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"Buy low, sell high, that's my motto."

An event study examining the Post Earnings Announcement Drift on the Swedish market

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1. Introduction

A goal and incentive for many actors in the financial market is to find investment opportunities that will generate easy money. Therefore, immense amounts of resources are spent each year to scour the stock market for trends and patterns in prices that can be capitalized on for a guaranteed positive return on investment. These trends and patterns are referred to as *market anomalies*, since they seem to contradict the notion that stock prices should change at near random. Finding market anomalies are not just the interest of market speculators but also in the interest of academics. Due to the fact that the anomalies indicate a market that does not function well and is behaving irrationally.

One of these market anomalies, commonly referred to as the *Post-Earnings Announcement Drift* (PEAD), was first discovered by Ray Ball and Phillip Brown (1968) in 1968. They noted that in the US stock exchange there seemed to occur a drift in a firm's stock prices after the firm had published its earnings report. If the firm reported earnings that were above what the market had expected, then there was a tendency for the firm's stock price to experience a positive drift after the announcement was made. The reverse was also true for firms that disclosed earnings that were lower than the market had anticipated. Ball and Brown's observations seemed to suggest that information, provided by the earnings report, was not incorporated fully into the firm's stock price at the time of publication. Instead it appeared that the market underreacted to the new information.

Since the PEAD discovery over five decades ago, vast amounts of studies have been carried out examining the PEAD effect. Although extensive research has been done on the US and other international markets, few have focused on the Swedish market. One paper that has aimed its attention at the Swedish market is Setterberg (2011). Setterberg found that the PEAD effect could be seen on the Swedish market from 1990 to 2005. The strategy generated an annualized abnormal return of 11.4% during a holding period of 12 months and was highly effective. According to Setterberg, this was the first time that the effect had been proven to exist on the Swedish market. Before Setterberg's paper, the Swedish market had been an anomaly in contrast to other international markets due to the lack of PEAD drift.

This thesis aims to join and extend this body of research by seeing if the PEAD effect can be observed on the Swedish market between the years 2006 and 2019 by doing an event study on

a sample of 121 firms. The firms selected were either currently listed on the Stockholm OMX Large Cap or Small Cap Index. A price based method was used to see the sign and magnitude of the earnings surprises. Firms were then ranked, highest to lowest, based on the size of their earnings surprise. The top 10% of the ranked firms were put into a portfolio called LONG, while the bottom 10% was put into a portfolio called SHORT. The holding period of the portfolios started three days after the earnings announcement and lasted 60 days. This analysis was done on the sample as whole and on two subsamples. The two subsample consisted solely of firms either listed on the Large Cap or Small Cap index. This was done to see if firm size has an impact on the PEAD effect. A t-test, formulated by MacKinlay (1997), was carried out to see if the drift in prices was statistically significant.

With the above stated methods and sample this thesis found that both good and bad news firms experienced a drift in prices. The drift was at its strongest in bad news firms, they had an absolute drift of 2,55% during the 60 day holding period, which was statistically significant at a 1%-level. Good news firms also experienced a drift at 1,12%, but was only statistically significant at a 10%-level. The subanalysis indicates that the drift in the overall sample is driven by the Small Cap firms. The drift in Small Cap firms for position LONG and SHORT was 2,23% and 4,02% respectively, almost twice the size of the overall sample in both positions. Although, the drift was only statistically significant in position SHORT at a 10%-level. On the other hand, the drift in large cap firms was close to zero and statistically insignificant. Although a drift was observed in the stocks, the practical implications of the results were limited. Firstly, the drift seems to mostly occur in small bad news firms. To take a position in these firms, that would exploit the effect, would certainly induce high transaction costs that could erode away any profit from the strategy. Secondly, when looking at the quarterly data, the positions induces large losses in the short term. Finally, there are issues with the methodology that question the validity of the results.

This thesis is structured as follows. In section 2, *Past research*, the reader is briefly introduced to event studies and research papers examining the PEAD effect are thoroughly examined. Then, in section 3, *Sample and methodology*, the sample selection and construction is presented along with the steps taken to bring about the result, which is shown in section 4, *Result.* The results are then further examined and contrasted against past research in section 5, *Discussion.* Finally, the main result and insight from the thesis is summarized in section 6, *Conclusions*.

2. Past research

The section *Past research* is divided up into three main parts. The first part is a brief explanation of event studies. This is done to make the reader acquainted with the basic methodology and terminology used by researchers to study the PEAD effect. In the second part, research done on markets internationally, as well as studies done on the Swedish market, will be addressed. Furthermore, the methodology, such as the holding periods of the portfolios and time period examined, varies across the papers. Thus, these aspects will also be deliberated in this section. And in the last part, three possible explanations for the PEAD effect will be presented.

As noted in the introduction, there is a substantial amount of literature written about the PEAD effect. This thesis is only able to present a relatively small selection of papers that have been produced since PEAD discovery five decades ago. Also, there exists a wide array of possible explanations for the PEAD effect (see Setterberg, 2011). The three explanations given in this thesis, therefore, is not an exhaustive list of all possible reasons. Nonetheless, the explanations brought up in this thesis were considered by the author as the most valuable to obtain a better grasp of the PEAD in the context of this thesis.

2.1 An introduction to event studies

The goal of an event study is to see if an event moves the price of a stock above or below its normal level of return. The underlying assumption of an event study is the *Efficient market hypothesis* (EMH) (MacKinlay, 1997). EMH states that markets are able to incorporate all available information about a firm into its stock price. Thus, when new information is released to the market, prices change accordingly to the new information. One can therefore see the market's reaction, and the magnitude of the reaction, to an event by analyzing stock prices movement during the time space of the event. Such an event can be a firm's quarterly report, in which a firm discloses their earnings for the past quarter. If the reported earnings were above market expectation, and the EMH holds, then prices would rise. The opposite would be true for earnings below expectations. However, the interest of this thesis and the papers presented in past research is not only to see how returns of a stock react initially to a firm's earnings, but if the abnormal level of return persists after the announcement in the form of a drift in prices.

The procedure of an event study is straight-forward and simple, but involves several steps that have been outlined by MacKinlay (1997). Firstly, you need to define three time intervals: event window, post-event window and estimation window. The *event window* is the time interval when the new information is brought to the market. In this thesis, the event window is the announcement of the quarterly earnings report. It is also the window where earnings surprises are measured for respective firms. The *post-event window* is the time after the event window. This time period is the main interest of this thesis, since it is in this interval where the PEAD effect shows itself. The *estimation window* is the time interval before the event when the expected return of the stock is approximated. A detailed outline of this thesis definition of the time intervals for the different windows will be provided in section 3.2, *Methodology.*

To see the extent of the event one needs to then calculate the daily *abnormal return* for a stock during the event and post-event window. Abnormal return is merely the difference between the actual return and the expected return of the stock at a given date. The expected return can be approximated during the estimation window with several different models. One of these models, which is also used in this thesis, is the *market model*. This model involves running an OLS regression on the return of a stock during the estimation period against the return of a portfolio that represents the overall market. With the intercept and slope coefficient of the best fit linear line, the daily expected return of a stock can be calculated for the next two event time intervals given the return of the market portfolio on the specific day.

2.2 Result and methodology of past research

PEAD studies performed on stocks listed on the US market have achieved similar results. Foster et al. (1984) and Bernard and Thomas (1989) both looked at the US market using similar methods, but at slightly different time intervals. The studied time periods were 1974 to 1981 and 1974 to 1986 respectively. Both papers arrived at parallel results. Foster et al. (1984) found a positive (negative) drift for positive (negative) earnings news firms during a 60 day holding period. Bernard and Thomas (1989) also used a 60 day holding period and found the same drift patterns as Foster et al. (1984). Using the long-short strategy, they could generate an annualized return of 18%. The strategy was also fruitful, giving a positive return 88% of the time it was implemented.

Other international markets have shown similar behavior as the US market. Liu et al. (2003) looked at the UK market between 1988 and 1998. They tested a range of methods to detect a possible PEAD effect. What they found was a significant drift for both positive and negative news firms with all measurements, even when controlling for risk. Employing a long-short strategy, as Bernard and Thomas (1989), they could create profits of 10.8% for a holding time of 12 months. When the holding time was reduced to 3-, 6-, 9-months the profits decreased to 2.9%, 5.2% and 8.2% respectively. Booth et al. (1996) looked at the Finnish market from 1981 to 1993 and found limited evidence of the drift. It could not be established statistically that there was a positive drift for firms with good news. Nevertheless, the negative drift for bad news firms was statistically significant. Kallunki (1996), who also looked at Finnish stock, found the same results as Booth et al. (1996). Kallunki argues that, in contrast to the US market, Finnish investors can not capitalize on negative news firms due to short-sale constraints. It should be noted that both papers employed a relative short post-event window for their portfolios compared to other papers. Booth et al. had a 10 day holding period, while Kallunki used a 30 day holding period.

Setterberg (2011) looked specifically if the PEAD effect could be observed on the Swedish stock market. Setterberg found that from 1997 to 2004 a long-short strategy led to a risk adjusted monthly return of 11.4%. Moreover, the strategy was highly successful when looking at the returns for each individual quarter. Out of 28 quarters, 20 quarters generated positive returns and eight invoked negative returns. However, most of the return was made from the long portfolio. The short portfolio lacked a drift in prices, and was not significant when adjusted to risk. Setterberg (2011) further found that the PEAD effect becomes stronger when the holding period is increased from six months to 12 months. This result diverges from other research that shows that most of the drift occurs during the first 60 trading days and becomes statistically insignificant beyond 180 trading days (Bernard & Thomas, 1989). Setterberg ponders that the prolonged drift could either be the cause of: (i) an omitted risk factor, (ii) Swedish investors taking longer to process information or (iii) that transaction costs limit investors' capacity to exploit the effect. These possible explanations for the PEAD will be further explored in section 2.2, *three possible explanations for the PEAD effect,* of this thesis.

One aspect that differs between the studies is the effect of firm size on the drift. When Setterberg (2011) accounted for firm size in the long and short portfolios the drift became insignificant. Setterberg concludes that small stocks were the primary factor behind the return

created by the strategy. Foster et al. (1984) arrived at the same conclusion that smaller firms show a large drift. About 65% of the drift could be explained by the size of the firm. Bernard and Thomas (1989) further showed that average abnormal return for small-sized (large-sized) firms during the 60 days holding period for position LONG and SHORT was 2.19% (1.45%) and -3.13% (-1.29%) respectively. Through regression analysis, they saw that the magnitude of the absolute drift was negatively correlated with firm size. Demonstrating, once again, that firm size has an impact on the return of the strategy.

The method used to quantify the magnitude of the positive and negative earnings surprise varies between the reviewed studies. One can identify three main methods to operationalize the *unexpected* earning for a firm. First, one can use the *standardized unexpected earnings* (SUE). SUE requires one to run a basic AR(1) process on a firm's past earnings to forecast future earnings. The forecasted earnings then act as the firm's expected earnings. These expected earnings are then subtracted from the actual earnings and divided by the standard deviation of expected earnings. This is the most commonly used measurement in the reviewed studies (see Bernard & Thomas, 1989, 1990; Foster et al., 1984; Setterberg, 2011; Liu et al., 2003; Chordia et al., 2009: Rendleman et al., 1982). Second, one can calculate the abnormal returns for the days before, under and after the announcement date. This will encapsulate both the positive and negative earnings surprise by seeing if the stock price, respectively, rises or drops unexpectedly around the earnings announcement date (Foster et al., 1984: Liu et al., 2003). Third, a method similar to SUE, is using actual earnings forecasts done by market analysts as the measure for expected earnings (Liu et al., 2003).

Each one of these measures (SUE, price based and analyst forecast method) comes with its own disadvantages. Using SUE will limit the time period of the sample where one can perform PEAD analysis, because one needs an ample amount of past earnings to forecast assured future earnings. This will limit one's ability to draw conclusions about the PEAD on the market, since the studied time period has to be narrowed. The drawback of the price based method's is that it measures *all* value-relevant news that affects the firm around the announcement date, not just the earnings news (Liu et al. 2003). Changes in interest rate, the world economy, firm management etc. might happen around the quarterly earnings report and have an impact on the price of a stock. Finally, the analyst forecast method can often only be used for large firms, due to the fact that analyst forecasts for small firms are sparse. As seen in Liu et al. (2003), this can become a hindrance if you want to see how firm-size affects the

PEAD. Additionally, Liu et al. (2003) points out that analyst forecasts can be biased due to a conflict of interest for the market analyst, between having impartial forecasts and favouring firms that are their clientele.

Furthermore, the way you operationalize unexpected earnings can have an effect on your conclusions. Foster et al. (1984) and Liu et al. (2003) employed several of these approaches on their respective data to see if they would generate the same results. Foster et al. (1984) used both the SUE and a price based method in their paper. The outcome was that the PEAD effect could be distinguished with the SUE variable, but not when using the price based method. The reasons for this were not explored further by the authors. On the other hand, Liu et al. (2003) came to a different conclusion. They applied all three measures on their data and they were able to identify a PEAD effect with all applied measurements. The three measurements showed a strong correlation with each other when it came to classifying unexpected earnings. However, in this case the price based model was able to recognize the strongest drift. These conflicting results could be attributed to the fact that the event window varies between the studies. Foster et al. (1984) looked at the abnormal return of the preceding and the day of the announcement, while Liu et al. (2003) looked at a four day period. It could be the case that Foster et al. (1984) method missed the market's reaction to the event with the limited event window. Whatever the case may be, these studies show the impact of methodology implemented.

The choice of time period studied can affect one's conclusions. Rendleman et al. (1982) examined if stocks on the US market experienced the PEAD effect, from the third quarter of 1971 to the first quarter of 1980, to see if they could replicate the result of a study done by Reinganum (1981). Reinagnum had found no signs of the PEAD effect in his study. However, he had only analyzed stocks between the fourth quarter of 1975 and third quarter of 1977. Replicating Reinganums method, Renleman et al. (1982) found evidence of the PEAD effect during the whole time period. They noted that the effect was at its weakest during the period which Reinagnum had analyzed. Therefore, they concluded that a primary reason for the conflicting results was Reinganum choice of studied time period. He had chosen “the one subperiod out of almost an entire decade that would lead him to his conclusion [...]” (Renleman et al. 1982, p. 277).

2.3 Three possible explanations for the PEAD effect

2.3.1 An excluded risk factor

One simple cause of the PEAD effect that has been proposed is that there is an unknown risk that drives the drift. Nonetheless, the papers considered in this thesis have used several models to see if different stock risk exposure is the cause. One of them being the single index model that tries to explain a stock return based on the stocks exposure to market risk. Rendleman et al. (1982) created long and short portfolios with an equal exposure to market risk. Hence, when a long-short strategy is implemented, their returns should cancel out each other. However, the differences in return between the two portfolios were statistically significant from zero. Bernard & Thomas (1989) points out if systematic risk induced drift, then the drift return would move with the return of the market. Further, Setterberg (2011) calls attention to the fact that the drifts for the good and bad news move in opposite directions. If risk were the main cause for PEAD, then the two drifts would move in conjunction with each other.

The Fama-French three factor model has also been utilized in several of the research papers. The Fama-French three factor model is a multifactor model that identifies three risk factors that affect a stock's return. They are the stocks: exposure to market risk, market capitalization (i.e. firm size) and book-to-market ratio. It has been shown that this model can be more effective in explaining a stock's return than the single index model (Fama & French, 1992). Setterberg (2011) and Liu et al. (2003) both applied this model in their studies. However, both researchers found that even when these risk factors were accounted for, they still could not explain the drift in prices.

Furthermore, most of the return from the PEAD strategy, noted by Bernard & Thomas (1989, 1990) and Liu et al. (2003), comes from the days surrounding the subsequent quarterly report. They reason that a rapid change in risk during these few days, that would explain the increased return, is highly unlikely. Bernard & Thomas (1989) also found that the strategy is continuously profitable throughout their studied time period. They argue that the lack of downside risk shows that the return gained with the strategy is not a risk premium. With the above considered, many research have concluded that it is instead more probable that the drift is created by investors' underreaction to the earnings news than an excluded risk factor.

Still, Setterberg (2011) voices concern that researchers have to easily dismissed risk as an explanation. It is possible that the models used do not regard all risk factors that affect a firm. She reckons that the lack of drift in the bad news firms might be a result of an omitted risk factor. As Fama (1998) further explains, by definition, all models do not and can not fully explain the return of a stock. Therefore, when studying market anomalies, you are not only testing if the anomaly exist, but you are also testing the effectiveness of your model. In conclusion, bad-model problems, as Fama (1998) calls them, can never be avoided and should always be considered when performing event studies.

2.3.2 Behavioral biases

Patterns in stock prices, such as the PEAD, have been attributed to limitations of human psychology. Humans have shown to have an inclination to make suboptimal decisions due to difficulty processing information correctly and reasoning biases. *Conservatism* is such a limitation to human reasoning and has been proposed by Barberis et al. (1998) as a cause for the PEAD effect. Conservatism means that there is a lag in the human ability to absorb and update one's beliefs based upon new information. Consequently, the drift in prices after an earnings surprise is the result of investors underreacting to the new information and steadily correcting their mistakes as they slowly process the new information.

Bernard and Thomas (1990) also attribute the drift to the underreaction of investors to publicly available information. They argue that investors naïvely seem to assume that earnings follow a seasonal random walk and, therefore, ignoring the effect that current earnings have upon future earnings. The market does not revise its future earnings expectations when a quarterly earnings change relative to the corresponding quarter of last year. This leads to a positive autocorrelation in unexpected earnings surprises, that Bernard and Thomas (1990) used to predict future surprises confidently in their study.

Yet, even if one would accept these arguments as the cause of the PEAD effect it does not explain the persistence of the effect. One would assume that arbitrageurs would have realized the irrationality of the market, exploited it for their own gain and thus traded away the effect. However, as we have seen in section 2.2 *Past research*, the PEAD effect has continued to survive on the market. This could indicate that there are restrictions to perform arbitrage. Such a limitation could be the presence of market frictions. Nevertheless, market frictions

have not only been proposed as an explanation for the vitality of the effect, but also as the cause of its existence (Ng et al., 2008).

2.3.3 Presence of market frictions

Few of the studies examined have included the effect of market frictions, such as transaction cost, into their calculations. Still, this factor has not been ignored by the researchers. For example, Bernard and Thomas (1990) state that transaction cost might lead to a "'sluggishness' in prices" (p. 333) as markets react initially to the earnings announcement, but it cannot explain why the drift occurs for months after the announcement.

Ng et al. (2008), on the other hand, argue to the contrary. They looked specifically at how transaction cost, measured as the bid-ask spread plus commission cost, and immediacy costs, such as opportunity cost, affected the PEAD effect. They found that when cost had been deducted from the portfolios, created with the PEAD strategy, the profit turned statistically insignificant. Furthermore, the shares with higher transaction cost were the primary contributors to abnormal return in the portfolios. They concluded that market frictions are a barrier for traders to move stock prices to their fundamental values, leading to a drift in prices.

Ng et al. (2008) results are partially supported by Chordia et al. (2009). They observed that when short sale costs were included in the analysis, transaction costs amounted from 70% to 100% of the total return gained from the strategy. Additionally, the main brunt of return from the strategy came from highly illiquid stocks, which have a higher transaction cost. The fact that short sale constraints limit investors' ability to exploit the effect is also supported by Kallunki (1996) and Bernard & Thomas (1989) findings. Kallunki (1996) found only a drift for the short portfolio, which he attributed to short sale constraints on the Finnish market. Bernard & Thomas (1989) found some evidence that the short portfolio leads to a larger drift than the long portfolio, which can be contributed to short sale constraints.

3. Sample and methodology

The sample and methodology section will firstly provide an overview of the sample and data used. Then, a detailed examination of the methodology applied in the thesis will be laid out. The reason for the sample selection and methodology will also be presented and argued for, given the insights from past research.

3.1 Sample selection and data

The event study has been carried out on 121 firms that are currently listed on the OMX Stockholm Large Cap and Small Cap index. Out of the sample of 121 firms, 84 firms came from the Large Cap index, while the remaining 37 firms were gathered from the Small Cap index. In total, the effect of 6776 quarterly reports have been analyzed in this thesis.

A time period of 14 years have been studied for a sample that consists of both Large and Small Cap firms. The reason for choosing a time horizon of 14 years is to limit time specific effects on the result. As seen in Rendleman et al. (1982), a narrow time period can lead to faulty conclusions. Also, the time period looked at in this thesis starts right after Setterberg's (2011) studied time period. It is of interest to see if the effects seen by Setterberg can be detected in the years following her study. Research has also shown that the effect is widely connected with firm size. Therefore, two subsamples were created where firms were divided based on which index they belonged to. A subsample analysis was then executed to see if the PEAD effect was stronger in one of the subsamples.

All the data for the different variables was retrieved from Thomson Reuters Datastream. Datastream return index (RI) was the variable used to gauge the daily firm and market return. RI shows the value of a share, assuming that all dividends are reinvested into the stock. The Morgan Stanley Sweden Index (MSCI) was used as an approximation for the market return. The quarterly report dates for each firm were also obtained from Datastream. In the case of missing dates in the database, quarterly report dates were gathered from the affected firms website if available.

Certain limitations were implemented for the sample selection. Firstly, firms needed to be listed during the whole time period. Secondly, firms needed to have daily RI data and

quarterly announcement dates for the whole time period. Thirdly, firms fiscal year needed to follow the calendar year. If a firm in each respective index did not fulfill all three requirements, it was excluded from the sample. This has led to 48 firms from the OMX Stockholm Large Cap index and 56 firms from the OMX Stockholm Small Cap index being excluded from the sample. To reject such a large number of firms from each respective index is not favorable. However, these limitations were implemented to get accurate results. Without extensive daily RI data for the firms the OLS regression would be ineffective. Further, the constraints are in line with research done on the subject (see Liu et al., 2003).

On the other hand, a problem that arises from the sample selection is *survivorship bias.* The sample consists only of firms that have been active during the whole studied time period. No firms that seized trading during the timeline have been analyzed. There is a possibility that the effect differs between these two kinds of firms. It could be that the effect is more distinct in the firms that have survived during the time period, or vice versa. However, none of the papers, acquainted in section 2.2, *Past research*, have discussed the possible effect of a survivorship bias in the sample. Nonetheless, it is of value to point out this possible limitation in this thesis.

3.2 Methodology

3.2.1 Time intervals for the estimation, event and post-event windows

As stated in section 1, *Introduction*, to carry out an event study one needs to first define the time intervals for the estimation, event and post-event windows. This has been done for the three windows below. The different windows time intervals are defined relative to the event day (i.e. a stocks quarterly earnings announcement date), which is denoted as t_0.

Estimation Window - $[t_{-260}, t_{-11}]$

The time period begins 260 days before the event day and ends 11 days prior to the event day. Leading to the interval of $[t_{-260}, t_{-11}]$, i.e. an interval of 250 trading days, where a stock's expected return is approximated using OLS. This follows the methodology used by Booth et al. (1996) and Kallunki (1996), which used a similar sized estimation window. It also follows the guidelines by MacKinlay (1997). The estimation window is large enough to get accurate estimations of a stocks normal return. Further, the estimation and event window are separated

from each other, which makes sure that the event will not affect the estimation of a stock expected return.

Event Window - $[t_{-1}, t_2]$

The event window is the day prior, the day of the event and the two subsequent days after the event day, giving an event window of 4 days where the earnings surprise is measured. There are arguments for including more days in the event window than just the event day (t_0). Mackinlay (1997) states that information about the event might have been supplied to the market before the event date. Besides this, the announcement may have been made after the closure of stock markets. Therefore, the market reaction to the earnings announcement will happen on the day after the event day. The reason for extending the window to 4 days is to have the same event window as Liu et al. (2003). Since this thesis method of measuring earnings surprise follows the methodology used by Liu et al. (2003).

Post-event Window - $[t_3, t_{62}]$

The post window is defined as the 60 trading days after the event window. During this time interval the abnormal return of the stocks are measured to see if a drift occurs in the prices after the quarterly announcement. As noted by Bernard & Thomas (1989), most of the drift occurs during the 60 days after the announcement. Therefore, this thesis will look at the abnormal return during the 60 days succeeding the event window.

However, this goes against Setterberg's conclusions about the PEAD drift on the Swedish market. Setterberg could only observe a statistically significant drift when the post-event window was extended to 12 months. However, the justification for reducing the post-event period is that taking long and short positions in stocks for 12 months is not a viable investment horizon for most investors. On the other hand, 60 trading days, which is about 3 months, is a much more feasible investment horizon. This will increase the practical implication of the result, reflected in section 5, *Discussion and conclusions.*

3.2.2 Measuring the daily return and abnormal return

Using the Datastream RI values, the daily return for each stock, market index and 30-days treasury bill was calculated as follows:

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

where,

$R_{i,t}$	= is the daily return for stock i at day t
$RI_{i,t}$	= is the Datastream daily RI for stock i at day t

With the daily returns calculated, the expected return for each corresponding quarter needs to be approximated to measure the abnormal return. The model used to approximate the expected return is the *market model*. This model approximates the expected return of a stock by doing an OLS regression on the return of the stock against the return of the market portfolio, MSCI. The case for using a single index model instead of a multifactor model is that the benefits from using a multifactor model are limited (MacKinlay 1997). The regression is run on the return of the two equities during the estimation window. Doing the regression, we get this best fit line:

$$E[R_{i,t}] = \alpha_i + \beta_i R_{M,t}$$

where,

$E[R_{i,t}]$	= is the expected return for stock i at day t
α_i	= is the regression intercept for stock i
β_i	= is the regression coefficient for stock i, showing the stock's sensitivity to the market
$R_{M,t}$	= is the daily return of the market index, MSCI, at day t

It should be noted that the regression is run on the nominal return and not excess return, as this is the normal methodology when working with daily data (MacKinlay, 1997). With the expected return approximated, the abnormal return can be calculated. This is the difference between the actual and expected return during the post-event window. Therefore, abnormal return is measured with the following equation:

$$AR_{i,t} = R_{i,t} - \alpha_i - \beta_i R_{M,t}$$

where,

$AR_{i,t}$	= the abnormal return for stock i at day t

$R_{i,t}$ = is the daily return for stock i at day t

α_i = is the regression intercept for stock i

β_i = is the regression coefficient for stock i, showing the stock's sensitivity to the market

$R_{M,t}$ = is the daily return of the market index, MSCI, at day t

3.2.3 Measuring the earnings surprise

This thesis uses a price method approach to operationalize earnings surprises. The abnormal return of a stock on the day prior, the day of the event and the two subsequent days after the event day is summarized, giving the variable *cumulative 4 day abnormal return* (CAR4D). CAR4D therefore follows this equation:

$$CAR4D_i = \sum_{t=t_{-1}}^{t_2} AR_{it}$$

where,

$CAR4D_i$ = is the aggregated abnormal return for stock i, between the days t_{-1} and t_2

$AR_{i,t}$ = is the abnormal return for stock i at day t

This method is a variation of the method used by Liu et al. (2003). One of the ways that Liu et al. (2003) operationalized earnings surprise was through the variable AR4D, which also looked at the abnormal return during the same event window as CAR4D. However, the method with which they calculated the abnormal return differs from this thesis. Instead of using the market model they used a *benchmark model*. The benchmark model calculates the abnormal return by subtracting a firm's return by the return of a market portfolio that emulates the stock. Furthermore, instead of summing the 4 day abnormal return, they compounded it. Although this thesis methodology is not an exact replica of the one used by Liu et al. (2003), the principal is the same. The variable CAR4D will also indirectly capture the earnings surprise, the same way that AR4D does.

3.2.4 Measuring the cumulative average abnormal return (CAAR)

Each stock is then ranked based on their CAR4D value. Two equally weighted portfolios, LONG and SHORT, are then created for each quarter. LONG contained the 10% stocks that had the highest CAR4D value and SHORT contained the 10% stocks that had the lowest

CAR4D value. The *average abnormal return* (AAR) was then calculated for the two portfolios using the equation below,

$$AAR_{p,t} = \frac{1}{N_p} \sum_{i=1}^{N_p} AR_{t,i}$$

where,

$AAR_{p,t}$	= is the average abnormal return for the portfolio at day t for position p
N_p	= is the amount of firms contained in the position p
$AR_{t,i}$	= is the abnormal return for stock i at day t that is part of the portfolio

When the abnormal return for the two portfolios have been calculated they are summarized during the post-event window, giving the variable *cumulative average abnormal return* ($CAAR$). This step is shown in the equation below:

$$CAAR_{q,p}(t_{3,}t_{62}) = \sum_{t=t_3}^{t_{62}} AAR_{p,t}$$

where,

$CAAR_{q,p}(t_{3,}t_{62})$	= is the cumulative average abnormal return between day t_3 and t_{62} for position p at quarter q
$AAR_{p,t}$	= is the average abnormal return at day t for position p

With the above steps, a CAAR value was generated 56 times for each respective position, LONG and SHORT. To see the overall effect during the entire time period, the total mean CAAR for each position was calculated:

$$CAAR_p(t_3, t_{62}) = \frac{1}{56} \sum_{i=1}^{56} CAAR_{q,p}(t_{3,}t_{62})$$

Another measure that has been used instead of CAAR is the *buy-and-hold abnormal return* (BHAR) (see Setterberg, 2011 and Liu et al. 2003). The BHAR measure multiplies the

abnormal return during the post-event window instead of adding them together, as in CAAR. In other words, BHAR compounds the abnormal return, simulating investors' real life experience (Setterberg 2011). However, complications emerge when using BHAR as a metric. Firstly, statistical inference is complicated due to BHAR compounding nature. The distribution of BHARs are generally skewed and not centered around zero (Setterberg 2011). Secondly, it might lead to spurious results. Fama (1998) states that BHAR can report growth even though no abnormal return has occurred during the measured period.

On the other hand, using CAAR also comes with its disadvantages. As noted by MacKinlay (1997), CAAR implicitly assumes that the portfolios are continuously rebalanced to equal weights during the holding period. This can lead to an upward bias in the result if the stocks are subjected to high transaction costs. This issue is partially amended in this thesis by mainly analyzing large cap stocks, which often experience low trading cost. Although, CAAR upward bias will limit the conclusions made from the subsample analysis, where the above methodology is carried out on large and Small Cap stocks independently from each other. This complication, and its implication on the subsample result, will be addressed further in section 5, *Discussion*.

3.2.5 Statistical test on CAAR

To see if the CAAR is statistically significant, a t-test, formulated by MacKinlay (1997), is performed. This was done on the whole sample and the two subsamples. To carry out the test, the variance of CAAR during the post-event window for each respective portfolio needs to be calculated with the following equation:

$$V_p(CAAR(t_3, t_{62})) = \frac{1}{N_p^2} \sum_{i=1}^{N_p} (t_{62} - t_3 + 1)\sigma^2_{\varepsilon,i,p}$$

where,

$V_p(CAAR(t_{3,} t_{62}))_i$	= is the variance of cumulative average abnormal return for position p
N_p	= is the number for firms included in position p
$\sigma^2_{\varepsilon,i,p}$	= is the variance of the error term from the OLS regression for stock i included in position p

To find the t-value for each respective CAAR, we divide the CAAR value during the post event window with the square root of the CAAR variance during the post-event window. The equation is thus:

$$t_p = \frac{CAAR_p(t_3, t_{62})}{\sqrt{V_p(CAAR\,(t_{3,} t_{62}))}}$$

where,

t_p	= is the t-value for position p
$CAAR_p(t_{3,} t_{62})$	= is the cumulative average abnormal return value for position p
$V_p(CAAR(t_{3,} t_{62}))$	= is the variance of cumulative average abnormal return for position p

Using the above equation, CAAR should be distributed around zero with a variance equal to one. The null hypothesis tested, that there is no drift in either position, is two-tailed and formulated below with its corresponding alternative hypothesis:

$$H_0 : \; CAAR_p = 0$$
$$H_1 : CAAR_p \neq 0$$

4. Results

In this section the result of the data analysis will be shown. Firstly, the result for the whole sample will be presented. Afterwards, the subsample analysis, where firms have been divided in two subsamples based on their respective index, will be exhibited. Certain issues have arisen during the data analysis. These problems will also be addressed in this section.

4.1 Whole sample analysis

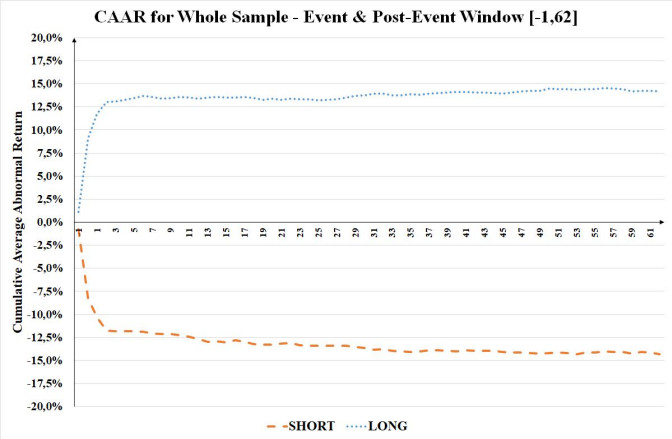

Figure 1 - *Shows how CAAR develops, in percentage, for position LONG and SHORT during the event and post-event window, i.e. from day* t_{-1} *to* t_{62}.

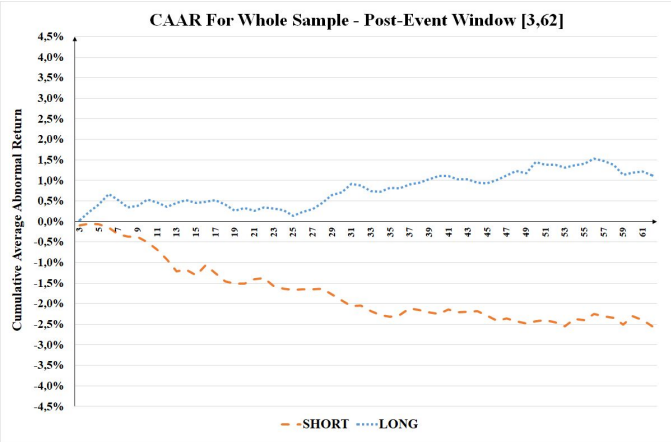

Figure 2 - *Shows how CAAR develops, in percentage, for position LONG and SHORT during the post-event window, i.e. from day* t_3 *to* t_{62}.

In Figure 1 we see how CAAR evolves from the day prior to and 63 days after the event date. The figure shows the initial steep reaction to the earnings news. From table 1 we can see that the CAR4D reported a 13,0416% and -11,7441% reaction for position LONG and SHORT respectively. Although it is not apparent in figure 1, one can see signs of a drift in both positions. The drift is made more evident in figure 2, where CAAR is measured during the post-event window. We see that the drift for the LONG position is negative from day t_3 to t_{25}. However, the drift then turns positive after day t_{25} increases until day t_{56}. Contrary to the LONG position, the drift is stronger and more prominent in the SHORT position. The drift is negative from day t_3 until day t_{35}, where it peters out till day t_{62}. The CAAR(t_3,t_{62}) values, seen in table 1, for position LONG and SHORT were 1,1240% and -2,5496% respectively.

Table 1 - *Shows the CAAR(t_3,t_{62}), t-stat for CAAR(t_3,t_{62}), CAR4D, average OLS beta values and the number of samples for position LONG and SHORT. ***, ** and * show statistical significance at the 1%-, 5%- and 10%-level respectively.*

	Whole Sample	
	LONG	**SHORT**
CAAR(t_3,t_{62}) *(t-stat)*	1,1240%* *(1,682844)*	-2,5496%*** *(-3,182218)*
CAR4D	13,0416%	-11,7441%
Average OLS Beta	0,701322	0,692925
N	672	672

Table 1 displays that drift in the LONG position is statistically significant at the 10% level, while the drift in the SHORT position is statistically significant at the 1% level. This confirms what was shown in figure 2, that the drift is larger and more pronounced for bad news firms. On the other hand, bad news firms experience a smaller initial reaction compared to the good news firm. This seems to contradict the notion that the magnitude of the initial reaction correlates with the level of drift. Even though the bad news firm had a smaller reaction to their news, their drift was double the size of the drift in the LONG position.

Both figure 2 and table 1 seem to indicate that the two drifts, although one being only slightly significant, is not a compensation for market risk. Firstly, figure 2 shows clearly that the two drift move in opposite directions. Furthermore, this is supported by the fact that the average OLS beta for the two positions are almost identical. If the return gained through the two positions was a risk premium for market risk exposure we would see them move parallel to each other. However, figure 3 below complicates this conclusion by showing the quarterly CAAR(t_3,t_{62}) value for both positions.

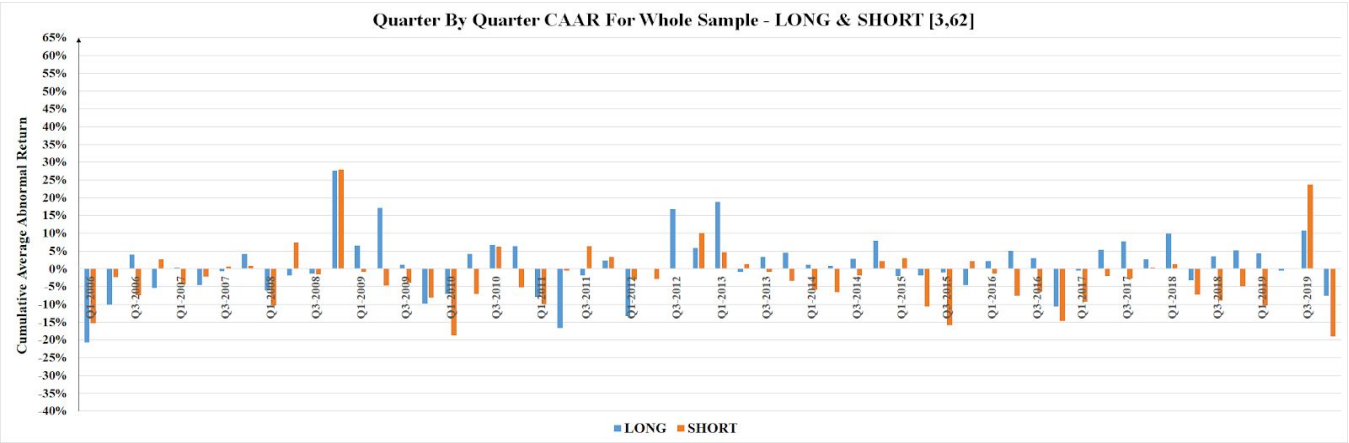

Figure 3 - *Shows quarterly CAAR(t_3,t_{62}) values for both LONG and SHORT positions.*

Figure 3 shows that there is an inherent risk in taking the positions. Out of the 56 times the LONG position was taken, 32 lead to a positive CAAR(t_3,t_{62}) value. While the SHORT position had a negative CAAR(t_3,t_{62}) value 37 times out of the 56 times the position was taken. Additionally, figure 3 also shows that there exist certain time intervals where the two positions move in parallel with each other. Such as: Q1-2006 to Q2-2006, Q3-2008 to Q4-2008, Q4-2009 to Q1-2010 and Q3-2019 to Q4-2019. The most extreme cases being Q4-2008 and Q3-2019. In figure 4, both positions move in parallel with each other upwards during Q4-2008. While for Q3-2019, seen in figure 5, there is a large jump at day t_{15} for the short position. In further examination of the data, the spike was likely caused by a single firm reporting a daily return of 185,38%. Although, the SHORT positions still have a positive drift. These results indicate that a multifactor model might have been the better choice for estimating return. It also questions the validity of results due to the influence of outliers.

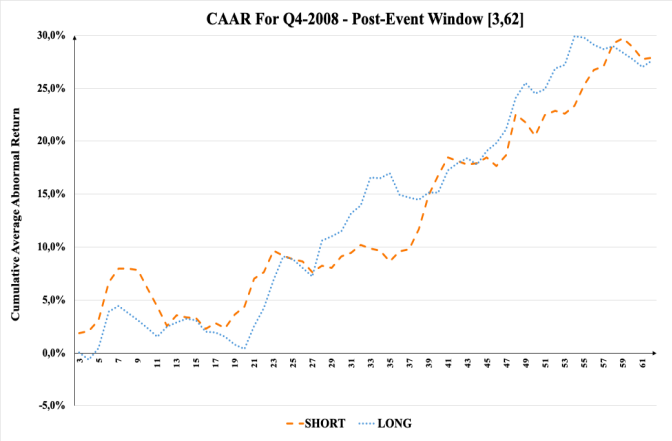

Figure 4 - *Shows how CAAR developed for position LONG and SHORT between day t_3 and t_{62} for the fourth quarter of 2008.*

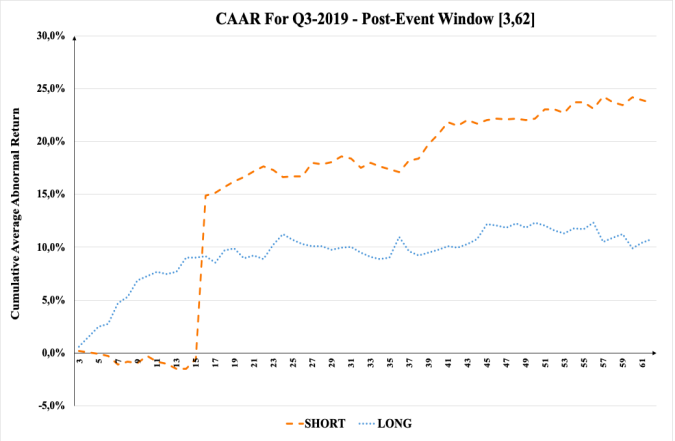

Figure 5 - *Shows how CAAR developed for position LONG and SHORT between day t_3 and t_{62} for the third quarter of 2019.*

Another issue related to the employed market model used to estimate stock return is low R-squared values for some regressions. R-squared shows how much of the variation of the dependent variable is explained by the OLS best fit line. In other words, how good the OLS regression line fits the data. The average R-squared value for the whole sample was 28,7%. However, there is a stark difference between firms in the Large Cap and Small Cap indexes. Large Cap firms had an average R-squared value of 34,8%, while the average R-squared value for Small Cap was 6,1%. This further demonstrates that a multifactor model would have been in order for this thesis, such as the Fama-French three factor model that accounts for return based on firm size.

4.2 Subsample analysis

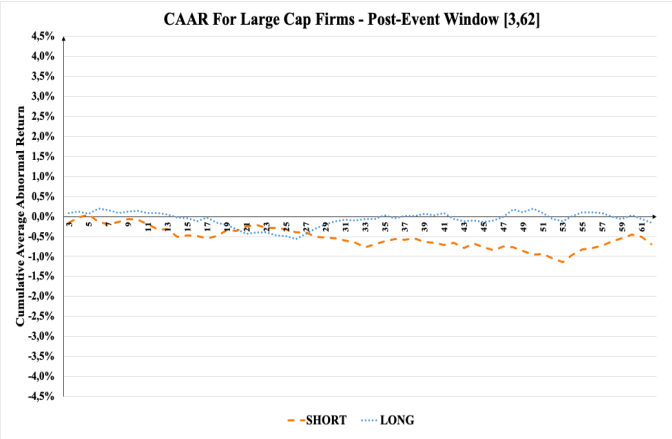

Figure 6 *- Shows how CAAR develops, in percentage, for positions LONG and SHORT for Large Cap firms between day t_3 and t_{62}.*

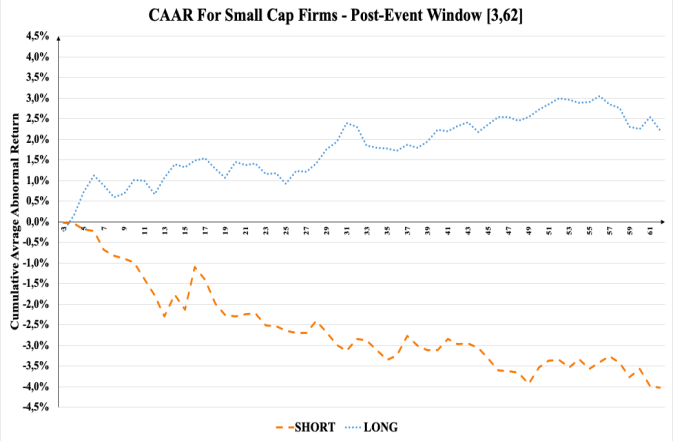

Figure 7 *- Shows how CAAR develops, in percentage, for positions LONG and SHORT for Small Cap firms between day t_3 and t_{62}.*

Figure 6 and 7 show how CAAR(t_3,t_{62}) develops for position LONG and SHORT for the subsamples, Large and Small Cap Firms, respectively. Figure 6 shows that the Large Cap firms have a nonexisting drift after the quarterly announcement. Both LONG and SHORT positions move closely to the value 0% the days subsequent the announcement date. On the other hand, Small Cap Firms have a drift in both positions. The SHORT position experienced a negative drift throughout the 60 day holding period. While, for the LONG position, the positive drift exists, but is weaker. And in the last few days CAAR goes down with around one percentage point. The differences increase when studying the initial earnings reaction. Small Cap firms have a large reaction in both positions as seen in table 2. However, although Small Cap firms are affected by a larger drift compared to Large Cap firms, and the overall sample, the drift is only statistically significant at a 10%- level in the short position.

Table 2 *- Shows the CAAR(t_3,t_{62}), t-stat for CAAR(t_3,t_{62}), CAR4D, average OLS beta values and the number of samples for position LONG and SHORT for both Large and Small Cap firms. ***, ** and * show statistical significance at the 1%-, 5%- and 10%-level respectively.*

	Large Cap Firms		Small Cap Firm	
	LONG	**SHORT**	**LONG**	**SHORT**
CAAR(t_3,t_{62}) *(t-stat)*	-0,1583% *(-0,223138)*	-0,6853% *(-1,026598)*	2,2290% *(1,490503)*	-4,0188%* *(-1,843986)*
CAR4D	11,1064%	-9,8565%	16,3326%	-14,1895%
Average OLS Beta	0,832314	0,865576	0,454374	0,514394
N	448	448	224	224

Comparing the OLS beta between the two subsamples, it can be noted that the Large Cap firms have larger market risk than the Small cap firms. When regarding the beta between the positions in each respective subsample we can also see that the differences are slight. Yet, the largest difference between the two positions can be seen in the Small Cap firm subsample. When studying the quarterly CAAR(t_3,t_{62}), seen in figure 8 for Large Cap and figure 9 for Small Cap Firms, the differences in between the two firms are further strengthened. Out of 56 quarters, Large Cap firms position LONG (SHORT) gave a positive (negative) CAAR(t_3,t_{62}) value 28 (35) times. While, Small Cap firms position LONG (SHORT) gave a positive (negative) CAAR(t_3,t_{62}) value 36 (34) times. From the data it is shown that taking the SHORT position is more proitble. It is clear that the abnormal return is much higher for Small Cap firms. Quarterly CAAR(t_3,t_{62}) for Small Cap firms reaches higher and lower values more often than Large Cap firms. This is a sign that Small Cap firms are subjected to higher risk compared to Large Cap firms and that the abnormal return generated is a compensation for this risk. Nevertheless, there are still substantial times when the strategy is not profitable for both subsamples.

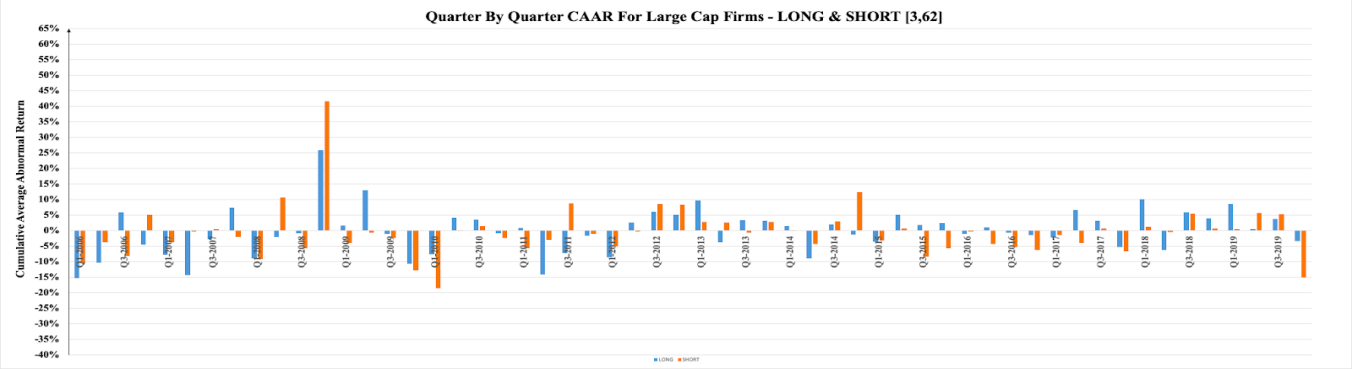

Figure 8 - *Shows quarterly CAAR(t_3,t_{62}) values for both LONG and SHORT positions for Large Cap firms.*

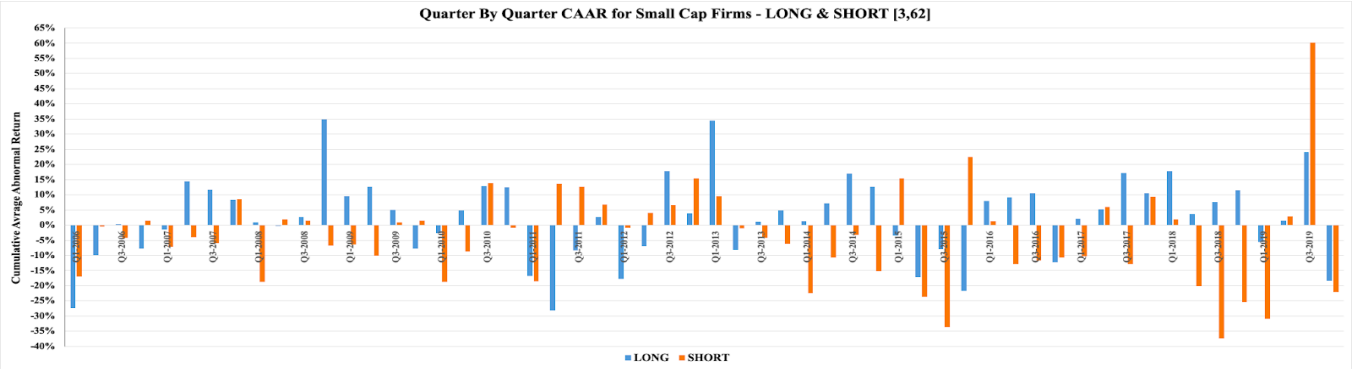

Figure 9 - *Shows quarterly CAAR(t_3,t_{62}) values for both LONG and SHORT positions for Small Cap firms.*

5. Discussion

The result of this thesis shows that there exists a PEAD effect on the Swedish market between the years 2006 and 2019. The drift was stronger in firms that had negative earnings surprises and was statistically significant at a 1% level. For good news firms the drift was weaker, only statistically significant at a 10%-level. Taking the positions, LONG and SHORT, an investor would generate an average rate of abnormal return of 1,12% and 2,55% respectively. Through the subsample analysis it was demonstrated that firm size has an apparent effect on the drift. Small Cap firms had much larger rates of abnormal return in both positions, in comparison to Large Cap firms. The LONG position in Small Cap firms gave an average abnormal returns of 2,23%, while position SHORT gave an abnormal rate of return of 4,02%. On the other hand, the positions in the Large Cap firms generated abnormal returns that are to be expected if no PEAD effect existed on the market. Both positions moved closely around average rate of return of 0% during the post-event window and were both statistically insignificant. The results imply that Small Cap firms are the driving factor behind the effect. However, statistical significance could only be proven for position SHORT at a 10%-level. But the low significance is most likely due to a smaller sample size of Small Cap firms.

Yet, when looking at the quarterly data, the results show that the strategies are not consistently successful. There exist time intervals in which the positions would generate significant losses if taken. In contrast to the similar exposure market risk in the position, this could indicate that the abnormal return from the positions are compensation for the risk taken when buying the stocks. This problem was especially strong in Small Cap firms that had large gains, but also considerable quarterly losses. Additionally there seems to exist certain time intervals when the strategies move in the same direction. As noted by the author, the time intervals Q1-2006 to Q2-2006, Q3-2008 to Q4-2008, Q4-2009 to Q1-2010 and Q3-2019 to Q4-2019 showed such signs. Since it was not the aim of this thesis to see what economic circumstances have an effect, this is not analyzed and elaborated on further. But, the result expresses that economic factors might help facilitate the PEAD drift. Some of these time periods were plagued by strong economic down- and upturns. It could be that certain factors changed during these time intervals that were not captured by the market model which uses market return as the only explanatory variable.

The results of this thesis both diverge and confirm other studies considering different markets. The overall result, that the drift is most prominent and statistically significant in the SHORT position is in line with Kallunki (1996) and Booth et al. (1996). Though, this goes against Foster et al. (1984) and Bernard & Thomas (1989) results that observed highly statistically significant drift in both positions. Furthermore, the success rate of the positions are lower than of the ones reported in Foster et. al. (1984) and Bernard & Thomas (1989) papers. On the other hand, the fact found in both papers that Small Cap firms drive the drift was also found in this thesis. However, for the 60 days following the event day, they found that the LONG and SHORT was statistically significant at a 1%-level for both firm types. This level of statistical significance could not be proven in this thesis. Additionally, in contrast to Foster et al. (1984) and in accordance with Liu et al. (2003), this thesis was able to identify statistically significant drift using a price based method. However, if this method was more or less efficient than the SUE method has not been established in this thesis. It could be the case that the SUE method, used by Foster et al. (1984) and Bernard & Thomas (1989), is a more powerful tool than a price base method.

Interesting differences and insights are also found when comparing the results with Setterberg (2011). Setterberg found only a statistically significant drift in position LONG and the abnormal return was continuously increasing throughout the entire holding period for the position. The opposite is the case in this thesis. The drift in good news firms exist to some extent in this thesis, but it is stronger in the SHORT position. What could cause this fundamental difference in result is hard to see. Sample size and composition is about the same in both papers. Different methodology was applied in the studies, Setterberg used SUE to gauge earnings surprises. However, it would be improbable that this difference in procedure would result in such dramatic change, as it has not been seen in past research. Perhaps, an underlying factor has changed during the studied period that has led to the surprising change in results. One of the severest financial crises, the 2008 financial crisis, occurred during the analyzed time period and led to fundamental changes for the financial sector. The fallout from the crisis might have sparked a shift in the economic environment that caused the switch for which firms are affected by the drift. Whatever the case may be, the conflicting results question the conclusions drawn in both papers. That these unexpected changes can occur in a relatively short time interval points toward the bad-model problems voiced by Fama (1998). It could be that these outcomes are the result of chance and not the signs of a drift in prices.

A question that naturally emerges in the thesis is what can possibly cause the observed drift. Despite the fact that the aim of the thesis was not to explore this subject, the result still points toward the existence of market frictions as the most possible explanation. The results have shown that drift is the strongest in the bad news firms. As shown by Ng et al. (2008), taking this position creates large transaction costs that can erode away the possible gain from exploiting the drift. The fact that transaction cost hinders investors from exploiting this effect is further supported by the fact that Small Cap firms seem to be the main driving force behind the significant drift. As discussed in section 2.2 and 3.2, *Past results* and *Methodology*, these types of firms have larger trading transaction costs than firms with higher market capitalization. This additional barrier deter investors even further from trading away the effect, leading to the drifts survival on the market. This in turn implies that the practical implications of this thesis are limited. To form a trading strategy based on the result will probably lead to an overall loss for an investor.

6. Conclusions

In conclusion, the results of the statistical test show that there exists a strong drift in bad news firms, and a weak drift in good news firms. The result also confirms to past research, which indicates that the result is not sample specific. As seen in past papers, the drift is closely connected to firm size and is stronger in the SHORT position. However, when looking at the quarterly data, subsample analysis and contrasting the results against Setterberg's (2011), some apprehensions have emerged. When looking at the quarterly data, the model used to measure abnormal return seems to have an omitted risk factor. Other signs of bad model problems are highlighted when the findings in this thesis diverge heavily from Setterberg (2011) without any obvious causes.

Therefore, further research is needed to be able to make a more certain verdict of PEAD existence on the Swedish market. Research could analyze the same time period with a different sample while utilizing a multi-factor model, such as the Fama-French three factor model, to see if the results can be replicated. Further, it would be interesting to see if the results can be reproduced when using a different method to measure earnings surprises, such as the SUE metric. Lastly, the sample constructions can be improved in future studies. The sample should consist more of Small Cap firms to improve the power of the subsample analysis. Furthermore, it has been seen in this thesis that the result may be affected by extreme outliers. More time should be used to scrutinize the sample to find and identify the effect of these outliers.

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