theory may help predict irrational investor behaviour creating arbitrage opportunities. In that sense, and as shown by Lamont and Frazzini (2007) behavioural finance theory may also provide explanations for market anomalies.

4. Presentation of Sources of Data and Methodology

This section presents the data utilised as input in the empirical analysis as well as the utilised methodology for testing the zero hypothesis. Due to differences in Norwegian stock market data compared to U.S. stock market data, this thesis test additional L/S portfolio trading strategies to those tested by Lamont and Frazzini (2007). This is mostly related to the fact that the large majority of the companies listed on the Oslo Stock Exchange have their fiscal year end in December. The chosen methodology is, except from some additional tests which are properly described further down in this section, otherwise similar to the methodology applied by Lamont and Frazzini (2007).

4.1 Sources of Data

Government bonds issued by stable governments are normally seen as a good approximation for the risk free rate. According to Harris (2007), the three month US Treasury Bill is commonly used by portfolio managers as an approximation for the risk-free rate. Having a sample including only Norwegian stocks, I have therefore chosen to use the three months Norwegian Treasury Bill as an approximation for the risk free rate. The three months Norwegian Treasury Bill for the period between 01.01.1999 to 31.12.2007 is provided from Reuters.

The monthly and daily stock prices, trading volume, shares issued, book-values and fiscal year for the period from 01.01.1999 to 31.12.2007 are provided from Børsprosjektet at NHH. The stock prices are generic and adjusted for dividends and splits. Børsprosjektet claims to have adjusted the stock prices according to formulas presented in an article[3] written by the NHH professor Thore Johnsen in 1983. Splits and dividends do not change the real value for an investor. Thus, the adjustment for splits and dividends is done in order to express current and past returns are on a comparable basis.

[3] The original title of the article is ”Aksjekurser og regnskapsdata ved kapitalutvidelser”.

Quarterly earnings announcement dates between 1998 and 2007 have partly been collected from the Daily Bulletin, called NewsWeb, of the Oslo Stock Exchange and partly provided from Bloomberg.

All the data sources I have downloaded data from contain full historical records. A stock is only eliminated from my sample the year it gets de-listed from the Oslo Stock Exchange. Survivorship bias will therefore not affect the sample selection.

4.2 Methodology

Børsprosjektet at NHH is in position a dataset containing all announcements made at the Oslo Stock Exchange from 1981. However, sorting earnings announcement dates out from all announcements ever made at the Oslo Stock Exchange for the whole period would be time-consuming. In addition, companies listed at the Oslo Stock Exchange were not required to report their earnings quarterly until in 2000 (Dyvik, 2008). Whether a company announced its earnings on a quarterly basis or not before 2000 was hence a decision to make for the company itself. The coverage of companies announcing their earnings quarterly is therefore likely to be relatively poor before 2000. Also, companies choosing to announce their earnings quarterly before they were legally required to may have other company-characteristics than companies that didn’t. Testing for an earnings announcement premium on companies choosing to announce quarterly before they were required to could therefore lead to results being relevant only for those companies, not a general result of if there is an earnings announcement premium at the Oslo Stock Exchange. I have chosen to focus on the period between 01.01.1998 and 31.12.2007. This period includes eight years of which there were quarterly earnings announcement requirements and two years without. That will help determine whether or not the coverage of earnings announcements mentioned below changes after the quarterly reporting requirement or not.

Bloomberg provides quarterly earnings announcement dates from July 1999 until 2008. However, their coverage proved to be somewhat inconsistent, especially for year 2000 and 2001. I have therefore checked the Oslo Stock Exchange NewsWeb for companies where Bloomberg reports three earnings announcements in a year, in order to verify whether there was a fourth earnings announcement that year for each of those companies. For companies with large market capitalisation where Bloomberg does not report full earnings announcement coverage for a given year I have performed the same procedure. Earnings announcements between 01.01.1998 and July 1999 is sorted manually from the Oslo Stock Exchange NewsWeb as well as from the dataset containing all announcements ever made at the Oslo Stock Exchange provided from Børsprosjektet.

A stock is included in the selection if it has 12 months of previous return-history. I will from now on refer to this as the stock universe for my sample-period. It was considered to exclude illiquid stocks from the sample due to the positive autocorrelation low trading volume stocks may cause in a portfolio. However, Lamont and Frazzini (2007) claims trading-volume provides part of the explanation for the earnings announcement premium, thus all stocks with 12 previous months of return-history is included in the stock universe no matter their trading volume. I will come back to this a potential source of error when discussing the results in section 6. The coverage of the companies in the sample with four earnings announcements in a year is then calculated.

In order to test if there is a predictable earnings announcement premium on the Oslo Stock Exchange, I use predictions of expected earnings announcement dates rather than actual announcement dates. The reason for this is mainly that the trading strategy would be impossible to implement in reality if actual announcement dates were used, since these are not publicly known in advance by all market participants. Also, if the actual *scheduled* announcement dates were publicly known in advance, they could be delayed, cancelled or even released too early. According to Lamont and Frazzini (2007), a discrepancy between the scheduled and the actual announcement could contain information itself. For example, a delayed earnings announcement may indicate unfavourable news. In order to predict earnings announcement dates I will use the same two algorithms as the ones used by Lamont and Frazzini (2007).

4.2.1 Algorithm 1: Previous Year’s Announcement Month

The first algorithm used for predicting earnings announcement dates is based on the previous year’s announcement month. If a company had an announcement in January 1998, it is expected to have an announcement in January 1999. In order to predict earnings announcements for a year I will hence require the company to have had four earnings announcements the previous year.

4.2.2 Algorithm 2: Fiscal Year End

The second algorithm used for predicting earnings announcement dates is based on the companies' fiscal year ends. A company's fiscal year ending is collected the first time the company appears in the universe, which is the first year after it has had 12 months of previous return history at the Oslo Stock Exchange. The advantage of this method is that it doesn't require a company to have had four announcements the previous year in order to predict this year's announcement dates. However, a substantial source of error here is that companies may change their fiscal years during the sample period. Børsprosjektet at NHH has fiscal year end information available for the companies listed at the Oslo Stock Exchange as far back as 1980. I have nevertheless chosen to focus on the period between 1998 and 2007 also here for three reasons: Firstly, this method for predicting earnings announcement date proved to be less accurate than the method based on previous year's announcement months in Lamont and Frazzini's study (2007). Secondly, and as already mentioned, quarterly earnings announcements were not required by law at the Oslo Stock Exchange before 2000. Thirdly, using both methods for predicting is mostly done for comparison reasons. Using a longer sample period for one of the forecasting methods would therefore be somewhat irrelevant.

The distribution of earnings announcement dates is found by matching actual announcements with fiscal year end month. Like this, it is possible to determine which months companies with a fiscal year ending I month X tend to announce in. For companies with fiscal year ending in month X, they are predicted to announce their earnings in the months with the most frequent announcement-activity in the table.

Further, the predicted announcement dates are compared with the actual announcement dates for both algorithms. For example, if one of the algorithms has predicted a company's earnings announcement in June 1999, but there is no earnings announcement in June 1999, this counts as an error.

According to Lamont and Frazzini (2007), news sources are more likely to report earnings announcements for large stocks. It is therefore interesting to investigate whether the accuracy of predicted announcement months increases with company size. Lamont and Frazzini (2007) assign companies to 10 different size deciles by using New York Stock Exchange breakpoints. A general rule of thumb is that a portfolio is well-diversified if it contains 30 or more stocks (Womack and Zhang, 2003). Given that my sample size is varying from 115 to 188 stocks I have chosen to assign companies into five different size groups. According to communications with Randi Hovde (2008) at the Oslo Stock Exchange, the Oslo Stock Exchange does not operate with breakpoints for sorting companies into size-groups like the New York Stock Exchange. The Oslo Stock Exchange classifies companies after their degree of liquidity. In order to assign companies into five different size group at the beginning of each month I simply sort the fifth of the companies with lowest market capitalisation at the beginning of the month into one size group etc.

There are several reasons for using monthly data and not daily:

1) The focus is on expected announcement returns. In order to increase the chance that a stock is bought before the earnings announcement and sold after the earnings announcement, it is convenient to have a longer period around the specific day (Lamont and Frazzini, 2007).
2) Different news sources may report earnings announcements on different days. In addition, earnings can be announced before, during and after the relevant stock exchange’s trading hours. In practise, it may therefore be difficult to determine the exact date of the earnings announcement (Lamont and Frazzini 2007).
3) Monthly returns will not reflect “*short-term asymmetric information and changes in liquidity*” around earnings announcement dates. In average, the utilised strategy will make sure that stocks are bought two weeks before the expected announcement date and sold two weeks after (Lamont and Frazzini 2007, p. 9).
4) Monthly returns are often used by other financial economists and will hence allow for comparisons with existing stock price patterns (Lamont and Frazzini, 2007).
5) According to Lamont and Frazzini (2007), a three day window around the earnings announcement date misses much of the earnings announcement premium. A longer window is therefore more informative.
6) It is very likely that some of the stocks on the Oslo Stock Exchange are not being exchanged during one day. By using monthly data instead of daily data it is possible to avoid problems related to non-synchronous trading (Harris, 2007).

4.2.3 Excess returns of the L/S Portfolio Based on Predicted Announcement by the Previous Year Method

Based on the monthly announcement dates predicted by the first forecasting algorithms, I form value weighted portfolios based on whether or not a company is expecting to have an announcement this month. The sample is restricted to companies that have exactly four earnings announcements in the previous 12 calendar months. Firstly, a value weighted portfolio of all stocks in the sample is formed, and its monthly average return in excess of the risk free rate is calculated. This portfolio's return may be regarded as the market's return.

Secondly, the monthly average excess return of a value-weighted portfolio of excepted non-announcers and the monthly average excess return of a value-weighted portfolio of expected announcers is calculated. At the beginning of each calendar month each stock is assigned to one of the two portfolios, based on whether the stock is predicted to have an announcement or not. That means that each stock jumps into the long portfolio four months per year and into the short portfolio eight months of the year. All stocks are value-weighted within their respective portfolios and the portfolios are rebalanced each month in order to maintain the value-weights.

And finally, the monthly average excess return of an L/S portfolio is calculated. The L/S portfolio is a value-weighted zero-cost portfolio that each month takes long positions in stocks that are expected to have an announcement that month and sells short the month's expected non-announcers, in other words, a combination of the two latter portfolios.

In the main part of the empirical analysis, arithmetic averages of simple returns is used.

Simple returns for each stock in the portfolio are calculated as follows:

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

The portfolios's monthly value-weighted return is calculated as follows:

$$R_{p,t} = \sum_{i}^{N} \left[R_{i,t} \times \frac{marketcap_{i,t}}{totalmarketcap_{t}} \right]$$

Arithmetic averages of the portfolios monthly returns are calculated as follows:

$$A_{average} = \frac{(R_{pi,t} + \ R_{p,t+1} + ... + R_{p,T})}{T}$$

However, continuously compounded returns, or logarithmic returns, are more likely to have statistically desirable properties, such as normality, than simple returns. Also, bad returns will have a greater impact on the geometric average than the arithmetic average. With return data that is relatively volatile, a geometric average will therefore be “more pessimistic” than a arithmetic average. Continuously geometric averages on compounded returns as a basis for computing average returns may thus provide different results than arithmetic averages of simple returns. Therefore, when robustness-checking my results, I have chosen to compare the arithmetic averages of simple returns with geometric averages of continuously compounded returns.

Continuously compounded returns for each stock are calculated as follows:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) = \ln(1 + R_{i,t})$$

The portfolios’s monthly value-weighted return is calculated as follows:

$$R_{p,t} = \sum_{i=1}^{N} \left[R_{i,t} \times \frac{marketcap_{i,t}}{totalmarketcap_t} \right]$$

Geometric averages of the monthly continuously compounded portfolio returns are calculated as follows:

$$G_{average} = (R_{p,t} \times R_{p,t+1} .. \times R_{p,T})^{\frac{1}{T}}$$

The geometric average of continuously compounded returns are normalised the following way:

$$G_{normalised} = \exp^{\ln(G_{Average})} - 1$$

Whether the L/S portfolio strategy is profitable or not is tested by the following zero-hypothesis:

A) **H$_0$**: Average monthly excess returns L/S portfolio = 0

H_1: Average monthly excess returns L/S portfolio > 0

The zero-hypothesis are tested by conducting a t-test, with n-1 degrees of freedom, of the average excess return with an unknown population variance:

$$t_p = \frac{(AverageExcess\,\mathrm{Re}\,turn_p - H_0)}{\sigma_p \big/ \sqrt{N}}$$

Where N is the number of observations, which in this case will be number of monthly average excess returns included in the sample the t-statistics is calculated for. If $|t| > t^{critical}$, the zero-hypothesis is rejected. At a 5 percent significance level, the zero-hypothesis is rejected if the absolute t-value is over 1.96. With a 5 percent significance level, there is a 5 percent chance for a type I error, namely that a correct zero-hypothesis is wrongly rejected. A type II error consists of *not* rejecting a false zero-hypothesis, and is equal to 1 minus the chosen significance level. In this case, with a 5 percent significance level, there would therefore be a 95 percent chance of wrongly not rejecting the zero-hypothesis. There is hence a trade-off between when choosing the significance level of a test. In general, a executing a type I error is seen as worse than executing a type II error. Therefore significance levels of 5 or 1 percent are most often used in practise (Brooks, 2002).

σ_p is the standard deviation of each portfolio as is calculated the following way:

$$\sigma_p = \sqrt{\frac{\sum (Excessreturn_{p,t} - AverageExcess\,\mathrm{Re}\,turn_{p,T})^2}{T-1}}$$

For all the portfolios, skewness and kurtosis are calculated. Skewness measures the risk that normal distribution (zero skew) is assumed while the data in reality is skewed to the right (positive skew) or to the left (negative skew) of the mean. Kurtosis describes the distribution of the data around the mean. A high kurtosis means that the data has fat tails and a low, even distribution. A low kurtosis means that the data has skinny tails and a distribution that is concentrated towards the mean. A normal distribution is not skewed and has a coefficient of kurtosis of 3. In other words, skewness and kurtosis are additional measures of the portfolio's riskiness.

The Sharpe-ratio is calculated for each of the value-weighted portfolios in order to compare their risk-adjusted performance:

$$S_p = \frac{\overline{R}_p - r_f}{\sigma_p}$$

Where:

$\overline{R}_p$ = Average portfolio return

r_f = Risk free rate

σ_p = Portfolio standard deviation

The greater the portfolio's Sharpe ratio, the better its risk-adjusted performance has been over the sample period. According to the CAPM, the market portfolio will by definition always have the highest possible Sharpe-ratio.

4.2.4 Excess returns of the L/S Portfolio Based on Predicted Announcement by the Fiscal Year Method:

Lamont and Frazzini (2007) also form a L/S portfolio based on announcements forecasted by the previous year method. However, the large majority of companies listed at the Oslo Stock Exchange are having their fiscal year end in December. This information was not known before looking at the dataset. As explained in section 3.3., is equal to data-snooping. Forming a trading-strategy after having looked at the dataset will obviously affect the way the trading-strategy is formed. When testing the trading strategy in the same dataset, it is hence likely that one will find the results one wishes to find. Thus, if the tested zero-hypothesis are rejected when testing this trading-strategy is tested, this has to be taken into account.

The four calendar months with the highest fraction of quarterly earnings announcements for companies with their fiscal year ending in December is found, and used as expected announcement moths for the companies with their fiscal year ending in December. Excluding the companies not having their fiscal year end in December, I test a trading strategy consisting of a value-weighted L/S portfolio that takes a long position in all stocks in the four predicted announcement months, and a short position in all stocks in the resting months is formed. The excess returns of this portfolio are tested the similar way as for the L/S portfolio based on the previous year method.

4.2.5 Excess Returns of the L/S Portfolio Based on Actual Announcement Dates

Lamont and Frazzini (2007) formed an L/S portfolio on the basis of actual announcement dates is also formed. This is not an implementable strategy in practise. However, it’s useful for determining whether or not it is theoretically possible to earn average excess returns larger than zero with the tested trading strategy. If any of these L/S portfolios based on actual announcement dates are generating average excess returns that are statistically significantly larger than zero, and the L/S portfolios based on predicted announcement dates are not, this indicates that one with a more accurate announcement date forecasting method can earn average excess returns larger than zero.

With actual announcement dates, I form the same portfolios as formed with the previous year method. The excess returns of the L/S portfolios based on actual announcement dates are tested the similar way as the portfolios based on forecasted dates by the previous year method.

4.2.6 Regression Analysis to Determine the Source of the Excess Returns

If any of the tested L/S portfolios are generating average monthly excess returns that are statistically significantly larger than zero, the following methodology is further applied:

In order to test whether or not the monthly returns generated by the rolling L/S strategy are abnormal or not, I run a regression based on the Carhart (1997) four-factor model explained in section 2.2.2:

$$R_{p,t} - r_{f,t} = \alpha_p + \beta_p MKT_t + s_p SMB_t + h_p HML_t + p_p PR1YR_t + e_{p,t}$$

Where $R_{p,t}$ is the portfolio’s return, $r_{f,t}$ is the riskfree rate, while $e_{p,t}$ is the error-term Alpha is the excess returns generated by the rolling L/S strategy that cannot be explained by the L/S portfolio’s sensitiveness to the market return (MKT), the Fama and French size factor (SMB), the Fama and French value factor (HML) or the Jeegadesh and Titman one-year momentum factor (PR1YR). The MKT, SMB, HML or PR1YR are time series calculated on the basis of monthly returns, and are all described more in detail in section 2.2.1. and 2.2.2. The coeffisients in front of each factor describes the portfolio's exposure towards these factors. If the L/S portfolio strategy is generating abnormal returns, the alpha will be statistically significantly larger than zero. It should however be mentioned that due to the way the L/S portfolio is created, it is not very probable that the factors in the Carhart four-factor model can explain eventual abnormal returns generated by the portfolio.

In other words, the following zero hypothesis is tested in the case of a L/S portfolio strategy generating statistically significant positive average excess monthly returns:

B) **H_0:** Average monthly abnormal returns L/S portfolio = 0

H_1: Average monthly abnormal returns L/S portfolio > 0

If the zero hypothesis is rejected, and the alternative hypothesis is accepted, this indicates that there is an earnings announcement premium at the Oslo Stock Exchange. This means that a monthly trading strategy buying stocks expected to announce their earnings and selling short stocks not expected to announce their earnings in the following month, generates excess returns over the Norwegian Government three month Treasury bill that can not be fully explained by the Carhart (1997) four-factor model. The abnormal return generated from this trading-strategy is statistically significant, which in that case is inconsistent with weak form efficiency at the Oslo Stock Exchange.

The zero-hypothesis is rejected if $|t| > t^{critical}$, which is 1.96 on a 5 percent significance level.

This may help to identify whether companies of specific company characteristics, such as small capitalisation companies or value companies, are announcing their earnings. This is especially important for the period before year 2000 when companies listed at the Oslo Stock Exchange were not legally required to announce their earnings on a quarterly basis.

4.2.7 Robustness Checks of the Results

In order to check the robustness of the results, I have chosen to report results for the whole period from 1999-2007, as well as for the two sub-periods 1999-2000 and 2001-2007. The period before and after 2000 is the period before and after quarterly earnings announcements were required for companies listed at the Oslo Stock Exchange. Since 1999 dates are used to predict 2000 dates, I have chosen to include 2000 in the first sub-period.

For the L/S portfolio based on previous year predicted announcement dates, and for the L/S portfolio based on actual announcement dates, I do the following robustness-checks:

1) If some of the months have zero expected announcers, I test how excluding these months affects the result.

2) It is likely that some of the months have several more expected announcers than others. In order to give these months “more importance” when the average excess returns are calculated, I make a managed L/S portfolio. That means that each month, the size of the value-weighted L/S portfolio is determined by the amount of expected announcers that month. For example, for year t, X announcements are expected to be made for the whole year, while Y announcements are expected to be made this current month. The size of the L/S portfolio depends on the number of expected announcers and is equalised to Y/X this current month.

In addition to looking at monthly average excess returns of the tested L/S portfolios for the whole sample period, the two sub-periods 1999-2000 and 2001-2007 are examined. Moreover, geometric averages are taken of logarithmic returns, in order to verify whether or not the method used for calculating the returns are affecting the results.

If any of the L/S portfolios are generating average excess returns that are statistically significantly larger than zero, the source of the excess returns will be tested with a regression with the four factors from Carhart (1997) as explanatory variables. Regressions will then be run for the sub-periods 1999-2000 and 2001-2007 as well as for the whole sample period.

5. Results and Analysis

This section presents the results and the analysis of the conducted empirical research. Firstly, the coverage and the distribution of the earnings announcement dates is presented and analysed. Further, the main results of the tested L/S portfolio trading strategies are presented and analysed. The complete overview of the results of the tested trading strategies may be found in the appendix. In contrary to the results of Lamont and Frazzini (2007), none of the L/S portfolio trading strategies that are tested in this thesis generates average monthly excess returns over the Norwegian Government three month Treasury bill that are statistically significantly larger than zero. Moreover, the results are robustness checked. None of the found results are rejecting zero-hypothesis A. The regression analysis is consequently not conducted.

5.1 Coverage and Distribution of Earnings Announcement Dates

	Exactly 4 Announcements			
Year	All Comp	Smaller Comp	Larger Comp	Market Value
1998	0,71	0,70	0,71	0,90
2007	0,87	0,87	0,86	0,92
1998-1999	0,66	0,65	0,66	0,83
2000-2007	0,78	0,78	0,78	0,86
1998-2007	0,75	0,75	0,75	0,86

Table 1: Coverage of Earnings Announcement Dates 1998-2007

Table 1 shows the fraction of companies in the universe with exactly four announcements that calendar year. For each year, the median of the market value of all stocks with 12 previous months of returns history is computed. Companies with market capitalisation above the median are assigned into “Larger Comp”, while companies with market capitalisation below the median are assigned into “Smaller Comp” each year. The “Market Value” is the total market capitalisation of companies with exactly four announcements in that calendar year divided by the total market value of the stocks with 12 previous months of return history.

The table shows that the coverage, or the number of companies in the universe announcing their quarterly results each year, has increased over the sample period. More particularly, the coverage for all companies is rising from 71 percent in 1998 to 87 percent in 2007, while the coverage for the full sample is 75 percent. The coverage for both smaller and larger companies has increased over the sample period. For comparison, Lamont and Frazzini (2007) found that the coverage of earnings announcements increased from 50 percent in 1974 to 95 percent in 2004.

When comparing the two sub-periods, 1998-1999 and 2000-2007, we can also see a substantial coverage increase. This is most likely related to the fact that companies at the Oslo Stock Exchange were not required by law to announce their earnings on a quarterly basis before year 2000.

Lamont and Frazzini (2007) find a substantial difference in the coverage for smaller versus larger firms. Especially in the earlier years of their sample, they find that the coverage for smaller stocks often is incomplete, which they claim is closely correlated with the fact that "*news sources are more likely to report earnings announcements for big stocks*" (p. 5). However, table 1 indicates that there is no substantial difference in the coverage of earnings announcements for smaller stock versus larger stocks at the Oslo Stock Exchange. In contrary, the coverage for smaller versus larger companies seems to be quite similar over the whole sample period.

Over the total sample, 86 percent of the companies measured in market value had exactly four announcements. The coverage of companies announcing their quarterly earnings calculated in market value has also increased over the sample period, from 90 percent in 1998 to 92 percent in 2007. For comparison, Lamont and Frazzini (2007) found that the coverage measured in market capitalisation increases from 84 percent in 1974 to 96 percent in 2004.

What might seem strange is that the coverage for all companies has increased from 71 percent in 1998 to 87 percent in 2007, while the coverage measured in market value has increased only from 90 percent in 1998 to 92 percent in 2007. This may indicate that the companies assigned to the "Large Comp" in 2007, and not having exactly four announcements in 2007, are larger measured in market capitalisation than the companies assigned to "Large Comp" in 1998 that did not have exactly four announcements.

	Fiscal yr end	Ann	all firms Q4	Q1-Q3
Jan	0,00	3,73	11,14	0,03
Feb	0,00	26,02	77,96	0,10
Mar	0,23	3,24	9,60	0,07
Apr	0,23	9,80	0,86	14,37
May	0,00	11,72	0,14	17,60
Jun	0,90	0,35	0,07	0,50
Jul	0,00	4,53	0,00	6,72
Aug	0,23	17,46	0,07	25,72
Sep	0,00	0,38	0,00	0,57
Oct	0,00	12,46	0,07	18,79
Nov	0,68	10,12	0,03	15,27
Dec	97,74	0,19	0,07	0,26

Table 2: Distribution of Earnings Announcement Dates 1998-2007

Table 2 shows the distribution of earnings announcement dates. Column one reports the fraction of companies with fiscal year ending in each calendar month. 97.74 percent of the companies listed at the Oslo Stock Exchange have their fiscal year end in December.

Column two reports the fraction of earnings announcements occurring in each calendar month. Column three reports the fraction of fourth fiscal quarter earnings announcements occurring in each calendar month. Column four reports the fraction first, second or third fiscal quarter earnings announcements occurring in each calendar month.

For comparison, Lamont and Frazzini (2007) also reports that most of the announcing activity is taking place in December. However, their sample contains companies with fiscal year endings also in other months of the calendar year. 62 percent of the announcing activity in their sample takes place in December compared to 97.74 percent in this sample. Lamont and Frazzini claim that each month in their sample "*has a sufficiently large number of earnings announcements*" (p. 6) so that the portfolios they form based on scheduled announcements will be "*sufficiently diversified each month*" (p. 6). This is clearly not the case for the sample utilised in this thesis. Yet, I have decided to form a version of the L/S portfolio based on announcement dates predicted by the fiscal year end method for comparison reasons.

	Fiscal Year End Month				
% of ann	Mar	Apr	Jun	Nov	Dec
Jan	0,00	0,00	0,00	2,33	3,77
Feb	25,00	33,33	29,41	25,58	26,17
Mar	11,11	0,00	0,00	11,63	3,19
Apr	0,00	0,00	29,41	6,98	9,86
May	25,00	0,00	5,88	4,65	11,76
Jun	0,00	0,00	0,00	4,65	0,34
Jul	0,00	0,00	17,65	9,30	4,44
Aug	16,67	33,33	0,00	6,98	17,22
Sep	2,78	0,00	0,00	9,30	0,32
Oct	0,00	0,00	17,65	11,63	12,56
Nov	16,67	33,33	0,00	4,65	10,19
Dec	2,78	0,00	0,00	2,33	0,17

Table 3: Distribution of Earnings Announcement Dates by fiscal Year 1998-2007

Table 3 shows the distribution of earnings announcement dates by fiscal year end month. The earnings announcement represents the date in which quarterly earnings were first reported. For every company with a fiscal year ending in calendar month t, the fraction of actual announcements occurring in every calendar month in the period 1998-2007 is reported. For fiscal year end month, the four calendar months with the highest fraction of announcements is reported in bold. January, February, May, July, August and October are not included in table 3 for the simple reason that none of the companies in the sample has a fiscal year end month in any of those months. Companies with a December fiscal year end month tend to announce their quarterly earnings in February, May, August and October.

Therefore, when predicting earnings announcement dates based on the fiscal year algorithm, companies with their fiscal year ending in December are expected to report their earnings in February, May, August and October.

	All firms	Four announcements in the previous year				
	1998 – 2007	1998	2007	1998-1999	2000-2007	1998-2007
Ann predicted based on fiscal year end						
% Announcement	0,69	0,62	0,71	0,64	0,69	0,69
% No Announcement	0,31	0,38	0,29	0,36	0,31	0,31
	1999-2007	1999	2007		2000-2007	1999-2007
Ann predicted based on previous year						
% Announcement	0,67	0,25	0,82		0,73	0,67
% No announcement	0,33	0,75	0,18		0,27	0,33

Size group	1 (small)	2	3	4	5 (large)
Ann predicted based on fiscal year end					
% Announcement	0,67	0,70	0,71	0,72	0,68
% No announcement	0,33	0,30	0,29	0,28	0,32
Ann predicted based on previous year					
% Announcement	0,64	0,70	0,63	0,64	0,74
% No announcement	0,36	0,30	0,37	0,36	0,26

Table 4: Accuracy of Announcement Dates Predictions 1998-2007

Table 4 shows the accuracy of announcement predictions based on the fiscal year end and previous year methods for the period from 1998 to 2007. The top panel of table 4 shows the accuracy of both methods for all firms, and then for firms with 4 earnings announcements in the previous year, including selected sub-periods. Regarding the announcements predicted based on the fiscal year end method, there has been little change in the accuracy of announcement predictions over the observation period. For announcements predicted based on previous year announcements the accuracy has significantly increased from 0.25 in 1999 to 0.82 in 2007. This can largely be attributed to the fact that companies listed at the Oslo Stock Exchange were not required by law to announce their earnings on a quarterly basis until year 2000. In addition, Bloomberg's coverage of earnings announcement dates for companies listed at the Oslo Stock Exchange has been limited until year 2000. This is largely solved by searching for earnings announcements manually from the daily bulletin at the Oslo Stock Exchange.

The lower panel of Table 4 shows the accuracy of both methods for companies divided into 5 size groups based on market capitalisation. For the fiscal year end method the is no significant difference between the size groups. For the previous year method the accuracy increases for the larger companies. Frazzini and Lamont (2007) argue this is because the coverage for small companies is incomplete and they are more likely to report earnings announcements of large companies. However, in the sample used here, the difference is not as large as with the sample used by Frazzini and Lamont (2007).

5.2 Excess returns of the L/S Portfolio Based on the Previous Year Method

Monthly Aritmethic Averages of Simple Returns
All Stocks With 4 Announcements the Previous Year

	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-0,416 %	-0,046 %	-0,772 %	-0,640 %
t-stat	0,58	0,06	0,91	0,91
1999-2000				
Mean	-1,221 %	-0,168 %	-2,062 %	-1,722 %
t-stat	0,67	0,10	0,95	1,02
2001-2007				
Mean	-0,186 %	-0,011 %	-0,388 %	-0,331 %
t-stat	0,22	0,01	0,43	0,43

Table 5: All Stocks With 4 Announcements the Previous Year- Previous Year Method

Table 5 shows that the monthly average returns of the value-weighted L/S portfolio including all stocks with exactly four earnings announcements in the previous year. “All stocks” refers to all stocks with four announcements in the previous year. The tested L/S portfolio seem to be generating negative monthly average excess returns for the sample period, as well as for the sub-periods. However, the t-values are indicating that the found results are not statistically significant. Zero-hypothesis A stating that the L/S portfolio does not generate excess returns over the three month Norwegian Treasury bill returns greater than zero, is not rejected. For comparison, Lamont and Frazzini (2007) found that a L/S portfolio formed on the basis of the previous year method generated positive statistically significant average monthly excess returns of 0.613 percent in their sample period between 1973 and 2004.

Months with zero expected Announcements Deleted	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	0,208 %	0,624 %	-0,772 %	-1,395 %
t-stat	0,31	0,95	0,85	1,78
1999-2000				
Mean	-0,691 %	0,457 %	-2,062 %	-2,519 %
t-stat	0,15	0,45	0,41	0,85
2001-2007				
Mean	0,475 %	0,673 %	-0,388 %	-1,061 %
t-stat	0,27	0,83	0,75	1,56

Table 6: Months with Zero Expected Announcers Deleted - Previous Year Method

Lamont and Frazzini (2007) reports that each month in their sample "*has a sufficiently large number of earnings announcements*" (p. 6) so that the portfolios they form based on scheduled announcements will be "*sufficiently diversified each month*" (p. 6). This is clearly not the case for this sample; Some of the months in this sample, no companies are expected to announce their earnings. Table 6 reports the monthly average excess returns over the Norwegian Government three month Treasury bill of a L/S portfolio traded only in the months with predicted quarterly earnings announcements. The table shows that the L/S portfolio traded only in the months with expected announcers, does not generate positive monthly average excess returns that are statistically significant for the sample period, nor for the sub-periods. However not statistically significant, also this L/S portfolio seem to generate negative monthly average excess returns. Zero-hypothesis A can not rejected on the basis of the results in table 6.

Managed L/S Portfolio	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-0,416 %	-0,018 %	-0,117 %	-0,099 %
t-stat	0,545	0,247	1,144	1,017
1999-2000				
Mean	-1,221 %	-0,059 %	-0,266 %	-0,208 %
t-stat	0,272	0,123	0,572	0,508
2001-2007				
Mean	-0,186 %	-0,006 %	-0,075 %	-0,069 %
t-stat	0,510	0,231	1,070	0,951

Table 7: Managed L/S Portfolio - Previous Year Method

Some of the months in the sample period tend to have more expected announcers than others. Consequently, some of the months in the sample have few expected announcers. In order to adjust for this, a managed L/S portfolio is constructed. For each month, the size of the value-weighted L/S portfolio is determined by the amount of expected announcers that month. For example, for year t, X quarterly earnings announcements are expected to be made for the whole year, while Y quarterly earnings announcements are expected to be made this current month. The size of the L/S portfolio depends on the number of expected announcers and is equalised to Y/X this current month. Table 7 shows that zero-hypothesis A can not be rejected. Like the results presented in table 5 and 6, the managed L/S portfolio seem to generate statistically insignificant negative monthly average excess returns over the sample period and in the sub-periods.

L/S Portfolio Traded in February, May, August and October

	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-1,416 %	-0,795 %	-1,740 %	-0,945 %
t-stat	1,31	0,79	1,20	0,69
1999-2000				
Mean	-3,663 %	-0,368 %	-5,385 %	-5,017 %
t-stat	1,75	0,16	2,11	1,66
2001-2007				
Mean	-0,774 %	-0,918 %	-0,698 %	0,219 %
t-stat	0,51	0,80	0,53	0,15

Table 8: L/S Portfolio Traded in February, May, August and October - Previous Year Method

Table 2 and 3 showed that most companies (97.74) listed at the Oslo Stock Exchange have their fiscal year end in December. Out of the companies having their fiscal year end in December, most of these companies (67.71 percent) tend to announce their earnings in February, May, August and October. Table 8 shows the average monthly excess returns of a L/S portfolio traded *only* in February, May, August and October. In other words, I form the same value-weighted zero cost L/S portfolio as previously, but it is only traded in February, May, August and October. This portfolio is different from the L/S portfolio based on the fiscal year method since the latter is traded in *all* months. The L/S portfolio traded in February, May, August and October, holds the portfolio of expected announcers in February, May, August and October and sells short the portfolio of expected non-announcers in February, May, August and October.

Table 8 shows that the L/S portfolio traded only in February, May, August and October does not generate positive statistically significant excess returns over the three month Norwegian Government Treasury bill returns over the sample period. In the sub-period from 2001-2007, the L/S portfolio seem to generate positive average excess returns. However, the t-statistics are too low for rejecting zero-hypothesis A in the sub-period between 2001 and 2007.

5.3 Excess Returns of the L/S Portfolio Based on the Fiscal Year Method

	All Stocks With 4 Announcements the Previous Year			
	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-0,416 %	0,050 %	-0,484 %	-0,533 %
t-stat	0,58	0,06	0,77	0,74
1999-2000				
Mean	-1,221 %	-0,011 %	-1,228 %	-1,217 %
t-stat	0,67	0,01	0,93	0,67
2001-2007				
Mean	-0,186 %	0,067 %	-0,271 %	-0,338 %
t-stat	0,30	0,08	0,07	0,44

Table 9: All Stocks with 4 Announcements the Previous Year - Fiscal Year Method

According to table 3, companies with their fiscal year ending in December are expected to report their earnings in February, May, August and October. Considering that only 2.26 percent of the companies in the universe of stocks with four announcements in the previous year have a fiscal year ending in other months than December, it does not make sense to form the same L/S portfolio based on announcements forecasted by the fiscal year method as Lamont and Frazzini (2007). Therefore, excluding the 2.26 percent of companies not having their fiscal year end in December, I test a trading strategy that takes a long position in all stocks (having their fiscal year end in December) in February, May, August and October, and a short position in all stocks (having their fiscal year end in December) in the rest of the months. Table 9 shows that nor does this trading strategy generate positive excess returns over the three month Norwegian Government Treasury bill returns over the sample period, nor in any sub-periods. Zero-hypothesis A can not be rejected. For comparison, Lamont and Frazzini (2007) found that a L/S portfolio based on company fiscal year end generated monthly average statistically significant excess returns of 0.723 percent.

5.4 Excess Returns of the L/S Portfolio Based on Actual Announcement Dates

Monthly Aritmethic Averages of Simple Returns
All Stocks With 4 Announcements Each Calendar Year

	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-0,416 %	-0,468 %	0,153 %	0,600 %
t-stat	0,58	0,57	0,17	0,73
1999-2000				
Mean	-1,221 %	-1,412 %	0,935 %	2,191 %
t-stat	0,67	0,67	0,43	1,04
2001-2007				
Mean	-0,186 %	-0,196 %	-0,053 %	0,145 %
t-stat	0,21	0,22	0,05	0,17

Table 10: All Stocks with 4 Announcements the Previous Year - Actual Announcement Dates

Table 10 reports the average monthly excess returns of a value-weighted zero cost L/S portfolio based on actual announcement dates. Based actual announcement dates, a value-weighted zero cost L/S portfolio holding the stocks that are announcing and selling short the stocks not announcing in a month. This trading strategy is not implementable in practise, but is useful for determining whether or not it is theoretically possible to earn average excess returns larger than zero with the tested trading strategy. None of the results in table 10 are statistically significant and the zero-hypothesis A can consequently not be rejected. If the zero-hypothesis had been rejected, this would have indicated that it is theoretically possible to obtain positive monthly average excess returns with the quarterly earnings announcement trading strategy at the Oslo Stock Exchange, only with a better method for predicting quarterly earnings announcement dates. However, this is not the case. For comparison, Lamont and Frazzini (2007) reports statistically significant average monthly excess returns of a L/S portfolio based on actual announcement dates of 0.603 percent.

	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-0,059 %	-0,216 %	0,154 %	0,368 %
t-stat	0,08	0,26	0,16	0,36
1999-2000				
Mean	-1,324 %	-2,414 %	0,823 %	3,237 %
t-stat	0,04	0,12	0,08	0,17
2001-2007				
Mean	0,317 %	0,446 %	-0,045 %	-0,485 %
t-stat	0,07	0,22	0,14	0,32

Months with Zero Actual Announcements Deleted

Table 11: Months with Zero Expected Announcers Deleted - Actual Announcement Dates

Table 11 reports the monthly average excess returns over the Norwegian Government three month Treasury bill of a value-weighted zero cost L/S portfolio traded only in the months with actual earnings announcements. The table shows that zero-hypothesis A can not be rejected. Neither this non implementable trading strategy does generate positive monthly average excess returns that are statistically significant for the sample period, nor for the sub-periods.

Managed L/S Portfolio

	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-0,416 %	-0,080 %	-0,063 %	0,018 %
t-stat	0,54	0,78	0,75	0,15
1999-2000				
Mean	-1,220 %	-0,183 %	-0,112 %	0,071 %
t-stat	0,27	0,39	0,37	0,08
2001-2007				
Mean	-0,186 %	-0,051 %	-0,049 %	0,002 %
t-stat	0,51	0,73	0,70	0,14

Table 12: Managed L/S Portfolio - Actual Announcement Dates

Table 12 reports the monthly average excess returns of the same managed value-weighted zero cost L/S portfolio as in table 7, only with actual announcement dates. In other words, it is the same L/S portfolio; lagged one year. Table 12 shows that the L/S portfolio seem to generate positive monthly average excess returns over the sample period as well as in the sub-periods. However, none of these results are statistically significant. Zero-hypothesis A can hence not be rejected.

L/S Portfolio Traded in February, May, August and October	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-1,416 %	-2,910 %	-0,565 %	2,264 %
t-stat	1,31	2,04	0,48	1,47
1999-2000				
Mean	-3,663 %	-5,122 %	-2,147 %	2,975 %
t-stat	1,75	1,25	1,01	0,60
2001-2007				
Mean	-0,774 %	-2,254 %	-0,112 %	2,061 %
t-stat	0,59	1,58	0,08	1,42

Table 13: L/S Portfolio Traded in February, May, August and October - Actual Announcement Dates

Like table 8, table 13 shows the average monthly excess returns of a value-weighted zero cost L/S portfolio traded *only* in February, May, August and October. Unlike table 8, the L/S portfolio is formed on the basis of actual announcement dates.

The L/S portfolio based on actual announcement dates traded in February, May, August and October earns positive average monthly excess returns over the sample period. However, this result is not statistically significant. Zero-hypothesis A is consequently not rejected for the sample period. It could nevertheless be interesting to see if one with a longer sample period, would be able to get statistically significant results. Given statistically significant results, a better method for predicting earnings announcement dates would consequently provide us with a L/S portfolio, traded only in February, May, August and October, generating monthly average excess returns larger than the Norwegian Government three month Treasury bill. However, this is not the case.

5.5 Robustness Checks of the Results with Geometric Averages of Logarithmic Returns

Logarithmic returns are more likely to have desirable statistical properties such as normal distribution than simple returns. In order to determine whether or not the way the returns are calculated has something to say for the results, geometric averages of logarithmic returns are calculated. This should not change the results dramatically, and if statistically significantly positive average excess returns were found previously, this part would have been more important since results rejecting a zero-hypothesis should be properly robustness checked.

5.5.1 Geometric Averages of Logarithmic Returns Previous Year Method

	Monthly Normalised Geometric Averages of Logarithmic Returns			
	All Stocks With 4 Announcements the Previous Year			
	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-1,970 %	-1,370 %	-2,268 %	-1,286 %
t-stat	2,44	1,77	2,38	1,68
	Months with zero expected Announcements Deleted			
	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-1,032 %	-0,344 %	-2,544 %	-2,305 %
t-stat	1,41	0,51	2,52	2,58
	Managed L/S Portfolio			
	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-1,970 %	-0,080 %	-0,256 %	-0,177 %
t-stat	2,30	1,06	1,92	1,41
	L/S Portfolio Traded in February, May, August and October			
	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-2,857 %	-1,637 %	-3,984 %	-2,479 %
t-stat	2,28	1,57	2,21	1,43

Table 14: Geometric Averages of Logarithmic Returns - Previous Year Method

In order to determine whether or not the way the returns are calculated has something to say for the results, table 14 reports geometric averages of logarithmic returns for the four different L/S portfolios formed on the basis of the previous year method. The table shows that none of the L/S portfolio trading strategies based on announcement dates predicted by the previous year method generate positive excess returns over the Norwegian Government three month Treasury bill over the sample period. However, when the geometric averages is taken of the logarithmic returns of the L/S portfolio that is not traded in months with zero expected announcers, it seems to generate excess returns that are statistically significantly different from zero. The sign of the excess returns is nevertheless negative. Zero hypothesis A can consequently not be rejected.

5.5.2 Geometric Averages of Logarithmic Returns Fiscal Year Method

	All Stocks With 4 Announcements the Previous Year			
	All Stocks	Expected Non-Announcers	Expected Annonuncers	L/S
1999-2007				
Mean	-1,970 %	-1,046 %	-0,983 %	-0,469 %
t-stat	2,44	1,24	1,31	0,57

Table 15: Geometric Averages of Logarithmic Returns - Fiscal Year Method

Table 15 shows that the geometric monthly average of logarithmic returns of the L/S portfolio based on earnings announcement dates predicted by the fiscal year method does not give us any reason to reject the zero hypothesis. Like table 9, table 15 shows that the L/S trading strategy based on fiscal year ends does not generate statistically significant positive excess returns over the Norwegian Government three month Treasury bill over the sample period. Zero-hypothesis A is not rejected.

5.5.3 Geometric Averages of Logarithmic Returns Actual Announcement Dates

	Monthly Normalised Geometric Averages of Logarithmic Returns All Stocks With 4 Announcements Each Calendar Year			
	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-1,970 %	-1,976 %	-1,313 %	0,050 %
t-stat	2,44	2,20	1,42	0,06
	Months with Zero Actual Announcers Deleted			
	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-1,457 %	-1,464 %	-1,475 %	-0,460 %
t-stat	1,90	1,66	1,51	0,43
	Managed L/S Portfolio			
	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-1,970 %	-0,162 %	-0,171 %	-0,018 %
t-stat	2,30	1,44	1,67	0,14
	L/S Portfolio Traded in February, May, August and October			
	All Stocks	Non-Announcers	Annonuncers	L/S
1999-2007				
Mean	-2,857 %	-4,176 %	-2,121 %	1,515 %
t-stat	2,28	2,70	1,52	0,83

Table 16: Geometric Averages of Logarithmic Returns - Actual Announcement Dates

Table 16 shows that the L/S portfolio based on actual announcement dates containing all stocks with four announcements in the previous year and the L/S portfolio based on actual announcement dates traded in February, May, August and October seem to generate positive excess returns, but that the t-statistics are not high enough for rejecting zero-hypothesis A. Improved methods for predicting earnings announcement dates would not assist in forming L/S portfolios generating average monthly returns statistically significantly larger than zero over the sample period.

5.6 Summary Statistics

To summarize, none of the tested trading strategies combining a value-weighted portfolio that buys expected announcers with a value-weighted portfolio that sells short expected non-announcers are generating excess returns over the Norwegian Government three month Treasury-bill that are statistically significantly larger than zero over the sample period. Zero-hypothesis A is not rejected for any of the tested trading strategies. Zero-hypothesis B is consequently not tested.

Some of the portfolios formed on the basis of actual announcement dates seem to generate positive monthly excess returns. However, none of these results are statistically significant. A longer sample period could therefore be interesting to examine in order to test whether or not some of the portfolios formed on the basis of actual announcement dates could generate statistically significantly positive monthly excess returns. In that case, better methods for predicting earnings announcement dates could assist in forming a L/S portfolio trading strategy generating positive monthly excess returns over the Norwegian Government three month Treasury bill.

The only statistically significant result is the geometric average of the logarithmic returns of the L/S portfolio that is not traded in months with zero expected announcers. The sign of the this L/S portfolio's excess returns is nevertheless negative. The tested trading strategies based on earnings announcement dates predicted by the previous year method or the fiscal year end method did not generate positive monthly average excess returns at the Oslo Stock Exchange over the sample period from 1999 to 2007, nor in the sub-periods from 1999 to 2000 and from 2001 to 2007. These results, which are contrasting to those of Lamont and Frazzini (2007), will be discussed in the next chapter.

6. Discussion of the Results

I test various versions of a monthly L/S portfolio trading strategy consisting of buying a value-weighted portfolio of stocks expected to announce their quarterly earnings, while selling short a value-weighted portfolio of stocks not expected to announce their earnings the following month. The found results are indicating that none of the tested trading strategies are generating monthly average statistically significant positive excess returns over the Norwegian Government three month Treasury bill over the sample period. In contrary, most of the tested L/S portfolio trading strategies are generating negative excess returns, however not statistically significant. That the results are not statistically significant is clearly related to that the sample period utilised in this analysis is relatively short. The presented results are contrasting with those of Lamont and Frazzini (2007) who found that the L/S portfolio trading strategy based on predicted earnings announcement dates generates statistically significant excess returns of between 7 and 18 percent per year. This section contains a discussion of my results as well as their validity. Moreover, the presented results are together with the results of Lamont and Frazzini (2007) placed in the market efficiency litterature. Further, and most importantly, I discuss different reasons for why my findings are in contrast to the findings of Lamont and Frazzini (2007). Finally, potential sources of errors and eventual proposals for further studies of the topic are presented.

6.1 Discussion of the Results

Lamont and Frazzini (2007) documented an earnings announcement premium in the U.S. stock market that is “*large, robust and strongly related to the fact that volume surges around announcement dates*” (p. 2). By examining the monthly returns of the value weighted portfolio of companies expected to announce as well as the monthly returns for companies not expected to announce, they found that U.S. stock-prices rise in average around earnings announcements. Based on predicted earnings announcement dates, they test a trading strategy consisting of holding a value-weighted portfolio of expected announcers while selling short a value-weighted portfolio of expected non-announcers. Lamont and Frazzini (2007) document that this trading strategy earns excess returns of between 7 and 18 percent per year. The positive excess returns, they claim, can not be explained by the factors included in the Carhart (1997) four-factor model. Measured by the Sharpe-ratio, their trading-strategy generates higher risk-adjusted returns over the sample period than other popular stock market anomalies such as the momentum-strategy. Lamont and Frazzini (2007) suggest that the documented earnings announcement premium is driven by small investor buying when an earnings announcement catches their attention. They documented that predictable increases in volume lead to predictable increases in stock prices around quarterly earnings announcement dates and that "*concepts such as liquidity, information flow, heterogeneous beliefs, and short sale constraints are potentially important in understanding this connection*" (p. 29). Uninformed investor trading activity combined with imperfect arbitrage trading by informed sophisticated investors is suggested as explanation for the earnings announcement premium.

I test if a similar trading strategy generates excess returns at the Oslo Stock Exchange in the time period between 1999 and 2007. At the last day of month t-1, the monthly trading strategy buys a value-weighted portfolio of stocks that are expected to announce their quarterly earnings the coming month and sells short a value-weighted portfolio of stocks that are not expected to announce their earnings the coming month. The expected announcement dates are predicted by two different algorithms, namely the previous year method and the fiscal year method. I test four versions of the L/S trading strategy based on quarterly earnings announcement dates predicted by the previous year method, and one version of the L/S trading strategy based on the fiscal year end method. Although not an implementable trading strategy in practise, I also test if four versions of a value-weighted zero cost L/S portfolio based on actual announcement dates generated average statistically significant excess returns relative to the three month Norwegian Treasury Bill.

I find that various versions of a L/S portfolio based on announcement dates forecasted by the previous year method and by the fiscal year end method generate negative monthly average excess returns over the sample period between 1999 and 2007. It should be emphasised that these results are not statistically significant, which may be due to the somewhat short sample period utilised in the empirical analysis. Some of the portfolios formed on the basis of actual announcement dates seem to generate positive monthly excess returns. However, none of these results are statistically significant. A longer sample period could therefore be interesting in order to test whether or not some of the portfolios formed on the basis of actual announcement dates could generate statistically significantly positive monthly excess returns. In that case, better methods for predicting earnings announcement dates could assist in forming a L/S portfolio trading strategy generating positive monthly excess returns over the Norwegian Government three month Treasury bill.

The results are robustness checked by comparing arithmetic averages of simple returns to geometric averages of logarithmic returns. I perform robustness checks of my results for all the tested trading strategies as well as for the sub-periods, and find that the way the excess returns are calculated do not affect the decision to not reject the zero-hypothesis; None of the results are indicating that the zero hypotheses, stating that the L/S portfolio trading strategy can not earn excess returns greater than zero, can be rejected. There is no sign of an earnings announcement premium at the Oslo Stock Exchange in the sample period between 1999 and 2007. In other words, I find no results that can reject that the Oslo Stock Exchange is weak form efficient. My results are in contrast to those of Lamont and Frazzini (2007) whose results are not according with weak-form efficiency in the U.S. stock market.

6.2 The Presented Results and the Results of Lamont and Frazzini (2007) versus the Market Efficiency Theory Literature

In addition to the earnings announcement premium, several stock market anomalies have been documented by various empirical studies. Momentum, mean-reversal, calendar effects, the value-effect and the size-effect are some of the anomalies that have been discussed in this thesis. However, when risk-adjusted, many of the anomalies seem to disappear. Fama and French presented an extended version of the CAPM in 1992 that, in addition to the overall market risk-factor contained a risk factor related to firm size and a risk-factor related to a firm's book-to-market value. Fama and French (1993) claim that several of the patterns previously found in stock price data are explained with their three-factor model. "Abnormal" returns may hence in reality be a compensation for increased risk related to trading on the strategies based on patterns found in stock market data. Further, Fama (1998) suggest that long-term market anomalies tend to disappear when the way they are measured changes. Carhart (1997) introduced a forth risk-factor to the Fama and French three-factor model, namely the momentum-factor. This factor is according to Carhart (1997) capturing the one-year momentum-anomaly discovered by Jegadeesh and Titman (1993) and explaining the cross-sectional variation in average stock returns. The results of Lamont and Frazzini (2007) are not explained by the Carhart four-factor model, and are considered abnormal in that sense.

Transaction costs, management fees, liquidity and constraints such as short selling constraints are often not considered in these studies. When included, such costs and constraints may eliminate the, considered abnormal, returns generated by following a certain trading strategy. In other words, returns, that by first sight might seem abnormal, generated by following a certain trading strategy, may in reality be a compensation for the excess risk or costs related to executing the trading strategy. Lamont and Frazzini (2007) have not considered these mentioned limits to arbitrage in their analysis. This is further discussed in section 6.3.

Financial models and theories, such as the efficient market theory, are often assuming rational investors. Various studies have been summarised in this text, and it is clear that human behaviour is not always rational. By predicting irrational investor behaviour, behavioural finance theory aims to fill the gap between traditional finance theory and the reality where investors with irrational behaviour exist. Cognitive biases such as mental accounting, herd behaviour, the representativeness-bias, the conservatism-bias, the disposition-bias, overconfidence and forecasting errors may lead to irrational behaviour amongst investors. Irrational investor driven returns may hence provide an explanation for abnormal returns. Lamont and Frazzini (2007) claim that the main explanation for the earnings announcement premium is uninformed or irrational demand by individual investors, coupled with imperfect arbitrage by sophisticated investors. Their results are not in accordance with weak-form market efficiency in the U.S. stock market, in the sense that historical information can be used to predict future stock prices.

The efficient market hypothesis claims that it is impossible to ” beat the market” since stock prices reflect all relevant information. In order for prices to reflect all available information, someone has to analyse the information available in the market. Above market returns may therefore be seen as a reward for the costs related to analysing stock price information. The market efficiency paradox is hence built on the fact that an efficient stock market has to have market participants believing that the market is inefficient. Although exceptions exist, most investors are not able to outperform the market in the long term. The results presented in this thesis *can not reject* market efficiency at the Oslo Stock Exchange: No earnings announcement premium is documented in the sample period between 1999 and 2007. However, the sample size and the sample period utilised is too small for concluding whether or not the Oslo Stock Exchange is an efficient market in general.

Regarding market efficiency at the Oslo Stock Exchange, previous studies have, with few exceptions, not been able to reject that the Oslo Stock Exchange is efficient. Johansen (1995) found a Friday effect and a Monday effect at the Oslo Stock Exchange in the time period between 1984 and 1995. Also Holm (2007) documents a Friday effect at the Oslo Stock Exchange in the period between 1996 and 2005. However, Holm (2007) finds that the effect has diminished over the last half of the studied period. Åsland (2006) did not find evidence for a December effect in the Norwegian stock market in the period between 1999 and 2004. Jensen (2006) found that a momentum strategy tested at the Oslo Stock Exchange between 1996 and 2005 generated positive excess returns, but that the generated excess returns were mainly compensation for systematic risk. Myklebust (2007) found significant that a momentum strategy tested at the Oslo Stock Exchange generated positive returns for the period between 1984 and 2006, but not for all sub-periods. He claims that the obtained positive returns are not explained by beta, but underlines that other variables explaining risk have not been considered. Mamelund (2006) claims to have found evidence for an overreaction at the Oslo Stock Exchange between 1989 and 2005, indicating weak-form market inefficiency. Åkre and Røsdal (2000) examines how quickly new information is incorporated in stock prices at the Oslo Stock Exchange and their results are not indicating market inefficiency at the Oslo Stock Exchange.

Some of previous studies conducted on Norwegian stock prices are hence showing that when risk adjusted, stock returns at the Oslo Stock have not historically been abnormal. With the exception of Mamelund (2006), Johansen (1995) and Holm (2007), the results of the above-mentioned studies are indicating that the Oslo Stock Exchange is efficient. Regarding the documented abnormal patterns, it should be emphasised that transaction costs have not been considered in their studies. In December 2000, the Oslo Stock Exchange joined the NOREX, which claim that they have "*one of the most effective surveillance systems in the world*". NOREX' goal for the future is "*to be one of the world's most efficient securities markets*". One possibility is that the Oslo Stock Exchange has become more efficient since it joined the NOREX. This is confirmed by Holm (2007) who found that the Friday effect first documented by Johansen (1995) has diminished after 2000, indicating that the Oslo Stock Exchange has become more efficient since that. A more efficient market at the Oslo Stock Exchange would be in accordance with the findings of Gjerde et al. (2005) who claim that the usefulness of financial reporting for investors trading on the Oslo Stock Exchange has increased over the later years. Further, increased market efficiency at the Oslo Stock

Exchange after year 2000 would be in accordance with the results presented in this thesis in the sense that no earnings announcement premium is documented in the sample period between 1999 and 2007, which *can not reject* weak form market efficiency at the Oslo Stock Exchange.

6.3 Suggestions to why the Presented Results are Contrasting to the Results of Lamont and Frazzini (2007)

The found results are indicating that none of the tested trading strategies are generating monthly average statistically significant positive excess returns over the Norwegian Government three month Treasury bill over the sample period. In contrary, most of the tested L/S portfolio trading strategies are generating negative excess returns. However, the results presented in this thesis are not statistically significant. This is clearly related to the fact that the sample period utilised in this analysis is relatively short. My findings are contrasting with those of Lamont and Frazzini (2007) who found that the L/S portfolio trading strategy generates statistically significant excess returns of between 7 and 18 percent per year over the sample period from 1972 to 2004, contrasting with weak-form market efficiency in the U.S. stock market. Theoretically, one would expect the much smaller and younger Norwegian stock market, the Oslo Stock Exchange, to be less efficient than the much larger and older U.S. stock market. This opens for a discussion of whether or not the Norwegian stock market really is more efficient than the U.S. stock market, or if Lamont and Frazzini (2007) have found random results.

Considering the efficiency of the two different stock markets, it has to be emphasised that the Norwegian stock market is much smaller and more concentrated than the U.S. stock market. Given that there are fewer companies listed at the Oslo Stock Exchange, and that the amount of analyst firms analysing these stocks have grown over the later years, it is reasonable to think that the amount of companies listed at the Oslo Stock Exchange being analysed by at least one analyst company also has increased over the later years. Especially the large companies listed at the Oslo Stock Exchange are analysed by at least one, and often more than one, equity research analysts. A mainly speculative possible explanation for the differing results is therefore that equity analyst companies, e.g. sophisticated investors, expect small investor buying and consequently arbitrages away any eventual earnings announcement premium which is eventually caused by individual investor attention-driven demand around quarterly earnings announcements at the Oslo Stock Exchange. In that case, like the “fashion leaders” described in section 2.5.3, sophisticated investors are “*front-running”* small investors by ”*initiating purchases of announcement stocks in the weeks prior to an earnings announcement*” (Lamont and Frazzini, 2007, p. 26-27). This is consistent with efficient market theory: Sophisticated investors are trading to eliminate predictable returns, and hence smoothing stock prices, that are driven by the predictable demand-shock caused by small investors around earnings announcement dates.

The sample period used by Lamont and Frazzini (2007), which is from 1972 to 2004, is much longer than the sample period used in this study, which is from 1999 to 2007. One could consequently think that the chosen sample period in this study could have something to do with the different results. However, Lamont and Frazzini (2007) reports that the earnings announcement premium is “*large and highly statistically significant across the entire sample period, delivering between 40 and 92 basis points a month*” (p. 13). Consequently, my results should not be dependent of the chosen sample period. Given the fact that companies listed at the Oslo Stock Exchange not were required by law to announce their earnings on a quarterly basis until year 2000 (Dyvik, 2008), it would not make sense to compare the period before year 2000 with the results of Lamont and Frazzini (2007).

Some of the portfolios formed on the basis of actual announcement dates seem to generate positive monthly excess returns. However, none of these results are statistically significant. A longer sample period could therefore be interesting in order to test whether or not some of the portfolios formed on the basis of actual announcement dates could generate statistically significantly positive monthly excess returns. If that was the case, a possible explanation for the differing results presented in this thesis is that the methods for predicting earnings announcement dates utilised by Lamont and Frazzini (2007) in the U.S. stock market are not accurate enough for predicting earnings announcement dates in the Norwegian stock market.

Another possible explanation for the different results is that the results of Lamont and Frazzini are random. As mentioned in section 3.3., data-mining and data-snooping may cause patterns that are not real to appear in a dataset (Stamland, 2007). Considering that the dataset utilised by Lamont and Frazzini (2007) consists of U.S. stock prices between 1972 and 2004 that have been analysed by many financial economists, there is at least a possibility for data-mining; When a dataset is analysed a many times, it is likely that some patterns will be found at some point.

Further, Lamont and Frazzini (2007) do not mention whether or not they have removed illiquid stocks from their sample. Due to the fact that they test whether or not trading volume is connected with the earnings announcement premium, it is assumed that they have not removed stocks with low trading volume from their sample. A possible explanation for the earnings announcement premium is consequently that positive autocorrelation, as a result of non-synchronous trading of illiquid stocks, has resulted in the found patterns.

An additional problem related to including stocks with low trading volume in the sample is that it makes the trading strategy less feasible in real life. Especially, it is not realistic to expect to be able to take short positions in small stocks with low trading volume.

Finally, Lamont and Frazzini (2007) have not considered the transaction costs related to the tested trading strategy. Given that each stock jumps in and out of the long and the short portfolio four times per year, relatively large transaction costs are related to the tested trading strategy. However, a good reason for not including transaction costs when considering whether or not a trading strategy theoretically generates positive excess returns, is that trading costs are varying from investor to investor. For example, a large institutional investor will have very different transaction costs than a small, private investor. When transaction costs are not included in a study, it is therefore up to each investor to determine whether or not his transaction costs will be lower than the potential profits by exploiting a trading strategy claiming to generate positive abnormal excess returns.

6.4 Critisism of the Presented Results and Potential Sources of Error

There are several potential sources of error that may have affected the results presented in this thesis. However, most of these sources of error would have been more important to examine in the case of a rejected zero hypothesis. This section goes roughly through the most important potential sources of error.

The main potential source of error is that the data is provided from different sources. While return-data is provided from Børsprosjektet at NHH, earnings announcement dates are provided from Bloomberg and the Oslo Stock Exchange NewsWeb. The risk free rate is provided from Reuters. The potential source of error consists of that the different sources may have had different ways of collecting, processing and presenting the data. Most of these problems are avoided due to the fact that monthly data is used in the analysis.

Regarding the earnings announcement dates between 1998 and 2007, they have partly been collected from the NewsWeb of the Oslo Stock Exchange and partly provided from Bloomberg. Earnings announcements between 01.01.1998 and July 1999 is sorted manually from the Oslo Stock Exchange NewsWeb as well as from the dataset containing all announcements ever made at the Oslo Stock Exchange provided from Børsprosjektet. As mentioned in section 4.2., Bloomberg coverage of quarterly earnings announcement dates between 1999 and 2007 proved to be somewhat inconsistent, particularly for the years 2000 and 2001. I have therefore checked the Oslo Stock Exchange NewsWeb for companies where Bloomberg reports three earnings announcements in a year, in order to verify whether there was a fourth earnings announcement that year for each of those companies. For companies with large market capitalisation where Bloomberg does not report full earnings announcement coverage for a given year I have performed the same procedure. In other words, a relatively large part of the dataset conserning the quarterly earnings announcement dates is manually sorted. This presents a relatively large potential source of error in the sense that some companies that in reality did announced their earnings four times in one year, might have been excluded from the sample. However, given that the sample size varies from 115 to 188, it is unlikely that a possible inclusion of more stocks in the sample would lead to results very different from the presented results. Also, the potential source of error related to registering the wrong earnings announcement date is minimised due to the fact that monthly data is used in the analysis.

Another potential source of error regarding the earnings announcement dates is that some companies listed at the Oslo Stock Exchange are announcing their preliminary quarterly earnings before they're announcing their final quarterly earnings. In many occasions, the preliminary report contains the same numbers as in the final report. It is therefore reasonable to assume that the market is reacting to preliminary earnings announcements. The dates used in my analysis are mostly final earnings announcements, unless the only quarterly announcement made for a company was preliminary. However, preliminary quarterly earnings and final quarterly earnings are often announced within the same month, minimising this potential source of error.

Some of the companies listed at the Oslo Stock Exchange have A and B series of stocks with different voting rights. This presents a potential source of error due to that this has been manually adjusted.

Another potential source of error is autocorrelation caused by non-synchronous trading. Some of the stocks listed at the Oslo Stock Exchange have low trading volume, and were considered to be removed from the sample due to the positive autocorrelation stocks with non-synchronous trading may cause in a portfolio. In other words, non-synchronous trading may lead to patterns in the data that are not really there. However, Lamont and Frazzini (2007) claim that trading-volume provides part of the explanation for the earnings announcement premium, thus all stocks with 12 previous months of return-history is included in the stock universe no matter their trading volume. Due to the fact that most of the stocks with low trading volume at the Oslo Stock Exchange are small stocks, and that the L/S portfolios are value-weighted, the importance of these stocks is relatively small. In addition, this potential source of error would have been more important to consider if the zero-hypothesis were rejected, which is not the case.

If the L/S portfolio trading strategy had generated statistically significant positive excess returns, it would have been important to consider limits to arbitrage of the tested trading strategy. The most relevant potential limits to arbitrage related to the L/S portfolio trading strategy is related to transaction costs and if whether or not the trading strategy is feasible in real life. Regarding whether or not the trading strategy is feasible in real life, it is important to mention that taking short positions in small and less liquid stocks at the Oslo Stock Exchange probably would introduce problems.

6.5 Proposal of Further Studies of This Topic

Some of the portfolios formed on the basis of actual announcement dates seem to generate positive monthly excess returns. However, none of these results are statistically significant. It could therefore be interesting to examine a longer sample period, in order to test whether or not some of the portfolios formed on the basis of actual announcement dates could generate statistically significantly positive monthly excess returns. In that case, better methods for predicting earnings announcement dates could assist in forming a L/S portfolio trading strategy generating positive excess returns. A suggested further study of this topic is therefore to test if the portfolios formed on the basis of actual announcement dates generates statistically significant positive excess returns over a longer sample period.

A suggested method for predicting earnings announcement dates in the case of a rejected zero-hypothesis A for portfolios based on actual announcement dates over a longer sample period is the following: If a substantial amount of the companies listed at the Oslo Stock Exchange are announcing an earnings announcement calendar, it could be interesting to test a L/S trading strategy based on those dates. In other words, it could be interesting to test if a trading strategy holding stocks scheduled to announce their earnings while selling short stocks not scheduled to announce their earnings could generate positive excess returns. However, companies listed at the Oslo Stock Exchange were not required to announce their earnings on a quarterly basis until year 2000 (Dyvik, 2008) , so looking at the period before year 2000 would mean that rather than testing if there is an earnings announcement premium at the Oslo Stock Exchange, one would test if there was an earnings announcement premium associated with companies choosing to announce their earnings on a quarterly basis. The companies choosing to announce their earnings on a quarterly basis could have company specific characteristics, meaning that one would not test if there in general is an earnings announcement premium at the Oslo Stock Exchange.

A second possibility is to sort the dataset containing all announcements ever made at the Oslo Stock Exchange with more accuracy, and redo the whole data analysis. As mentioned in section 6.4., a potential source of error is that some of the data is manually sorted, which may have conducted to exclusions of stocks that in reality had four earnings announcements one year. However, given that the sample size varies from 115 to 188, it is unlikely that a possible inclusion of more stocks in the sample would lead to results very different from the results presented in this thesis.

7. Conclusion

Lamont and Frazzini (2007) document that a trading strategy consisting of buying every stock expected to announce within the coming month and selling short every stock not expected to announce the coming month earns excess returns of between 7 and 18 percent per year in the U.S. stock market between 1972 and 2004. The positive excess returns, they claim, can not be explained by the factors included in the Carhart (1997) four-factor model. Lamont and Frazzini (2007) claim that the main explanation for the earnings announcement premium is uninformed or irrational demand by individual investors, coupled with imperfect arbitrage by sophisticated investors. Their results are not in accordance with weak-form market efficiency in the U.S. stock market in the sense that historical information can be used to predict future stock prices. In this thesis related trading strategies based on predicted quarterly earnings announcement dates are tested at Oslo Stock Exchange in the period between 1999 and 2007 with the following zero-hypothesis:

A) **H_0**: Average monthly excess returns L/S portfolio = 0

H_1: Average monthly excess returns L/S portfolio > 0

B) **H_0:** Average monthly abnormal returns L/S portfolio = 0

H_1: Average monthly abnormal returns L/S portfolio > 0

Zero-hypothesis A is not rejected for any of the tested L/S portfolio trading strategies. Subsequently, zero-hypothesis B has not been tested in this thesis. The presented results show that the large majority of the tested L/S portfolio strategies based on predicted earnings announcement dates are generating negative monthly average excess returns. However, these results are not statistically significant.

The results of the conducted analysis show no signs of an earnings announcement premium at the Oslo Stock Exchange in the sample period between 1999 and 2007. The sample size and the sample period is too short for making a general conclusion about whether or not the Oslo Stock Exchange is an efficient market. Nevertheless, in accordance with the results of Åkre and Røsdal (2000), Åsland (2006), Jensen (2006), and the aim of NOREX, my results *can not reject* market efficiency at the Oslo Stock Exchange in the sample period between 1999 and 2007.

The main reasons for that the presented results are differing from the results of Lamont and Frazzini (2007) may be related to the possibility that the dataset of earnings announcement dates utilised in the analysis is not representative for the sample period regarding the real coverage of earnings announcement dates. Another, and relatively speculative, explanation is that if there is an eventual earnings announcement premium at the Oslo Stock Exchange, sophisticated investors trading in the Norwegian stock market may have managed to fully exploit the arbitrage opportunity by “front-running” the individual irrational or uninformed investors. Finally, there is a possibility that the patterns found by Lamont and Frazzini (2007) are random, and caused by for example data-mining, and that the earnings announcement premium consequently does not exist in reality.

Conclusively, I would not recommend following the earnings announcement premium trading strategy of Lamont and Frazzini (2007) at the Oslo Stock Exchange.

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Appendix

7.1 Full list of Companies with 4 announcements

Companies with 4 announcements in 1998

ACL	Atlantic Container Line	HEX	Hexagon Composites	PRS	Prosafe
AGR	Agresso Group	HIT	Hitec	PRV	Provida
AIK	Aktiv Kapital	HJE	Hjellegjerde	PRX	Proxima
AKE	Aker RGI A	HYD	Hydralift	RANG	Sparebanken Rana
ALV	Alvern	IBY	IBY Eiendom	RAU	Raufoss
ALX	Altinex	IGNIS	Ignis	RCL	Royal Caribbean Cruises
AMA	Aker Maritime	IMSK	I.M. Skaugen	RING	Ringerikes Sparebank
ARK	ARK	IPL	Iplast	RNA	Reitan Narvesen
AVA	Avantor	JIN	Jinhui Shipping and Transport	ROGG	Sparebanken Rogaland
AVE	Avenir	KBK	KredittBanken	SADG	Sandnes Sparebank
AWS	Awilco ser. A	KEN	Kenor	SANG	Sandsvr Sparebank
AXI	Axis Biochemicals	KIT	Kitron gammel	SASB	SAS Norge B
BBA	Bergensbanken	KLI	Klippen Invest	SCH	Schibsted
BEA	Bergesen d.y ser. A	KOA	Kongsberg Automotive	SCI	Scana Industrier
BMA	Byggma	KVI	Kvrner	SEL	Selmer
BNR	Bergen Nordhordland Rutelag	LEG	Legra	SEN	SensoNor
BON	Bonheur	LHO	Leif Hegh & Co	SFJ	DSND Subsea
BRA	Braathens	LIN	Linde-Group	SLA	SE Labels gammel
BSH	Bona Shipholding	MBN	MediaBin	SME	Smedvig ser. A
CAG	Computer Advances	MDX	Mindex	SNOG	Gjensidige NOR Sparebank
CHS	Choice Hotels Scandinavia	MHO	Media Holding	SOFF	Solstad Offshore
CKR	Chr. Bank og Kreditkasse	MING	Sparebanken Midt-Norge	SPC	SPCS-Gruppen
COL	Color Group	MORG	Sparebanken Mre	SST	Steen & Strm
COV	ContextVision	MSL	Mosvold Shipping Ltd.	STB	Storebrand
DNBNOR	DnB NOR	NAV	Navia	STN	Stento
DNO	DNO	NBK	Nordlandsbanken	SUO	SuperOffice
DOF	District Offshore	NCL	NCL Holding	SVEG	Sparebanken Vest
DYN	Dyno	NCO	Norcool Holding	TAA	Tandberg
EDB	EDB - Elekt. Databeh.	NER	Nera	TAD	Tandberg Data
EKJ	Elkjp	NHY	Norsk Hydro	TAT	Tandberg Television
EKO	Ekornes	NLD	Norsk Lotteridrift	TCA	Telecast
ELK	Elkem	NOD	Nordic Semiconductor	TEC	Technor
EME	Ementor	NONG	Sparebanken Nord-Norge	TGS	TGS-NOPEC Geophysical Company

EVE	Evercom Network	NOR	Norman	THR	Thrane-Gruppen
FAR	Farstad Shipping	NOV	Norsk Vekst	TOM	Tomra Systems
FIN	Finansbanken	NSG	Norske Skogindustrier	TOTG	Totens Sparebank
FOE	Fred. Olsen Energy	NTC	NetCom	TTS	TTS Marine
FOK	Fokus Bank	NWS	Norway Seafoods	ULS	Ulstein Holding
FOT	First Olsen Tankers	OCR	Ocean Rig	UNS	Ugland Nordic Shipping
FRO	Frontline	ODF	Odfjell ser. A	UTO	Unitor
GOD	Goodtech	ORC	Oslo Reinsurance Co	WAT	Waterfront Shipping
GRE	Gresvig	PDR	Petrolia Drilling	VEI	Veidekke
GRO	Ganger Rolf	PFI	P4 Radio Hele Norge	VIS	Visma
HAG	HG	PGS	Petroleum Geo-Services	VSBG	SpareBanken Vestfold

Total 132 Companies

Table 17: Companies with 4 announcements in 1998

Companies with 4 announcements in 1999

ACL	Atlantic Container Line
AGR	Agresso Group
AIK	Aktiv Kapital
ALV	Alvern
AMA	Aker Maritime
ASC	ABG Sundal Collier
AURG	Aurskog Sparebank
AVA	Avantor
AVE	Avenir
BBA	Bergensbanken
BEA	Bergesen d.y ser. A
BET	Benor Tankers
BLO	Blom
BNR	Bergen Nordhordland Rutelag
BRA	Braathens
CAG	Computer Advances
CKR	Chr. Bank og Kreditkasse
DNO	DNO
DOF	District Offshore
DYN	Dyno
EKJ	Elkjp
EKO	Ekornes
ELK	Elkem
ELT	Eltek
EME	Ementor
EVE	Evercom Network
FAR	Farstad Shipping
FOE	Fred. Olsen Energy
FOT	First Olsen Tankers
GOD	Goodtech
GRE	Gresvig
HAG	HG
HEX	Hexagon Composites
HJE	Hjellegjerde
IFB	Industrifinans Boligeiendom
IFN	Industrifinans Nringseiendom
IGNIS	Ignis
KBK	KredittBanken
KEN	Kenor
KIT	Kitron
KOG	Kongsberg Gruppen
KVI	Kvrner
LHO	Leif Hegh & Co
LUX	Luxo
MDX	Mindex
MELG	Melhus Sparebank
MHG	Pan Fish
MING	Sparebanken Midt-Norge
MOE	Moelven Industrier
MORG	Sparebanken Mre
MSL	Mosvold Shipping Ltd.
NAV	Navia
NBK	Nordlandsbanken
NCL	NCL Holding
NER	Nera
NESG	Nes Prestegjelds Sparebank
NHY	Norsk Hydro
NIS	NAVIS
NLD	Norsk Lotteridrift
NOD	Nordic Semiconductor
NONG	Sparebanken Nord-Norge
NOR	Norman
NOV	Norsk Vekst
OCR	Ocean Rig
ODF	Odfjell ser. A
OTR	Otrum
PDR	Petrolia Drilling
PFI	P4 Radio Hele Norge
PGS	Petroleum Geo-Services
PLUG	Sparebanken Pluss
PRO	Profdoc
PRV	Provida
RANG	Sparebanken Rana
RAU	Raufoss
ROGG	Sparebanken Rogaland
ROX	Roxar
SADG	Sandnes Sparebank
SASB	SAS Norge B
SCH	Schibsted
SCI	Scana Industrier
SEL	Selmer
SEN	SensoNor
SFJ	DSND Subsea
SFM	Synnve Finden
SMA	Stavdal
SME	Smedvig ser. A
SNIB	Stolt-Nielsen B
SNOG	Gjensidige NOR Sparebank
SOI	Software Innovation
SST	Steen & Strm
STB	Storebrand
STN	Stento
SUO	SuperOffice
SVEG	Sparebanken Vest
TAA	Tandberg
TAD	Tandberg Data
TEC	Technor
TGS	TGS-NOPEC Geophysical Company
TOM	Tomra Systems
TOTG	Totens Sparebank
TSH	Team Shipping
TTS	TTS Marine
UNS	Ugland Nordic Shipping
UTO	Unitor
WAT	Waterfront Shipping
WBS	Western Bulk Shipping
VEI	Veidekke
VIS	Visma
VME	VMetro
VSBG	SpareBanken Vestfold
VVL	Voss Veksel- og Landmandsbank

ITE	Itera Consulting Group	RCL	Royal Caribbean Cruises
JIN	Jinhui Shipping and Transport	RING	Ringerikes Sparebank

Total 115 Companies

Table 18: Companies with 4 announcements in 1999

Companies with 4 announcements in 2000

AAV	Adresseavisen
ACL	Atlantic Container Line
AFG	AF Gruppen
AFK	Arendals Fossekompani
AIK	Aktiv Kapital
ALX	Altinex
AMA	Aker Maritime
ATG	Andvord Tybring-Gjedde
AURG	Aurskog Sparebank
AVA	Avantor
AWS	Awilco ser. A
BEA	Bergesen d.y ser. A
BEL	Belships
BLO	Blom
BNB	Bolig- og Nringsbanken
BON	Bonheur
BRA	Braathens
CKR	Chr. Bank og Kreditkasse
COV	ContextVision
DNBNOR	DnB NOR
DNO	DNO
DOF	DOF
EKO	Ekornes
ELK	Elkem
ELT	Eltek
EME	Ementor
ENI	Enitel
EVE	Evercom Network
FAR	Farstad Shipping
FOE	Fred. Olsen Energy
FSL	Fesil
GOD	Goodtech
GRE	Gresvig
IFN	Industrifinans Nringseiendom
IGE	Int. Gold Exploration
IGNIS	Ignis
IMSK	I.M. Skaugen
INM	Inmeta
ISSG	Indre Sogn Sparebank
ITE	Itera Consulting Group
KBK	KredittBanken
KEN	Kenor
KIT	Kitron
KLI	Klippen Invest
KOG	Kongsberg Gruppen
KVE	Kverneland
LHO	Leif Hegh & Co
LUX	Luxo
MHG	Pan Fish
MING	Sparebanken Midt-Norge
MORG	Sparebanken Mre
MSL	Mosvold Shipping Ltd.
NBK	Nordlandsbanken
NER	Nera
NESG	Nes Prestegjelds Sparebank
NHY	Norsk Hydro
NIS	NAVIS
NKI	Norsk Kjkkeninvest
NOD	Nordic Semiconductor
NOL	Nortrans Offshore
NONG	Sparebanken Nord-Norge
NOV	Norsk Vekst
NSG	Norske Skogindustrier
OCR	Ocean Rig
ODF	Odfjell ser. A
OLT	Olav Thon Eiendomsselskap
RANG	Sparebanken Rana
RAU	Raufoss
RCG	RC Gruppen
RCL	Royal Caribbean Cruises
RIC	Rica Hotels
RIE	Rieber & Sn
RING	Ringerikes Sparebank
RNA	Reitan Narvesen
ROGG	Sparebanken Rogaland
ROX	Roxar
SADG	Sandnes Sparebank
SANG	Sandsvr Sparebank
SASB	SAS Norge B
SCH	Schibsted
SCI	Scana Industrier
SFJ	DSND Subsea
SFM	Synnve Finden
SME	Smedvig ser. A
SNOG	Gjensidige NOR Sparebank
SOFF	Solstad Offshore
SOI	Software Innovation
SPC	SPCS-Gruppen
STA	Stavanger Aftenblad
STB	Storebrand
SUO	SuperOffice
SVEG	Sparebanken Vest
SWR	Swan Reefer
TAA	Tandberg
TAD	Tandberg Data
TEC	Technor
TGS	TGS-NOPEC Geophysical Company
TOM	Tomra Systems
TOTG	Totens Sparebank

GRR	Green Reefers	OTR	Otrum	TSH	Team Shipping
HAG	HG	PCL	PC LAN	TTS	TTS Marine
HJE	Hjellegjerde	PDR	Petrolia Drilling	UNS	Ugland Nordic Shipping
HNA	Hafslund ser. A	PFI	P4 Radio Hele Norge	UTO	Unitor
HSPG	Hland Sparebank	PGS	Petroleum Geo-Services	VEI	Veidekke
HSU	Havila Supply	PLUG	Sparebanken Pluss	VME	VMetro
HYD	Hydralift	PRO	Profdoc	VSBG	SpareBanken Vestfold
IFB	Industrifinans Boligeiendom	PRS	Prosafe	VVL	Voss Veksel- og Landmandsbank

Total 123 Companies

Table 19: Companies with 4 announcements in 2000

Companies with 4 announcements in 2001

AAV	Adresseavisen	IMSK	I.M. Skaugen	PRS	Prosafe
ACL	Atlantic Container Line	INM	Inmeta	RCL	Royal Caribbean Cruises
AFG	AF Gruppen	INN	Intellinet	RIC	Rica Hotels
AFK	Arendals Fossekompani	INVEST	Investra	RIE	Rieber & Sn
AIK	Aktiv Kapital	ITE	Itera Consulting Group	RING	Ringerikes Sparebank
AMA	Aker Maritime	JIN	Jinhui Shipping and Transport	ROGG	Sparebanken Rogaland
ASC	ABG Sundal Collier	KBK	KredittBanken	ROX	Roxar
AURG	Aurskog Sparebank	KEN	Kenor	SADG	Sandnes Sparebank
AWS	Awilco ser. A	KLI	Klippen Invest	SANG	Sandsvr Sparebank
BEA	Bergesen d.y ser. A	KOG	Kongsberg Gruppen	SCH	Schibsted
BEL	Belships	KOM	Komplett	SCI	Scana Industrier
BLO	Blom	KVE	Kverneland	SLA	SE Labels
BMA	Byggma	KVI	Kvrner	SME	Smedvig ser. A
BNR	Bergen Nordhordland Rutelag	LHO	Leif Hegh & Co	SNOG	Gjensidige NOR Sparebank
BON	Bonheur	LOI	Loki	SNS	Sense Communications International
DAT	Data Respons	LUX	Luxo	SOFF	Solstad Offshore
DNO	DNO	MELG	Melhus Sparebank	SOI	Software Innovation
EKO	Ekornes	MHG	Pan Fish	SOLV	Solvang
ELK	Elkem	MING	Sparebanken Midt-Norge	SPOG	Sparebanken st
ELT	Eltek	MOE	Moelven Industrier	SST	Steen & Strm
EME	Ementor	MORG	Sparebanken Mre	STB	Storebrand
EVE	Evercom Network	NBK	Nordlandsbanken	STP	Stepstone
EXPERT	Expert	NEC	Norse Energy Corp.	SVEG	Sparebanken Vest
FJO	Fjord Seafood	NESG	Nes Prestegjelds Sparebank	TAA	Tandberg
FLOG	Sparebanken Flora-Bremanger	NHY	Norsk Hydro	TAT	Tandberg Television
FOE	Fred. Olsen Energy	NOD	Nordic Semiconductor	TCO	TeleComputing
FOS	Fosen Trafikklag	NOF	Northern Offshore	TEC	Technor
FSL	Fesil	NONG	Sparebanken Nord-Norge	TEL	Telenor
GRE	Gresvig	NOW	Nordic Water Supply	TGS	TGS-NOPEC Geophysical Company
GRO	Ganger Rolf	NSG	Norske Skogindustrier	TOM	Tomra Systems
HAG	HG	NUT	Nutri Pharma	TOR	Tordenskjold
HELG	Helgeland Sparebank	OCR	Ocean Rig	TOTG	Totens Sparebank
HEX	Hexagon Composites	ODF	Odfjell ser. A	TTS	TTS Marine
HJE	Hjellegjerde	OFL	Office Line	UTO	Unitor
HNA	Hafslund ser. A	ORK	Orkla	VEI	Veidekke
HSPG	Hland Sparebank	OSH	OfficeShop Holding	VIS	Visma

HSU	Havila Supply	OTR	Otrum	VME	VMetro
HYD	Hydralift	PFI	P4 Radio Hele Norge	VOI	Voice
IFN	Industrifinans Nringseiendom	PGS	Petroleum Geo-Services	VSBG	SpareBanken Vestfold
IGNIS	Ignis	PHO	PhotoCure	WWI	Wilh. Wilhelmsen ser. A
IGR	iGroup	PLUG	Sparebanken Pluss	VVL	Voss Veksel- og Landmandsbank

Total 123 Companies

Table 20: Companies with 4 announcements in 2001

Companies with 4 announcements in 2002

AAV	Adresseavisen	HYD	Hydralift	PGS	Petroleum Geo-Services
ACTA	Acta Holding	IFB	Industrifinans Boligeiendom	PHO	PhotoCure
AFG	AF Gruppen	IFN	Industrifinans Nringseiendom	PLUG	Sparebanken Pluss
AFK	Arendals Fossekompani	IGE	Int. Gold Exploration	PRO	Profdoc
AIK	Aktiv Kapital	IGNIS	Ignis	PRS	Prosafe
ALX	Altinex	IGR	iGroup	RANG	Sparebanken Rana
APR	A-pressen	IMSK	I.M. Skaugen	RAU	Raufoss
ASC	ABG Sundal Collier	INM	Inmeta	RCL	Royal Caribbean Cruises
ATG	Andvord Tybring-Gjedde	INVEST	Investra	RGT	Rocksource
AURG	Aurskog Sparebank	ISSG	Indre Sogn Sparebank	RIC	Rica Hotels
AVA	Avantor	ITE	Itera Consulting Group	RIE	Rieber & Sn
AWS	Awilco ser. A	JIN	Jinhui Shipping and Transport	RING	Ringerikes Sparebank
BEA	Bergesen d.y ser. A	KBK	KredittBanken	ROGG	Sparebanken Rogaland
BEL	Belships	KDP	Kristiansand Dyrepark	ROX	Roxar
BLO	Blom	KEN	Kenor	SADG	Sandnes Sparebank
BMA	Byggma	KIT	Kitron	SANG	Sandsvr Sparebank
BNB	Bolig- og Nringsbanken	KLI	Klippen Invest	SCH	Schibsted
BNR	Bergen Nordhordland Rutelag	KOG	Kongsberg Gruppen	SCI	Scana Industrier
BON	Bonheur	KOM	Komplett	SFM	Synnve Finden
BOR	Borgestad	KVE	Kverneland	SKI	Skiens Aktiemlle
COV	ContextVision	KVI	Kvrner	SME	Smedvig ser. A
CRP	Crystal Production	LHO	Leif Hegh & Co	SNS	Sense Communications International
DAT	Data Respons	LIN	Linde-Group	SOFF	Solstad Offshore
DNBNOR	DnB NOR	LOI	Loki	SOLV	Solvang
DNO	DNO	LUX	Luxo	SPOG	Sparebanken st
DOF	DOF	MBN	MediaBin	SRI	Star Reefers Inc.
DOM	Domstein	MEF	Mefjorden	SST	Steen & Strm
EKO	Ekornes	MELG	Melhus Sparebank	STA	Stavanger Aftenblad
ELK	Elkem	MHG	Pan Fish	STB	Storebrand
ELT	Eltek	MING	Sparebanken Midt-Norge	STL	Statoil
EME	Ementor	NBK	Nordlandsbanken	STP	Stepstone
EXE	Exense	NEC	Norse Energy Corp.	SUO	SuperOffice
EXPERT	Expert	NER	Nera	SVEG	Sparebanken Vest

FAR	Farstad Shipping	NESG	Nes Prestegjelds Sparebank	TAA	Tandberg
FAST	Fast Search & Transfer	NHY	Norsk Hydro	TAT	Tandberg Television
FDR	Frontier Drilling	NOD	Nordic Semiconductor	TCO	TeleComputing
FJO	Fjord Seafood	NOF	Northern Offshore	TEC	Technor
FOE	Fred. Olsen Energy	NONG	Sparebanken Nord-Norge	TEL	Telenor
FOS	Fosen Trafikklag	NOR	Norman	TGS	TGS-NOPEC Geophysical Company
GGS	Global Geo Services	NOV	Norsk Vekst	TOM	Tomra Systems
GOD	Goodtech	NOW	Nordic Water Supply	TOR	Tordenskjold
GRE	Gresvig	NSG	Norske Skogindustrier	TOTG	Totens Sparebank
GRO	Ganger Rolf	NUT	Nutri Pharma	TTS	TTS Marine
GRR	Green Reefers	OCR	Ocean Rig	UTO	Unitor
GYL	Gyldendal	ODF	Odfjell ser. A	VEI	Veidekke
HAG	HG	OFL	Office Line	VIS	Visma
HELG	Helgeland Sparebank	OLT	Olav Thon Eiendomsselskap	VME	VMetro
HEX	Hexagon Composites	ORK	Orkla	VOI	Voice
HJE	Hjellegjerde	OSH	OfficeShop Holding	VSBG	SpareBanken Vestfold
HNA	Hafslund ser. A	OTR	Otrum	WWI	Wilh. Wilhelmsen ser. A
HND	Hands	PDR	Petrolia Drilling	VVL	Voss Veksel- og Landmandsbank
HSPG	Hland Sparebank	PEL	Pan Pelagic		
HSU	Havila Supply	PFI	P4 Radio Hele Norge		

Total 157 Companies

Table 21: Companies with 4 announcements in 2002

Companies with 4 announcements in 2003

AAV	Adresseavisen	HOLG	Hol Sparebank	PRO	Profdoc
ACTA	Acta Holding	HSPG	Hland Sparebank	PRS	Prosafe
AFG	AF Gruppen	IFN	Industrifinans Nringseiendom	PSI	PSI Group
AFK	Arendals Fossekompani	IGE	Int. Gold Exploration	QFR	Q-Free
AIK	Aktiv Kapital	IGNIS	Ignis	RANG	Sparebanken Rana
ALX	Altinex	IMSK	I.M. Skaugen	RAU	Raufoss
APP	Apptix	INM	Inmeta	RCL	Royal Caribbean Cruises
ASC	ABG Sundal Collier	ISSG	Indre Sogn Sparebank	RGT	Rocksource
ATG	Andvord Tybring-Gjedde	ITE	Itera Consulting Group	RIC	Rica Hotels
AURG	Aurskog Sparebank	JIN	Jinhui Shipping and Transport	RIE	Rieber & Sn
AVA	Avantor	KBK	KredittBanken	RING	Ringerikes Sparebank
BEL	Belships	KDP	Kristiansand Dyrepark	ROGG	Sparebanken Rogaland
BIRD	Birdstep Technology	KEN	Kenor	SADG	Sandnes Sparebank
BLO	Blom	KIT	Kitron	SANG	Sandsvr Sparebank
BMA	Byggma	KLI	Klippen Invest	SCH	Schibsted
BNB	Bolig- og Nringsbanken	KOG	Kongsberg Gruppen	SCI	Scana Industrier
BON	Bonheur	KOM	Komplett	SFM	Synnve Finden
BOR	Borgestad	KVE	Kverneland	SIN	Sinvest
COV	ContextVision	KVI	Kvrner	SKI	Skiens Aktiemlle
DAT	Data Respons	LIN	Linde-Group	SME	Smedvig ser. A
DNBNOR	DnB NOR	LSG	Lery Seafood Group	SOFF	Solstad Offshore
DNO	DNO	LUX	Luxo	SOI	Software Innovation
DOF	DOF	MEF	Mefjorden	SOLV	Solvang
DOM	Domstein	MELG	Melhus Sparebank	SPOG	Sparebanken st
EKO	Ekornes	MHG	Pan Fish	SRI	Star Reefers Inc.
ELK	Elkem	MING	Sparebanken Midt-Norge	SST	Steen & Strm
ELT	Eltek	MORG	Sparebanken Mre	STA	Stavanger Aftenblad
EME	Ementor	NAM	Namsos Trafikkselskap	STB	Storebrand
EXE	Exense	NEC	Norse Energy Corp.	STL	Statoil
EXPERT	Expert	NER	Nera	STP	Stepstone
FAR	Farstad Shipping	NESG	Nes Prestegjelds Sparebank	SUB	Subsea 7
FAST	Fast Search & Transfer	NHY	Norsk Hydro	SUO	SuperOffice
FDR	Frontier Drilling	NOD	Nordic Semiconductor	SVEG	Sparebanken Vest
FJO	Fjord Seafood	NOF	Northern Offshore	TAA	Tandberg
FOE	Fred. Olsen Energy	NONG	Sparebanken Nord-Norge	TAD	Tandberg Data

FOS	Fosen Trafikklag	NOR	Norman	TAT	Tandberg Television
FRO	Frontline	NOV	Norsk Vekst	TCO	TeleComputing
FSL	Fesil	NSG	Norske Skogindustrier	TEC	Technor
GGS	Global Geo Services	NUT	Nutri Pharma	TEL	Telenor
GOD	Goodtech	OCR	Ocean Rig	TGS	TGS-NOPEC Geophysical Company
GOL	Golar LNG	ODF	Odfjell ser. A	TOM	Tomra Systems
GRE	Gresvig	OFL	Office Line	TOTG	Totens Sparebank
GRO	Ganger Rolf	OLT	Olav Thon Eiendomsselskap	TTS	TTS Marine
GRR	Green Reefers	OPC	Opticom	UTO	Unitor
GYL	Gyldendal	ORK	Orkla	VEI	Veidekke
HAG	HG	OTR	Otrum	VIS	Visma
HELG	Helgeland Sparebank	PDR	Petrolia Drilling	VME	VMetro
HEX	Hexagon Composites	PFI	P4 Radio Hele Norge	VSBG	SpareBanken Vestfold
HJE	Hjellegjerde	PGS	Petroleum Geo-Services	WWI	Wilh. Wilhelmsen ser. A
HNA	Hafslund ser. A	PHO	PhotoCure	VVL	Voss Veksel- og Landmandsbank
HND	Hands	PLUG	Sparebanken Pluss		

Total 152 Companies

Table 22: Companies with 4 announcements in 2003

Companies with 4 announcements in 2004

AAV	Adresseavisen	HNA	Hafslund ser. A	RCL	Royal Caribbean Cruises
ACTA	Acta Holding	HND	Hands	RIC	Rica Hotels
AFG	AF Gruppen	HSPG	Hland Sparebank	RIE	Rieber & Sn
AFK	Arendals Fossekompani	IGE	Int. Gold Exploration	RING	Ringerikes Sparebank
AIK	Aktiv Kapital	IGNIS	Ignis	ROGG	Sparebanken Rogaland
ALX	Altinex	IMSK	I.M. Skaugen	SADG	Sandnes Sparebank
APP	Apptix	INM	Inmeta	SANG	Sandsvr Sparebank
ASC	ABG Sundal Collier	ISSG	Indre Sogn Sparebank	SCH	Schibsted
ATG	Andvord Tybring-Gjedde	ITE	Itera Consulting Group	SCI	Scana Industrier
AURG	Aurskog Sparebank	KIT	Kitron	SFM	Synnve Finden
BEL	Belships	KOG	Kongsberg Gruppen	SIN	Sinvest
BIRD	Birdstep Technology	KOM	Komplett	SKI	Skiens Aktiemlle
BLO	Blom	KVE	Kverneland	SME	Smedvig ser. A
BMA	Byggma	KVI	Kvrner	SOFF	Solstad Offshore
BNB	Bolig- og Nringsbanken	LSG	Lery Seafood Group	SOI	Software Innovation
BON	Bonheur	LUX	Luxo	SOLV	Solvang
BOR	Borgestad	MELG	Melhus Sparebank	SPOG	Sparebanken st
COV	ContextVision	MHG	Pan Fish	SRI	Star Reefers Inc.
DAT	Data Respons	MING	Sparebanken Midt-Norge	SST	Steen & Strm
DNBNOR	DnB NOR	MORG	Sparebanken Mre	STB	Storebrand
DNO	DNO	NAM	Namsos Trafikkselskap	STL	Statoil
DOF	DOF	NAS	Norwegian Air Shuttle	STP	Stepstone
DOM	Domstein	NEC	Norse Energy Corp.	SUB	Subsea 7
EID	Eidsiva Rederi	NER	Nera	SUO	SuperOffice
EKO	Ekornes	NESG	Nes Prestegjelds Sparebank	SVEG	Sparebanken Vest
ELK	Elkem	NEXT	NextGenTel Holding	TAA	Tandberg
ELT	Eltek	NHY	Norsk Hydro	TAD	Tandberg Data
EME	Ementor	NOD	Nordic Semiconductor	TAT	Tandberg Television
EXE	Exense	NONG	Sparebanken Nord-Norge	TCO	TeleComputing
EXPERT	Expert	NOV	Norsk Vekst	TEC	Technor
FAR	Farstad Shipping	NSG	Norske Skogindustrier	TEL	Telenor
FAST	Fast Search & Transfer	NUT	Nutri Pharma	TFDS	Troms Fylkes Dampskibsselskap
FJO	Fjord Seafood	OCR	Ocean Rig	TGS	TGS-NOPEC Geophysical Company
FOE	Fred. Olsen Energy	ODF	Odfjell ser. A	TOM	Tomra Systems
FOS	Fosen Trafikklag	OFL	Office Line	TOTG	Totens Sparebank

FRO	Frontline	OLT	Olav Thon Eiendomsselskap	TST	Tandberg Storage
FSL	Fesil	OPC	Opticom	TTS	TTS Marine
GOD	Goodtech	ORK	Orkla	UTO	Unitor
GOL	Golar LNG	OTR	Otrum	VEI	Veidekke
GRE	Gresvig	PFI	P4 Radio Hele Norge	VIS	Visma
GRO	Ganger Rolf	PHO	PhotoCure	VME	VMetro
GYL	Gyldendal	PLUG	Sparebanken Pluss	VSBG	SpareBanken Vestfold
HAG	HG	PRO	Profdoc	WWI	Wilh. Wilhelmsen ser. A
HELG	Helgeland Sparebank	PRS	Prosafe	VVL	Voss Veksel- og Landmandsbank
HEX	Hexagon Composites	PSI	PSI Group		
HJE	Hjellegjerde	QFR	Q-Free		

Total 136 Companies

Table 23: Companies with 4 announcements in 2004

Companies with 4 announcements in 2005

AAV	Adresseavisen	HOLG	Hol Sparebank	QFR	Q-Free
ACTA	Acta Holding	HSPG	Hland Sparebank	RCL	Royal Caribbean Cruises
AFG	AF Gruppen	IBAS	IBAS Holding	RGT	Rocksource
AFK	Arendals Fossekompani	IGNIS	Ignis	RIC	Rica Hotels
AIK	Aktiv Kapital	IMSK	I.M. Skaugen	RIE	Rieber & Sn
AKER	Aker	INM	Inmeta	RING	Ringerikes Sparebank
AKY	Aker Yards	ISSG	Indre Sogn Sparebank	ROGG	Sparebanken Rogaland
ALX	Altinex	ITE	Itera Consulting Group	SADG	Sandnes Sparebank
APP	Apptix	KIT	Kitron	SANG	Sandsvr Sparebank
ASC	ABG Sundal Collier	KOG	Kongsberg Gruppen	SCH	Schibsted
ATG	Andvord Tybring-Gjedde	KOM	Komplett	SCI	Scana Industrier
AURG	Aurskog Sparebank	KVE	Kverneland	SEVAN	Sevan Marine
BEL	Belships	LSG	Lery Seafood Group	SFM	Synnve Finden
BIRD	Birdstep Technology	LUX	Luxo	SIN	Sinvest
BJORGE	Bjrge	MAMUT	Mamut	SKI	Skiens Aktiemlle
BLO	Blom	MEC	Medicult	SME	Smedvig ser. A
BMA	Byggma	MEDI	Medi-Stim	SNI	Stolt-Nielsen
BON	Bonheur	MELG	Melhus Sparebank	SOFF	Solstad Offshore
BOR	Borgestad	MHG	Pan Fish	SOI	Software Innovation
CNS	Conseptor	MING	Sparebanken Midt-Norge	SOLV	Solvang
COV	ContextVision	MORG	Sparebanken Mre	SPOG	Sparebanken st
DAT	Data Respons	NAM	Namsos Trafikkselskap	SRI	Star Reefers Inc.
DNBNOR	DnB NOR	NAS	Norwegian Air Shuttle	SST	Steen & Strm
DNO	DNO	NEC	Norse Energy Corp.	STB	Storebrand
DOF	DOF	NER	Nera	STL	Statoil
DOM	Domstein	NESG	Nes Prestegjelds Sparebank	STP	Stepstone
EID	Eidsiva Rederi	NEXT	NextGenTel Holding	SUB	Subsea 7
EKO	Ekornes	NHY	Norsk Hydro	SUO	SuperOffice
ELT	Eltek	NOD	Nordic Semiconductor	SVEG	Sparebanken Vest
EME	Ementor	NONG	Sparebanken Nord-Norge	TAA	Tandberg
EXE	Exense	NORMAN	Norman	TAD	Tandberg Data
EXPERT	Expert	NOV	Norsk Vekst	TAT	Tandberg Television
FAR	Farstad Shipping	NSG	Norske Skogindustrier	TCO	TeleComputing
FAST	Fast Search & Transfer	NUT	Nutri Pharma	TEC	Technor
FJO	Fjord Seafood	OCR	Ocean Rig	TEL	Telenor
FOE	Fred. Olsen Energy	ODF	Odfjell ser. A	TFDS	Troms Fylkes Dampskibsselskap

FOS	Fosen Trafikklag	OFL	Office Line	TGS	TGS-NOPEC Geophysical Company
FRO	Frontline	OLT	Olav Thon Eiendomsselskap	TOM	Tomra Systems
FSL	Fesil	OPC	Opticom	TOTG	Totens Sparebank
GGS	Global Geo Services	OPERA	Opera Software	TST	Tandberg Storage
GOD	Goodtech	ORK	Orkla	TTS	TTS Marine
GOL	Golar LNG	OTR	Otrum	UTO	Unitor
GRE	Gresvig	PDR	Petrolia Drilling	VEI	Veidekke
GRO	Ganger Rolf	PFI	P4 Radio Hele Norge	VIS	Visma
GRR	Green Reefers	PGS	Petroleum Geo-Services	VME	VMetro
GYL	Gyldendal	PHO	PhotoCure	VSBG	SpareBanken Vestfold
HAG	HG	PLUG	Sparebanken Pluss	WWI	Wilh. Wilhelmsen ser. A
HEX	Hexagon Composites	PRO	Profdoc	VVL	Voss Veksel- og Landmandsbank
HJE	Hjellegjerde	PRS	Prosafe	YAR	Yara International
HNA	Hafslund ser. A	PSI	PSI Group		

Total 149 Companies

Table 24: Companies with 4 announcements in 2005

Companies with 4 announcements in 2006

AAV	Adresseavisen	GOD	Goodtech	PGS	Petroleum Geo-Services
ACTA	Acta Holding	GOGL	Golden Ocean Group	PHO	Photocure
AFG	AF Gruppen	GOL	Golar LNG	PLUG	Sparebanken Pluss
AFK	Arendals Fossekompani	GRO	Ganger Rolf	PRO	Profdoc
AIK	Aktiv Kapital	GRR	Green Reefers	PRS	Prosafe
AKASA	Aker American Shipping	GYL	Gyldendal	PSI	PSI Group
AKER	Aker	HAVI	Havila Shipping	QFR	Q-Free
AKS	Aker Seafoods	HEX	Hexagon Composites	RCL	Royal Caribbean Cruises
AKY	Aker Yards	HJE	Hjellegjerde	REVUS	Revus Energy
ALX	Altinex	HNA	Hafslund ser. A	RGT	Rocksource
APL	APL	HOLG	Hol Sparebank	RIE	Rieber & Sn
APP	Apptix	HSPG	Hland Sparebank	RING	Ringerikes Sparebank
ASC	ABG Sundal Collier	IGNIS	Ignis	SADG	Sandnes Sparebank
AURG	Aurskog Sparebank	IMAREX	IMAREX NOS	SANG	Sandsvr Sparebank
AWO	Awilco Offshore	IMSK	I.M. Skaugen	SCH	Schibsted
BEL	Belships	INM	Inmeta	SCI	Scana Industrier
BIOTEC	Biotec Pharmacon	ISSG	Indre Sogn Sparebank	SDRL	Seadrill
BIRD	Birdstep Technology	ITE	Itera Consulting Group	SEVAN	Sevan Marine
BJORGE	Bjrge	KIT	Kitron	SFM	Synnve Finden
BLO	Blom	KOA	Kongsberg Automotive Holding	SIN	Sinvest
BLU	Bluewater Insurance	KOG	Kongsberg Gruppen	SIT	Simrad Optronics
BMA	Byggma	KOM	Komplett	SKI	Skiens Aktiemlle
BON	Bonheur	KVE	Kverneland	SOFF	Solstad Offshore
BOR	Borgestad	LSG	Lery Seafood Group	SOI	Software Innovation
CECO	Camillo Eitzen & Co	MAMUT	Mamut	SOLV	Solvang
CEQ	Cermaq	MEDI	Medi-Stim	SRI	Star Reefers Inc.
CNS	Conseptor	MELG	Melhus Sparebank	SST	Steen & Strm
COV	ContextVision	MHG	Pan Fish	STA	Stavanger Aftenblad
DAT	Data Respons	MING	Sparebanken Midt-Norge	STB	Storebrand
DEEP	DeepOcean	MORG	Sparebanken Mre	STL	Statoil
DIAG	DiaGenic	NAM	Namsos Trafikkselskap	STP	Stepstone
DNBNOR	DnB NOR	NAS	Norwegian Air Shuttle	SUB	Subsea 7
DNO	DNO	NEC	Norse Energy Corp.	SUO	SuperOffice
DOF	DOF	NESG	Nes Prestegjelds Sparebank	SVEG	Sparebanken Vest
DOM	Domstein	NHY	Norsk Hydro	TAA	Tandberg
EDRILL	Eastern Drilling	NOD	Nordic Semiconductor	TAD	Tandberg Data
EID	Eidsiva Rederi	NONG	Sparebanken Nord-Norge	TAT	Tandberg Television
EKO	Ekornes	NORD	NorDiag	TCO	TeleComputing

ELT	Eltek	NORGAN	Norgani Hotels	TEL	Telenor
EME	Ementor	NORMAN	Norman	TGS	TGS-NOPEC Geophysical Company
EXE	Exense	NOV	Norsk Vekst	TOM	Tomra Systems
EXPERT	Expert	NSG	Norske Skogindustrier	TOTG	Totens Sparebank
FAR	Farstad Shipping	NUT	Nutri Pharma	TST	Tandberg Storage
FARA	Fara	OCR	Ocean Rig	TTS	TTS Marine
FAST	Fast Search & Transfer	ODF	Odfjell ser. A	VEI	Veidekke
FOE	Fred. Olsen Energy	ODIM	Odim	WILS	Wilson
FOS	Fosen Trafikklag	OLT	Olav Thon Eiendomsselskap	VME	VMetro
FRO	Frontline	OPERA	Opera Software	VSBG	SpareBanken Vestfold
FSL	Fesil	ORK	Orkla	WWI	Wilh. Wilhelmsen ser. A
GAS	Bergesen Worldwide Gas	OTR	Otrum	VVL	Voss Veksel- og Landmandsbank
GGG	Grenland Group	PDR	Petrolia Drilling	YAR	Yara International

Total 153 Companies

Table 25: Companies with 4 announcements in 2006

Companies with 4 announcements in 2007

AAV	Adresseavisen	GAS	BW Gas	PGS	Petroleum Geo-Services
ACTA	Acta Holding	GGG	Grenland Group	PHO	Photocure
AFG	AF Gruppen	GGS	Global Geo Services	PLUG	Sparebanken Pluss
AFK	Arendals Fossekompani	GOD	Goodtech	POWEL	Powel
AGR	AGR Group	GOGL	Golden Ocean Group	PRO	Profdoc
AIK	Aktiv Kapital	GOL	Golar LNG	PRS	Prosafe
AKASA	Aker American Shipping	GRO	Ganger Rolf	PSI	PSI Group
AKBM	Aker BioMarine	GRR	Green Reefers	QFR	Q-Free
AKD	Aker Drilling	GYL	Gyldendal	RCL	Royal Caribbean Cruises
AKER	Aker	HAVI	Havila Shipping	REC	Renewable Energy Corporation
AKFP	Aker Floating Production	HELG	Helgeland Sparebank	REPANT	Repant
AKS	Aker Seafoods	HEX	Hexagon Composites	REVUS	Revus Energy
AKVA	AKVA Group	HJE	Hjellegjerde	RGT	Rocksource
AKY	Aker Yards	HNA	Hafslund ser. A	RIE	Rieber & Son
APP	Apptix	HOLG	Hol Sparebank	RING	Ringerikes Sparebank
ASC	ABG Sundal Collier	HRG	Hurtigruten	ROGG	SpareBank 1 SR-Bank
AURG	Aurskog Sparebank	HSPG	Holand Sparebank	RVSBG	Rygge-Vaaler Sparebank
AUSS	Austevoll Seafood	IGNIS	Ignis	SADG	Sandnes Sparebank
AWO	Awilco Offshore	IMAREX	IMAREX	SANG	Sandsvar Sparebank
BEL	Belships	IMSK	I.M. Skaugen	SBX	SeaBird Exploration
BIOTEC	Biotec Pharmacon	INM	Inmeta	SCH	Schibsted
BIRD	Birdstep Technology	IOX	InterOil Exploration and Production	SCI	Scana Industrier
BJORGE	Bjorge	ISSG	Indre Sogn Sparebank	SDRL	Seadrill
BLO	Blom	ITC	Intelecom Group	SEVAN	Sevan Marine
BLU	Bluewater Insurance	ITE	Itera Consulting Group	SFM	Synn?ve Finden
BMA	Byggma	JACK	Petrojack	SIT	Simrad Optronics
BON	Bonheur	KIT	Kitron	SKI	Skiens Aktiem?lle
BOR	Borgestad	KOA	Kongsberg Automotive Holding	SOFF	Solstad Offshore
BWG	BWG Homes	KOG	Kongsberg Gruppen	SOI	Software Innovation
BWO	BW Offshore Limited	KOM	Komplett	SOLV	Solvang
CECO	Camillo Eitzen & Co	KVE	Kverneland	SONG	Songa Offshore
CEQ	Cermaq	LSG	Leroy Seafood Group	SPOG	Sparebanken Ost
CLAVIS	Clavis Pharma	LUX	Luxo	SRI	Star Reefers Inc.
COD	Codfarmers	MAFA	Marine Farms	STA	Stavanger Aftenblad
COMROD	Comrod Communication	MAMUT	Mamut	STB	Storebrand
CONF	Confirmit	MEDI	Medi-Stim	STL	StatoilHydro
COP	Copeinca	MELG	Melhus Sparebank	STP	Stepstone

COV	ContextVision	MHG	Marine Harvest	SUB	Subsea 7
DAT	Data Respons	MING	Sparebanken Midt-Norge	SUO	SuperOffice
DEEP	DeepOcean	MORG	Sparebanken M?re	SVEG	Sparebanken Vest
DIAG	DiaGenic	NAM	Namsos Trafikkselskap	TAA	Tandberg
DNBNOR	DnB NOR	NAS	Norwegian Air Shuttle	TAD	Tandberg Data
DNO	DNO International	NAVA	Navamedic	TCO	TeleComputing
DOF	DOF	NEC	Norse Energy Corp.	TECO	Teco Maritime
DOFSUB	DOF Subsea	NESG	Nes Prestegjelds Sparebank	TEL	Telenor
DOLP	Dolphin Interconnect Solutions	NHY	Norsk Hydro	TELIO	Telio Holding
DOM	Domstein	NOD	Nordic Semiconductor	TGS	TGS-NOPEC Geophysical Company
ECHEM	Eitzen Chemical	NONG	Sparebanken Nord-Norge	TIDE	Tide
EID	Eidsiva Rederi	NORD	NorDiag	TOM	Tomra Systems
EIOF	Eidesvik Offshore	NORMAN	Norman	TOTG	Totens Sparebank
EKO	Ekornes	NPRO	Norwegian Property	TPO	Teekay Petrojarl
ELT	Eltek	NSG	Norske Skogindustrier	TREF	Trefoil
EME	Ementor	NSTAT	Norstat	TROLL	Trolltech
EMS	Eitzen Maritime Services	NUT	Nutri Pharma	TST	Tandberg Storage
FAIR	Fairstar Heavy Transport	OCR	Ocean Rig	TTS	TTS Marine
FAKTOR	Faktor Eiendom	ODF	Odfjell ser. A	VEI	Veidekke
FAR	Farstad Shipping	ODIM	Odim	WILS	Wilson
FARA	Fara	OILRIG	Odfjell Invest	VME	VMetro
FAST	Fast Search & Transfer	OLT	Olav Thon Eiendomsselskap	VSBG	SpareBanken Vestfold
FOE	Fred. Olsen Energy	OPERA	Opera Software	WWI	Wilh. Wilhelmsen ser. A
FOS	Fosen Trafikklag	ORK	Orkla	VVL	Voss Veksel- og Landmandsbank
FRO	Frontline	OTR	Otrum	YAR	Yara International
FUNCOM	Funcom	PDR	Petrolia Drilling		

Total 188 Companies

Table 26: Companies with 4 announcements in 2007

Figure 3: CAR and volume around earnings announcements, 1973–2004

This figure shows event–time daily cumulative abnormal return and cumulative turnover in trading day t+k for firms announcing earnings at date t. Abnormal return is defined as daily return minus an equally weighted portfolio of non-announcing firms. Scaled volume is defined as share volume in month t divided by average volume in the previous 250 trading days. Abnormal volume is defined as scaled volume minus the equal weight average of scaled volume for all firms on that day. This figure includes firms in the period 1973 – 2004 with market capitalization (as of the previous month) above the median market capitalization of CRSP firms. Volume and return are in percent.

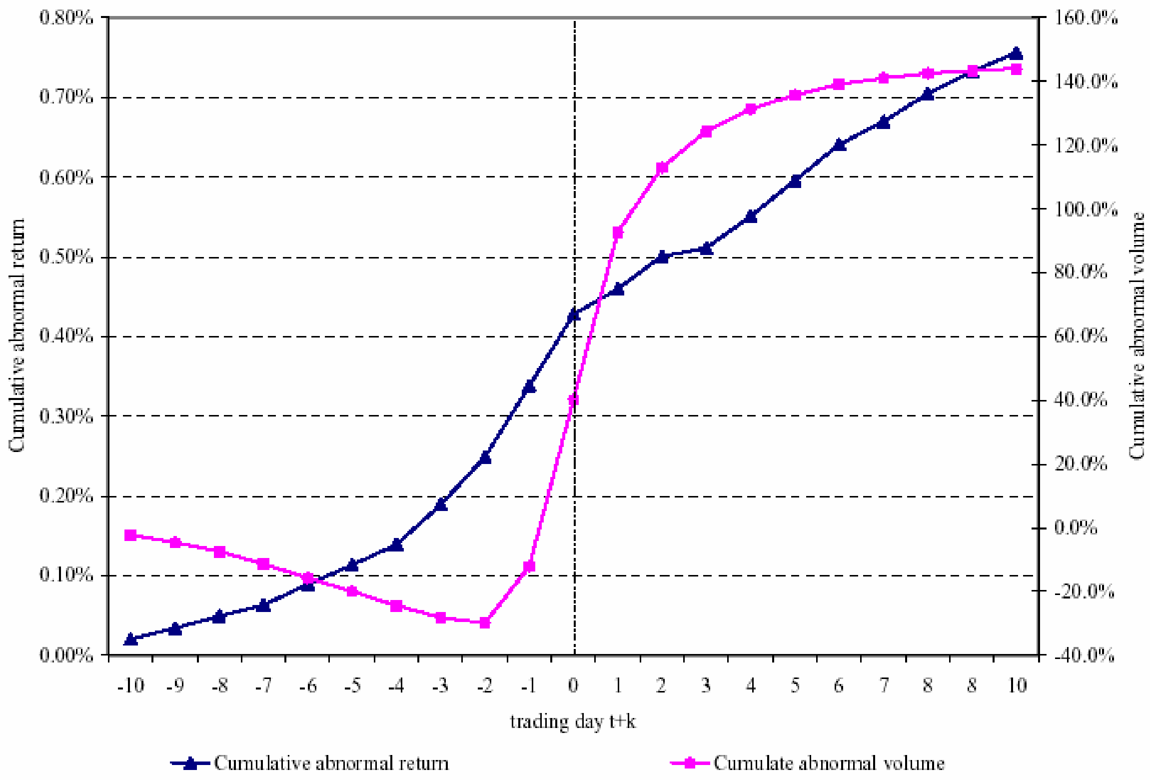

Figure 2: Figure 3 in Frazzini and Lamont (2007) – Cumulated Abnormal Returns and volume around earnings announcements, 1973–2004

7.2 Excess Returns L/S Portfolios Based on Previous Year Method

Arithmetic averages of simple returns:

All Stocks With 4 Announcements the Previous Year	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-0.416%	-0.046%	-0.772%	-0.640%
t-stat	0.58	0.06	0.91	0.91
Std deviation	0.075	0.074	0.089	0.073
Skewness	-0.718	-0.729	-0.046	0.055
Kurtosis	1.264	1.404	0.403	2.134
Sharpe Ratio	-0.056	-0.006	-0.087	-0.087
1999-2000				
Mean	-1.221%	-0.168%	-2.062%	-1.722%
t-stat	0.67	0.10	0.95	1.02
Std deviation	0.089	0.083	0.107	0.083
Skewness	-0.091	-0.193	0.002	0.044
Kurtosis	-0.844	1.755	-0.747	-0.569
Sharpe Ratio	-0.137	-0.020	-0.193	-0.207
2001-2007				
Mean	-0.186%	-0.011%	-0.388%	-0.331%
t-stat	0.22	0.01	0.43	0.43
Std deviation	0.078	0.071	0.083	0.071
Skewness	-1.004	-0.957	0.013	0.064
Kurtosis	2.627	2.422	1.077	3.108
Sharpe Ratio	-0.024	-0.002	-0.047	-0.047

Table 27: All Stocks with 4 Announcements the Previous Year – Previous Year Method

	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	0.208%	0.624%	-0.772%	-1.395%
t-stat	0.31	0.95	0.85	1.78
Std deviation	0.066	0.065	0.089	0.077
Skewness	-0.273	-0.184	-0.046	-0.512
Kurtosis	-0.020	-0.265	0.403	1.910
Sharpe Ratio	0.031	0.097	-0.087	-0.182
1999-2000				
Mean	-0.691%	0.457%	-2.062%	-2.519%
t-stat	0.15	0.45	0.41	0.85
Std deviation	0.088	0.081	0.107	0.082
Skewness	-0.112	-0.178	0.002	-0.052
Kurtosis	-0.797	-0.603	-0.747	-0.740
Sharpe Ratio	-0.078	0.057	-0.193	-0.308
2001-2007				
Mean	0.475%	0.673%	-0.388%	-1.061%
t-stat	0.27	0.83	0.75	1.56
Std deviation	0.059	0.060	0.083	0.076
Skewness	-0.245	-0.169	0.013	-0.668
Kurtosis	0.167	-0.229	1.077	3.143
Sharpe Ratio	0.081	0.113	-0.047	-0.140

Table 28: Months with Zero Expected Announcements Deleted – Previous Year Method

Managed L/S Portfolio	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-0.416%	-0.018%	-0.117%	-0.099%
t-stat	0.54	0.25	1.14	1.02
Std deviation	0.075	0.007	0.010	0.010
Skewness	-0.718	-0.830	-1.671	-0.631
Kurtosis	1.264	2.598	8.984	10.802
Sharpe Ratio	-0.056	-0.025	-0.117	-0.104
1999-2000				
Mean	-1.221%	-0.059%	-0.266%	-0.208%
t-stat	0.27	0.12	0.57	0.51
Std deviation	0.089	0.007	0.010	0.008
Skewness	-0.091	-0.623	-0.620	-0.613
Kurtosis	-0.844	1.860	0.005	0.699
Sharpe Ratio	-0.137	-0.086	-0.274	-0.245
2001-2007				
Mean	-0.186%	-0.006%	-0.075%	-0.069%
t-stat	0.51	0.23	1.07	0.95
Std deviation	0.071	0.007	0.010	0.010
Skewness	-1.004	-0.895	-1.968	-0.668
Kurtosis	2.627	2.921	11.579	12.357
Sharpe Ratio	-0.026	-0.009	-0.074	-0.069

Table 29: Managed L/S Portfolio – Previous Year Method

L/S Portfolio Traded in February, May, August and October	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-1.416%	-0.795%	-1.740%	-0.945%
t-stat	1.31	0.79	1.20	0.69
Std deviation	0.065	0.061	0.087	0.082
Skewness	-0.353	-0.224	-0.641	-0.405
Kurtosis	-0.725	-0.655	1.065	1.707
Sharpe Ratio	-0.219	-0.131	-0.201	-0.115
1999-2000				
Mean	-3.663%	-0.368%	-5.385%	-5.017%
t-stat	1.75	0.16	2.11	1.66
Std deviation	0.059	0.064	0.072	0.086
Skewness	-0.091	-0.345	-0.682	-0.398
Kurtosis	-1.984	2.366	0.313	-1.060
Sharpe Ratio	-0.620	-0.057	-0.746	-0.587
2001-2007				
Mean	-0.774%	-0.918%	-0.698%	0.219%
t-stat	0.51	0.80	0.53	0.15
Std deviation	0.081	0.061	0.070	0.079
Skewness	-0.502	-0.209	-0.841	-0.425
Kurtosis	-0.423	-1.040	1.687	3.157
Sharpe Ratio	-0.096	-0.151	-0.099	0.028

Table 30: L/S Portfolio Traded in February, May, August and October – Previous Year Method

7.3 Excess Returns L/S Portfolio Based on Fiscal Year Method

Arithmetic averages of simple returns:

	All Stocks With 4 Announcements the Previous Year			
	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-0.416%	0.050%	-0.484%	-0.533%
t-stat	0.58	0.06	0.77	0.74
Std deviation	0.075	0.065	0.038	0.075
Skewness	-0.718	-1.058	-1.327	0.669
Kurtosis	1.264	4.127	4.428	1.630
Sharpe Ratio	-0.056	0.008	-0.129	-0.071
1999-2000				
Mean	-1.221%	-0.011%	-1.228%	-1.217%
t-stat	0.67	0.01	0.93	0.67
Std deviation	0.089	0.081	0.037	0.089
Skewness	-0.091	-0.428	-1.843	0.560
Kurtosis	-0.844	4.913	2.663	-0.430
Sharpe Ratio	-0.137	-0.001	-0.330	-0.136
2001-2007				
Mean	-0.186%	0.067%	-0.271%	-0.338%
t-stat	0.30	0.08	0.07	0.44
Std deviation	0.057	0.060	0.038	0.071
Skewness	-1.004	-1.457	-1.256	0.790
Kurtosis	2.627	7.054	5.260	2.981
Sharpe Ratio	-0.033	0.011	-0.072	-0.048

Table 31: All Stocks with 4 Announcements the Previous Year – Fiscal Year Method

7.4 Excess Returns L/S Portfolios Based on Actual Announcement Dates

All Stocks With 4 Announcements Each Calendar Year				
	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-0,416%	-0,468%	0,153%	0,600%
t-stat	0,58	0,57	0,17	0,73
Std deviation	0,075	0,086	0,093	0,085
Skewness	-0,718	-0,331	0,483	0,374
Kurtosis	1,264	1,002	1,113	1,387
Sharpe Ratio	-0,056	-0,055	0,016	0,070
1999-2000				
Mean	-1,221%	-1,412%	0,935%	2,191%
t-stat	0,67	0,67	0,43	1,04
Std deviation	0,089	0,103	0,107	0,104
Skewness	-0,091	-0,085	0,151	0,398
Kurtosis	-0,844	1,413	-0,406	-0,312
Sharpe Ratio	-0,137	-0,136	0,088	0,212
2001-2007				
Mean	-0,186%	-0,196%	-0,053%	0,145%
t-stat	0,21	0,22	0,05	0,17
Std deviation	0,083	0,080	0,090	0,080
Skewness	-1,004	-0,410	0,600	0,312
Kurtosis	2,627	2,206	1,899	2,344
Sharpe Ratio	-0,022	-0,024	-0,006	0,018

Table 32: All Stocks with 4 Announcements Each Calendar Year – Actual year method

Months with Zero Actual Announcements Deleted	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-0,059%	-0,216%	0,154%	0,368%
t-stat	0,08	0,26	0,16	0,36
Std deviation	0,070	0,082	0,093	0,100
Skewness	-0,314	-0,018	0,483	0,234
Kurtosis	-0,337	0,369	1,113	1,297
Sharpe Ratio	-0,008	-0,026	0,017	0,037
1999-2000				
Mean	-1,324%	-2,414%	0,823%	3,237%
t-stat	0,04	0,12	0,08	0,17
Std deviation	0,084	0,104	0,104	0,124
Skewness	-0,098	0,052	0,160	0,397
Kurtosis	-0,708	-0,898	-0,419	-0,540
Sharpe Ratio	-0,158	-0,232	0,079	0,261
2001-2007				
Mean	0,317%	0,446%	-0,045%	-0,485%
t-stat	0,07	0,22	0,14	0,32
Std deviation	0,066	0,074	0,090	0,091
Skewness	-0,341	0,185	0,609	-0,104
Kurtosis	-0,197	1,094	1,953	2,201
Sharpe Ratio	0,048	0,060	-0,005	-0,053

Table 33: Months with Zero Actual Announcements Deleted – Actual year method

Managed L/S Portfolio	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-0,416%	-0,080%	-0,063%	0,018%
t-stat	0,54	0,78	0,75	0,15
Std deviation	0,075	0,010	0,008	0,011
Skewness	-0,718	-0,888	-1,058	1,602
Kurtosis	1,265	4,952	4,481	10,839
Sharpe Ratio	-0,056	-0,080	-0,077	0,016
1999-2000				
Mean	-1,220%	-0,183%	-0,112%	0,071%
t-stat	0,27	0,39	0,37	0,08
Std deviation	0,089	0,014	0,009	0,016
Skewness	-0,091	-0,530	-0,353	1,875
Kurtosis	-0,844	4,511	1,586	8,711
Sharpe Ratio	-0,137	-0,133	-0,130	0,044
2001-2007				
Mean	-0,186%	-0,051%	-0,049%	0,002%
t-stat	0,51	0,73	0,70	0,14
Std deviation	0,071	0,009	0,008	0,010
Skewness	-1,004	-1,050	-1,290	0,992
Kurtosis	2,627	3,891	5,736	9,248
Sharpe Ratio	-0,026	-0,058	-0,060	0,002

Table 34: Managed L/S Portfolio – Actual year method

L/S Portfolio Traded in February, May, August and October	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-1,416%	-2,910%	-0,565%	2,264%
t-stat	1,31	2,04	0,48	1,47
Std deviation	0,065	0,085	0,070	0,092
Skewness	-0,353	-0,145	-0,363	0,726
Kurtosis	-0,725	-0,566	0,032	1,127
Sharpe Ratio	-0,219	-0,340	-0,081	0,245
1999-2000				
Mean	-3,663%	-5,122%	-2,147%	2,975%
t-stat	1,75	1,25	1,01	0,60
Std deviation	0,059	0,116	0,060	0,141
Skewness	-0,091	0,480	0,108	0,703
Kurtosis	-1,984	0,325	-0,701	0,024
Sharpe Ratio	-0,620	-0,440	-0,356	0,211
2001-2007				
Mean	-0,774%	-2,254%	-0,112%	2,061%
t-stat	0,59	1,58	0,08	1,42
Std deviation	0,070	0,076	0,074	0,077
Skewness	-0,502	-0,330	-0,510	0,582
Kurtosis	-0,423	-1,201	0,275	1,311
Sharpe Ratio	-0,111	-0,298	-0,015	0,268

Table 35: L/S Portfolio Traded in February, May, August and October – Actual year method

7.5 Robustness Checks

7.5.1 Geometric Averages of Logaritmic Returns Previous Year Method

All Stocks With 4 Announcements the Previous Year				
	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-1.970%	-1.370%	-2.268%	-1.286%
t-stat	2.44	1.77	2.38	1.68
Std deviation	0.085	0.081	0.100	0.080
Skewness	-1.356	-1.377	-1.047	-0.226
Kurtosis	3.777	4.285	3.928	5.167
Sharpe Ratio	-0.233	-0.169	-0.226	-0.160
1999-2000				
Mean	-3.444%	-2.166%	-3.684%	-1.828%
t-stat	1.82	1.22	1.66	1.03
Std deviation	0.095	0.088	0.111	0.088
Skewness	-0.257	-0.460	-0.256	-0.151
Kurtosis	-0.836	4.976	-0.487	0.022
Sharpe Ratio	-0.364	-0.246	-0.332	-0.208
2001-2007				
Mean	-1.540%	-1.140%	-1.855%	-1.130%
t-stat	1.56	1.33	1.77	1.33
Std deviation	0.091	0.079	0.097	0.078
Skewness	-1.799	-1.725	-1.364	-0.274
Kurtosis	6.374	6.516	6.334	6.464
Sharpe Ratio	-0.169	-0.144	-0.191	-0.144

Table 36: All Stocks with 4 Announcements the Previous Year – Geometric Previous Year Method

	Months with Zero Expected Announcers Deleted			
	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-1.032%	-0.344%	-2.544%	-2.305%
t-stat	1.41	0.51	2.52	2.58
Std deviation	0.072	0.066	0.100	0.089
Skewness	-0.837	-0.504	-1.047	-1.365
Kurtosis	1.603	0.068	3.928	5.269
Sharpe Ratio	-0.143	-0.052	-0.254	-0.260
1999-2000				
Mean	-2.477%	-1.053%	-4.006%	-3.086%
t-stat	0.67	0.24	1.21	1.24
Std deviation	0.091	0.082	0.111	0.088
Skewness	-0.381	-0.562	-0.256	-0.414
Kurtosis	-0.618	-0.136	-0.487	-0.076
Sharpe Ratio	-0.271	-0.128	-0.361	-0.350
2001-2007				
Mean	-0.594%	-0.131%	-2.101%	-2.071%
t-stat	1.24	0.45	2.21	2.27
Std deviation	0.066	0.061	0.097	0.089
Skewness	-1.017	-0.400	-1.364	-1.652
Kurtosis	3.315	-0.083	6.334	7.070
Sharpe Ratio	-0.091	-0.021	-0.216	-0.232

Table 37: Months with Zero Expected Announcers Deleted – Geometric Previous Year Method

Managed L/S Portfolio	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-1.970%	-0.080%	-0.256%	-0.177%
t-stat	2.30	1.06	1.92	1.41
Std deviation	0.085	0.007	0.013	0.012
Skewness	-1.356	-1.228	-4.119	-3.196
Kurtosis	3.777	3.194	28.986	25.677
Sharpe Ratio	-0.233	-0.108	-0.195	-0.143
1999-2000				
Mean	-3.444%	-0.143%	-0.398%	-0.257%
t-stat	1.15	0.53	0.96	0.70
Std deviation	0.095	0.007	0.011	0.009
Skewness	-0.257	-1.062	-0.899	-0.866
Kurtosis	-0.836	2.428	0.233	1.255
Sharpe Ratio	-0.364	-0.204	-0.376	-0.274
2001-2007				
Mean	-1.540%	-0.062%	-0.215%	-0.154%
t-stat	2.15	0.99	1.79	1.32
Std deviation	0.082	0.008	0.014	0.013
Skewness	-1.799	-1.293	-4.543	-3.402
Kurtosis	6.374	3.536	31.663	26.438
Sharpe Ratio	-0.188	-0.082	-0.156	-0.118

Table 38: Managed L/S Portfolio – Geometric Previous Year Method

L/S Portfolio Traded in February, May, August and October	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-2.857%	-1.637%	-3.984%	-2.479%
t-stat	2.28	1.57	2.21	1.43
Std deviation	0.076	0.063	0.110	0.105
Skewness	-1.115	-0.377	-2.020	-1.777
Kurtosis	2.033	-0.603	7.088	6.555
Sharpe Ratio	-0.374	-0.259	-0.361	-0.236
1999-2000				
Mean	-5.006%	-1.343%	-7.097%	-6.133%
t-stat	2.25	0.58	2.46	1.80
Std deviation	0.064	0.066	0.085	0.099
Skewness	-0.415	-0.769	-1.136	-0.694
Kurtosis	-1.428	2.760	1.775	-0.032
Sharpe Ratio	-0.777	-0.205	-0.840	-0.617
2001-2007				
Mean	-2.224%	-1.721%	-3.055%	-1.382%
t-stat	1.50	1.44	1.42	0.70
Std deviation	0.079	0.064	0.116	0.106
Skewness	-1.372	-0.308	-2.354	-2.241
Kurtosis	2.995	-0.985	8.717	9.844
Sharpe Ratio	-0.281	-0.270	-0.264	-0.131

Table 39: L/S Portfolio Traded in February, May, August and October – Geometric Previous Year Method

7.5.2 Geometric Averages of Logarithmic Returns Fiscal Year Method

All Stocks With 4 Announcements the Previous Year				
	All Stocks	Expected Non-announcers	Excpected Announcers	L/S
1999-2007				
Mean	-1.969%	-1.046%	-0.982%	-0.469%
t-stat	2.44	1.24	1.31	0.57
Std deviation	0.085	0.072	0.045	0.086
Skewness	-1.356	-2.032	-2.772	0.930
Kurtosis	3.777	8.589	12.845	4.634
Sharpe Ratio	-0.232	-0.145	-0.216	-0.055
1999-2000				
Mean	-3.442%	-1.792%	-1.737%	-0.698%
t-stat	1.82	0.83	1.15	0.34
Std deviation	0.095	0.087	0.043	0.100
Skewness	-0.257	-0.769	-2.222	0.668
Kurtosis	-0.836	9.718	4.153	-0.261
Sharpe Ratio	-0.364	-0.205	-0.404	-0.070
2001-2007				
Mean	-1.539%	-0.830%	-0.765%	-0.404%
t-stat	2.15	0.93	0.17	0.45
Std deviation	0.066	0.067	0.046	0.082
Skewness	-1.799	-2.713	-2.991	1.034
Kurtosis	6.375	14.422	15.695	7.204
Sharpe Ratio	-0.233	-0.123	-0.166	-0.049

Table 40: Geometric Averages of Logarithmic Returns Fiscal Year Method – Geometric Fiscal Year Method

7.5.3 Geometric Averages of Logaritmic Returns Actual Dates

All Stocks With 4 Announcements Each Calendar Year				
	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-1,970%	-1,976%	-1,313%	0,050%
t-stat	2,44	2,20	1,42	0,06
Std deviation	0,085	0,094	0,096	0,094
Skewness	-1,356	-0,859	-0,159	0,512
Kurtosis	3,777	2,431	1,443	2,156
Sharpe Ratio	-0,233	-0,210	-0,136	0,005
1999-2000				
Mean	-3,444%	-3,882%	-0,599%	2,529%
t-stat	1,82	1,74	0,28	1,10
Std deviation	0,095	0,111	0,107	0,111
Skewness	-0,257	-0,309	-0,101	0,458
Kurtosis	-0,836	3,110	-0,086	-0,332
Sharpe Ratio	-0,364	-0,349	-0,056	0,227
2001-2007				
Mean	-1,540%	-1,417%	-1,515%	-0,636%
t-stat	1,59	1,48	1,49	0,67
Std deviation	0,089	0,089	0,094	0,088
Skewness	-1,799	-1,079	-0,201	0,451
Kurtosis	6,374	4,581	2,145	3,434
Sharpe Ratio	-0,172	-0,160	-0,161	-0,072

Table 41: All Stocks with 4 Announcements Each Calendar Year – Geometric Actual Method

Months with Zero Actual Announcers Deleted	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-1,457%	-1,464%	-1,475%	-0,460%
t-stat	1,90	1,66	1,51	0,43
Std deviation	0,076	0,087	0,096	0,104
Skewness	-0,758	-0,338	-0,159	0,155
Kurtosis	0,939	0,647	1,443	1,399
Sharpe Ratio	-0,192	-0,168	-0,153	-0,044
1999-2000				
Mean	-3,162%	-4,702%	-0,838%	3,129%
t-stat	0,91	0,79	0,72	0,21
Std deviation	0,087	0,113	0,104	0,131
Skewness	-0,354	-0,278	-0,076	0,554
Kurtosis	-0,575	-0,835	-0,103	-0,411
Sharpe Ratio	-0,363	-0,415	-0,080	0,239
2001-2007				
Mean	-0,938%	-0,457%	-1,662%	-1,480%
t-stat	1,67	1,44	1,32	0,38
Std deviation	0,072	0,076	0,095	0,093
Skewness	-0,897	0,026	-0,205	-0,499
Kurtosis	1,906	1,119	2,177	1,763
Sharpe Ratio	-0,131	-0,060	-0,176	-0,160

Table 42: Months with Zero Actual Announcers Deleted – Geometric Actual Year Method

Managed L/S Portfolio	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-1,970%	-0,162%	-0,171%	-0,018%
t-stat	2,30	1,44	1,67	0,14
Std deviation	0,085	0,011	0,010	0,013
Skewness	-1,356	-1,584	-3,061	1,261
Kurtosis	3,777	6,437	18,207	11,562
Sharpe Ratio	-0,233	-0,147	-0,171	-0,014
1999-2000				
Mean	-3,443%	-0,321%	-0,211%	0,090%
t-stat	1,15	0,72	0,84	0,07
Std deviation	0,095	0,015	0,009	0,017
Skewness	-0,257	-1,218	-0,809	2,091
Kurtosis	-0,836	5,094	1,865	8,943
Sharpe Ratio	-0,364	-0,214	-0,236	0,051
2001-2007				
Mean	-1,540%	-0,116%	-0,160%	-0,049%
t-stat	2,15	1,34	1,57	0,13
Std deviation	0,082	0,010	0,010	0,011
Skewness	-1,799	-1,678	-3,465	0,286
Kurtosis	6,374	6,169	20,780	11,918
Sharpe Ratio	-0,188	-0,120	-0,154	-0,043

Table 43: Managed L/S Portfolio – Geometric Actual Year Method

L/S Portfolio Traded in February, May, August and October				
	All Stocks	Non-announcers	Announcers	L/S
1999-2007				
Mean	-2,857%	-4,176%	-2,121%	1,515%
t-stat	2,28	2,70	1,52	0,83
Std deviation	0,076	0,095	0,084	0,108
Skewness	-1,115	-0,464	-1,552	0,492
Kurtosis	2,033	-0,356	4,941	1,708
Sharpe Ratio	-0,374	-0,441	-0,251	0,140
1999-2000				
Mean	-5,006%	-7,414%	-3,136%	2,931%
t-stat	2,25	1,67	1,47	0,52
Std deviation	0,064	0,130	0,061	0,157
Skewness	-0,415	0,082	0,038	0,783
Kurtosis	-1,428	-0,341	-1,054	-0,285
Sharpe Ratio	-0,777	-0,570	-0,512	0,187
2001-2007				
Mean	-2,224%	-3,208%	-1,827%	1,118%
t-stat	1,50	2,09	1,08	0,63
Std deviation	0,079	0,083	0,091	0,093
Skewness	-1,372	-0,552	-1,733	-0,060
Kurtosis	2,995	-0,718	5,276	3,042
Sharpe Ratio	-0,281	-0,389	-0,202	0,120

Table 44: L/S Portfolio Traded in February, May, August and October – Geometric Actual Year Method