PRICE SHOCKS AND INVESTOR IRRATIONALITY

A STUDY ON OVERREACTIONS IN THE SWEDISH STOCK MARKET

FREDRIKA BRUU

EMMA ÅKERSTÉN

Bachelor Thesis

Stockholm School of Economics

2020

Price Shocks and Investor Irrationality: A study on Overreactions in the Swedish Stock Market.

Abstract

This paper replicates the research conducted by Benou and Richie (2003) on overreactions among investors to news or events causing large price changes to occur in the stock market. While the original study focuses solely on large price decreases among well-established firms listed in the S&P 100 index on the U.S. stock market, this study analyzes the Swedish stock market. Furthermore, this paper extends the research to include both large and small firms, defined by market value, listed on Nasdaq Stockholm stock exchange. The two groups are studied separately, and we observe events defined both as positive and negative price shocks. This is done to study whether the stock market adjusts immediately according to the new circumstances due to the event, or if the investors invariably overreact or underreact to corporate news affecting the stock price. The latter alternative would result in mispriced stocks the following months after the large price movement. In contrast to the findings of Benou and Richie, where evidence for a systematic overreaction to large price declines is presented, our results show a tendency among investors to underreact to large price decreases while overreacting to large price increases. Therefore, we conclude that investors in the Swedish stock market show tendencies to be overly optimistic. This is only seen among large firms in the Swedish stock markets. Moreover, no inferences can be stated regarding stock price trends following a large price shock among companies with a lower market value, since all our results for smaller firms are statistically insignificant.

Keywords

Overreactions, Underreactions, Stock Market Reactions, Price Shocks, Contrarian Strategy

Authors

Fredrika Bruu (24224)
Emma Åkerstén (24231)

Tutor

Marieke Bos, Researcher, Swedish House of Finance, Stockholm School of Economics

Examiner

Adrien d'Avernas, Assistant Professor, Department of Finance, Stockholm School of Economics

Bachelor Thesis
Bachelor Program in Business and Economics
Stockholm School of Economics

Acknowledgments

We would like to express our sincere gratitude to Marieke Bos for her valuable input, support, and engagement throughout the writing of our thesis.

1. Introduction

1.1. Background

A central theory within the subject of finance is the efficient market hypothesis. It states that all available information, affecting the market value of a company, will be incorporated immediately in its stock price (Fama, 1970). The implication is that it should be impossible for investors to outperform the market, either by timing or by creating a portfolio consisting of certain stocks (Benou and Richie, 2003). Another assumption associated with the efficient market hypothesis is the random walk theory. It implies that it is impossible to predict future price movements of a stock since any information on tomorrow's stock price already is incorporated in today's price. Followingly, over time, it should not be possible to receive a better return of a portfolio than by obtaining a random and diversified selection of stocks (Malkiel, 2003).

Opposers to these theorems argue that the real world is much more complex, and explain that investors buy and sell stocks at a specific point of time for other reasons than solely pure information affecting the market value of a company (Wäneryd, 2001). Moreover, several research papers claim that it is possible to predict certain trends in the stock market since investors are not always absolutely rational (Benou and Richie, 2003; De Bont and Thalor, 1985; Ising et al., 2006). Knowing how to predict these trends would leave investors with an opportunity to make trades that generate excess returns compared to the average market.

Finding trends among certain stocks, specific industries, or the overall stock market has been of great interest for a long time. One finding on the topic is the overreaction hypothesis introduced by De Bondt and Thaler (1985). Their article presents evidence for a significant reversal of the stock price trend for stocks that recently have outperformed the overall market. The conclusion was that in *the upcoming period* (t), the worst-performing stocks in *the most recent period (t-1)* would outperform the best performers from *the period before that (t-2)*. They discuss that this was a consequence of the market constantly trying to adjust back to normal after a potential overreaction. An overreaction occurs when investors overvalue the most recent information presented. This results in a greater movement of the stock price than what can be motivated given the new information presented for the market. De Bondt and Thaler support their findings with the research on systematic errors in human judgment regarding investment decisions by psychologists and behavioral finance researchers Kahneman and Tversky (1977).

The overreaction hypothesis presented is a direct violation of the efficient market hypothesis (Zarowin, 1990). By shorting (longing) stocks that have outperformed the market (underperformed), investors could earn excess returns due to market inefficiency. This investment strategy became known as the contrarian strategy. The strategy builds upon the assumption that individuals overvalue recent information while undervaluing data from the past (Ising et al., 2006). The opposing strategy is the momentum strategy, where investors assume that the performance of a stock will continue in the same direction as of the initial price change. This investment strategy could be successful if there is a tendency for underreactions among investors to the newly presented information. Underreactions occur when investors are not reacting strongly enough to new market information. This leads to a smaller change in the stock price than what is reasonable, given the new circumstances (Jegadeesh and Titman, 1993). This results in a continued price movement in the same direction as the initial price change in order to reach the new equilibrium. Continued price movement could also be explained by a protracted overreaction which pushes the prices into the same direction over several months (Lansdorp and Jellema, 2013).

Zarowin (1990) further researched the overreaction hypothesis and dismissed its existence. He distinguished the extreme performing stocks by ranking them according to their monthly price change. The top quintile was defined as winner stocks and the bottom quintile as loser stocks. Zarowin concluded that the tendency for last period's loser stocks to outperform the following period's winner stocks was due to the loser stocks typically were smaller firms than the winner stocks. The conclusion is supported by the theory of the size effect stating that smaller firms, on average, have higher risk-adjusted returns (Banz, 1981). Zarowin showed that when loser stocks were compared to winner stocks of equal size, the overreaction tendencies in the stock market were no longer significant. The fact that firm size could impact the results was something that had been dismissed by De Bondt and Thaler in their work. Another common concern regarding the subject is that the patterns of arbitrage opportunities tend to be exploited until they disappear (Malkiel, 2003).

Benou and Richie (2003) researched the overreaction phenomenon among large and well-established firms in the U.S market. Their paper focuses solely on large price decreases. They defined a stock as poorly performing when a decrease of at least 20% occurred in one month. The definition of poor performing stocks was new compared to previous research since Benou and Richie used a specific threshold of a monthly price change, rather than sorting the sample's monthly returns by quantiles. The stock price movements the months and years following these defined events were then studied. By using a threshold method, they found evidence for abnormal positive price movements for stocks that earlier had experienced a 20% price decrease. The study presented evidence for an initial overreaction occurring at the market. They concluded that investors who enter the market the month after a 20% price drop could earn approximately 10% more than they had expected when holding the stock for a year.

1.2 Objective and Purpose

We will conduct a study on the Swedish stock market while replicating the methodology used by Benou and Richie (2003). Studying potential reversal patterns on different geographical markets is of interest as previously conducted research on the overreaction hypothesis have shown various results depending on which market that is studied. The indication is that the behavioral pattern among investors differs across markets. Therefore, examining different markets provide valuable insights into whether the examined phenomenon is applicable or not on a specific market. The purpose of the study is to gain a deeper understanding of potential existing trends following a large price movement at the Swedish stock market. Significant findings could present deviations from the efficient market hypothesis. Such knowledge could be used to create a portfolio that should generate abnormal returns at the Swedish stock market.

1.2.1 Contributions

By studying the stock returns the months following a large stock price movement, defined as an increase or a decrease of at least 20% during one month, it is possible to analyze potential long-term trends following such an event. In order to study the potential trends, the generalized autoregressive conditional heteroskedastic (GARCH) model will be used. The model estimates what the stock price should have been if the unusually large price change had not occurred. The motive for using the GARCH method is its ability to incorporate volatility clustering among historical stock prices when calculating the estimates, which generates more realistic predictions than using a standard market model. We will then estimate the stock's abnormal returns (ARs) and cumulative abnormal returns (CARs) by analyzing the difference between the predicted values and observed values, as done in the study by Benou and Richie (2003).

Furthermore, the extended exponential version of the GARCH model, the EGARCH model, will be used to gain deeper insights into which of the models that give the most realistic predictions for our dataset. However, the market-adjusted model used by Benou and Richie (2003) will not be applied in our study. The reason is that their study was published in 2003 and since then it has become more evident that the GARCH model is superior for measuring financial volatility. Simpler models, as the market-adjusted model, do not contribute particularly to the inferences of the results (Ising et al., 2006; Molnár, 2016). The contribution of the use of the market-adjusted model is fairly limited in the study by Benou and Richie, which further supports the decision to exclude it.

We will extend our study further by analyzing the effect on both large and small firms, defined by the market value. As previously mentioned, Zarowin (1990) has shown that the size of a company has an impact on the stock returns reversal tendencies after a large price movement. By looking at firms with higher and lower market value separately, the aim is to find if different reversal patterns exist for large and small firms after a distinct increase or decrease in the stock price. The results could give indications on how to invest to generate excess returns. To our knowledge, a study researching potential long term trends after large stock price movements for companies of higher and lower market value at the Swedish stock market has not been done before.

2. Literature Review

2.1 Critique of The Overreaction Hypothesis

Chan (1988) presents evidence against the contrarian strategy and claims that the strategy should not provide any excess profits for investors. The potential profits received are rather normal since investors are rewarded for the riskiness of the strategy. This argument is aligned with modern portfolio theory, where investors are compensated when taking on higher risk (Elton and Gruber, 1997). Chan further presents three aspects to why the previous research, supporting the contrarian strategy, gives false implications. He claims that previous studies have not accounted for: (1) lack of risk-adjustment, (2) underestimating the size effect, and (3) not acknowledging the January effect. These concerns are presented below along with other sources of literature stating the results when each concern has been taken into consideration. Based on these findings, the method of our study is motivated.

2.1.1 Lack of risk-adjustment

The market value of a firm is given by the number of shares times the stock price. Followingly, a decrease in the stock price results in lower market value. Given that the firm size and book-to-market ratio are incorporated when creating a risk profile, a drop in a company's share price should make the investment in such a firm riskier (Fama and French, 1992). De Bondt and Thaler did not consider this in their original study. However, more recent studies in the field account for this and still find evidence supporting the overreaction hypothesis (Lakonishok and Rittner, 1991). For our study, this concern is addressed by using the GARCH methodology, which takes the time-varying beta into account when estimating future normal market prices, rather than the standard market model for estimation (Benou and Richie, 2003).

2.1.2 Underestimating the size effect

The size effect phenomenon was first introduced by Banz (1981) and states that smaller firms, on average, have greater long-term returns than larger firms. Amihud and Mendelson (1986) attribute the trend to the increased liquidity risk for smaller firms which results in a higher demanded risk premium among investors. This causes the price of smaller firms to be initially lower relative to large firms, and by that having a greater chance of growth. This would result in potentially higher returns over time seen among smaller firms. Fama and French (1986) argue that the size effect partially explains the reversal pattern discovered by De Bondt and Thaler, while Zarowin (1990) attributes the reversal pattern completely to the size effect. We consider the inference of the size effect by studying large and small firms separately.

2.1.3 Not acknowledging the January effect

The January effect is a phenomenon first observed and presented by Rozeff and Kinney (1976). It explains that stock prices tend to rise in January, as a consequence of the common investor behavior of selling loser stocks at the end of the year to realize losses and gain tax benefits. The stock prices are then unusually low for a short time before increasing to the equilibrium values in January. This results in positive abnormal returns for prior loser stocks during this month. Some studies suggest that the January effect might partially explain the reversal pattern found by De Bondt and Thaler. For example, Chopra et al. (1992) conduct a study of the reversal pattern which adjusts for the size effect and time-varying betas and conclude that a large portion of the reversal pattern can be explained by the January effect. However, they do not dismiss the existence of the reversal pattern overall. The January effect was a common concern in the earlier studies on overreactions but has lately been addressed less frequently since the effect is no longer significant. This is due to increased awareness of the phenomenon causing the effect to almost disappear (Malkiel, 2003).

2.2 Further Studies on The Contrarian Strategy

Studying investment strategies is rather complicated due to difficulties with establishing a realistic model representing the actual stock market. Moreover, a variety of methodologies are used in research as a result of the individual assumptions made about the specific market in focus (Kothari and Warner, 2007). Consequently, the results may vary across studies and followingly it becomes difficult to compare research across different markets. Therefore, findings on one specific market which are contradicting previously presented results from studies conducted at a different geographical market do not necessarily imply flaws in the first findings.

In a study on the German stock market, Ising et al. (2006) find evidence of reversal patterns after large price increases. The results indicate a tendency for overreaction during the time of the price shock. This is due to the reversal pattern following the event which can be seen as the market is correcting itself for not adjusting accordingly to the new equilibrium price at the time of the large price movement. However, in contrast to the findings of De Bondt and Thaler (1985), Ising et al. (2006) showed that large price decreases, defined as a 20% drop in the stock price during one month, was followed by further decreases of the stock price. These results indicated a tendency for underreactions among investors. The conclusion was that the German stock market is consistently overly optimistic since stock prices tend to decrease after both positive and negative price shocks.

At the Brazilian market, Da Costa (1994) found significant evidence for the overreaction hypothesis lasting for up to two years. Gaunt (2000) on the other hand, finds the contrary in a study of the Australian market. He attributes any potential evidence of reversal patterns to the size effect, dismissing the overreaction hypothesis. Clare and Thomas (1995) find reversal patterns in the UK market, but conclude that the effect is almost completely explained by the size effect. Lakonishok and Rittner (1991) also find evidence in support of the overreaction hypothesis in the U.S. stock market.

2.3 Studies on the Swedish Stock Market

Studies of the overreaction hypothesis at the Scandinavian markets have commonly been done by university students. Hansen Klungland and Sollie Klokk (2018) from BI Norwegian Business School research the overreaction effect in Nordic stock markets and find evidence in support of a long-term overreaction. Controlling for size effect, the January effect, and changing risk, they still find a significant reversal pattern. They defined winner and loser stocks by ranking them where the top and bottom quintiles in each sector were defined as extreme performers and used the BHARs method to measure abnormal returns.

Berg and Bergström (2015) from Linköping University conducted a short-term study on the contrarian strategy on the Swedish stock market. Their motive was to research the common critique of the findings of De Bondt and Thaler which is that the winner and loser portfolios are not risk-adjusted. They find no evidence in favor of any significant reversal pattern after a large price decrease which supports the claims of the critics to the overreaction hypothesis.

2.3.1 Contribution to the Research on the Swedish Stock Market

The studies on the Scandinavian market mentioned above are using methodologies that are updated versions of the one De Bondt and Thaler initially used. This is to account for the commonly mentioned potential flaws in the original study since they account for the size effect and the varying betas. However, the studies have not accounted for the tendency for volatility clustering of stock returns. Volatility clustering refers to the observation that times of large price movements tend to be followed by additional periods of higher volatility, and times for small price movements tend to be followed by periods of lower volatility. This result is an uneven distribution of a stock's volatility over time since it is clustered around certain periods. The GARCH and EGARCH models take this into account when estimating the future stock price. Therefore, the usage of these models is crucial since not incorporating volatility clustering when estimating expected returns can lead to unreliable results (Brockett, Chen, and Garven, 1999). By studying the Swedish stock market using the GARCH and EGARCH method the aim is to present a more realistic view of the potential behavioral patterns.

2.4 Hypothesis

Based on prior research, we hypothesize that investors in the Swedish stock market overreact to newly received information about large firms that affect the stock price. Previously conducted research, both in the Scandinavian markets as well as in other international markets, find support for an overreaction tendency when studying the returns of the months following a large price shock (Benou and Richie, 2003; Hansen Klungland and Sollie Klokk, 2018). Therefore, we believe that the outcome of our study will show that a large price movement during one month is followed by a reversal trend in the opposite direction of the initial event.

As evidence of an overreaction or underreaction is seen by the abnormal returns following the event, the null hypothesis tested is that there is no evident tendency for abnormal returns the months following a large price shock.

H_0 LargeCap: There is no tendency for abnormal returns among LargeCap firms
H_1 LargeCap: There is a tendency for abnormal returns among LargeCap firms

We are more doubtful regarding the potential outcomes when studying companies with a lower market value. The prior research on overreactions among small firms is limited and has shown various results (Zarowin, 1990). Therefore, we find it interesting to test the hypothesis at the Swedish stock market. The size effect phenomenon introduced by Banz (1981), implies that smaller firms on average have greater long-term returns than larger firms. Therefore, we believe that a large price movement among smaller firms generally is followed by a positive stock price trend the year after the event has taken place, regardless of the event being a price increase or decrease. We do not expect to see an effect on a short-term basis since the size effect is only observed for longer periods.

The null hypothesis we test to reject is that there is no evident tendency for abnormal returns following a large price shock.

H_0 SmallCap: There is no tendency for abnormal returns among SmallCap firms
H_1 SmallCap: There is a tendency for abnormal returns among SmallCap firms

3. Sample and Data Description

3.1 Stock Market Data

The data used is the stock market returns of a total of 182 companies listed on the Nasdaq Stockholm stock exchange within the time frame 01/02/2010 to 31/12/2019 (see Appendix for a complete list of companies). The sample period was chosen based on the availability of stock market data in the EIKON at the time when obtaining the dataset. Furthermore, the length of the sample period aligned well with Benou and

Richie's chosen timeframe of ten years, which further motivated the choice. To conduct the robustness test, data for the same stocks were collected for the period 01/01/2006 to 01/02/2010 as well (see section 6.6 for a detailed explanation). Aligned with similar studies of long-term market reactions to large price changes (Benou and Richie, 2003; Ising et al., 2006) the monthly average return for each company is obtained.

As one of the purposes of the study is to research if the market reacts differently to distinct price changes among large versus small firms, the data collected is of two segments labeled LargeCap and SmallCap. To be categorized as a LargeCap firm on the Nasdaq Stockholm stock exchange, the company needs to have a market value equivalent to at least one billion euros. A SmallCap firm is defined as a company that has a market value of less than 150 million euros. The thresholds set to define a company as a LargeCap or SmallCap firm varies across different markets (Avanza Bank, 2020). When firms are referred to as large or small throughout this paper, it is done based on the definitions for the Swedish market. In our sample, 90 firms are obtained from the LargeCap segment and 92 firms are obtained from the SmallCap segment.

Our sample of firms consists of all companies that have been listed as a LargeCap or SmallCap firm during any time of our sample period. Moreover, a specific company does not have to be listed as a LargeCap or SmallCap firm throughout the whole sample period. The reason to include companies that have not been listed throughout the whole sample period is to avoid creating a survival bias. The reasons why a company may not listed throughout the whole sample period are many; bankruptcy, a buyout from the stock market, or an increase or decrease in market value to that extent that the company is re-classified on the stock market. When analyzing large stock price changes, excluding such companies would lead to biased results due to the correlation between price shocks and market value changes (Baber and Lyon, 1997). The argument in favor of excluding the delisted or newly listed companies would be that it might become difficult to study the long-term effects when some of the observations only have short-term data. However, we argue the survival bias is the more crucial concern to address.

Between the market value divisions LargeCap and SmallCap there is a segment labeled MidCap. The motive for excluding the MidCap segment is the potential risks associated with the scenario where companies switch from one classification to another. This would occur if the firm's market value rises above or falls beneath the specific threshold within our time sample period. If including this the MidCap firms, there would be a risk that one sample firm appears in multiple segments within the sample period in the dataset. Therefore, it is crucial to exclude these companies to avoid analyzing the same company in multiple segments. In our data sample of SmallCap and LargeCap firms, no sample firm is classified as both LargeCap and SmallCap within our sample period.

Benou and Richie used data from May 1990 to May 2000 and only used firms listed on the S&P 100 index for their research. While still aiming to replicate their study we believe that it is not relevant for us to use data from the 1990s to study potential arbitrage patterns in the Swedish stock market, as the purpose is to investigate potential investment strategies that could be used today. Furthermore, instead of only studying a limited number of large index-listed firms as done by Benou and Richie, our data sample consists of all companies listed at the LargeCap and SmallCap on Nasdaq Stockholm within our sample period. This is due to the extension of the study where we analyze potential differences in trends for large and small firms separately. The belief is that a few sampled firms would give an inappropriate representation of the population since the Swedish stock market is much smaller in size than the U.S. market, resulting in a potential enhanced influence of a few firms at the Swedish market.

3.2 Event Definition

The monthly average returns of the listed companies have been compared to a chosen threshold to determine if a large price change has occurred. The threshold is set to 20% in absolute terms. A monthly return of a stock that exceeds the threshold is marketed as an event (Benou and Richie, 2003). The used threshold value is arbitrary and differs across studies in the field (Ising et al., 2006). Regardless, the chosen threshold must exceed the monthly return of the chosen benchmark market index to distinguish which unusual events to observe (Benou and Richie, 2003). Therefore, the threshold is usually set rather high for the studied observation windows not to be inconsistent, since the event months where the index exceeds the threshold value needs to be discarded. In our study, the index OMX Stockholm PI has been used as the benchmark index. The index represents the Swedish stock market excluding any dividend payouts occurring (Nasdaq OMX Nordic, 2020). This specific index was chosen since dividend payouts might be a cause for a price shock, and consequently an event. To estimate predictions of the returns we argue OMXSPI is the most appropriate index. Table 1-4 provides the distribution of the events across years and months.

Table 1. Distribution of Events Across Time at LargeCap With a Threshold Value of -20%

Table 1 shows the distribution of months defined as an event among companies listed as LargeCap firms. A month is defined as an event if the price of a stock has decreased by 20% or more during one month.

	2010	2011	2012	2013	2014	2015	2016	2017	2018
January						1	2		
February									
March					1		1		
April							1		
May	2	2				1			
June	1						1		
July		1							
August		7							
September		2	1		6				
October			1				1		1
November							1	1	
December						1			

Table 2. Distribution of Events Across Time at LargeCap With a Threshold Value of +20%

Table 2 shows the distribution of months defined as an event among companies listed as LargeCap firms. A month is defined as an event if the price of a stock has increased by 20% or more during one month.

	2010	2011	2012	2013	2014	2015	2016	2017	2018
January			2	1		2		1	
February			2	5	5	6		1	
March	4					2	1		
April	2		1		3	1	1	1	1
May									
June	0								
July	1			4		2	5	2	2
August						3	3		
September	13	1	1	2		1		1	1
October	2	9		1	1	6		1	
November				1		6	2	0	
December	5			1		1	1		

Table 3. Distribution of Events Across Time at SmallCap With a Threshold Value of -20%

Table 3 shows the distribution of months defined as an event among companies listed as SmallCap firms. A month is defined as an event if the price of a stock has decreased by 20% or more during one month.

	2010	2011	2012	2013	2014	2015	2016	2017	2018
January					3	2	9	1	1
February		3	5	4	1	2	7	1	5
March		3	3	0	4	1	3	4	1
April	5	3	3	4	5	2	4	2	
May	6	6	8	3	4	1	6	3	3
June	4	5	2	5	2	2	2	1	1
July		3	3	2	4	1	1	2	
August	2	12	2	2	3	4		2	1
September	1	7	1	2	5	2	2	4	2
October	6	2	8	2	6	1	7	5	17
November	3	7	7	2	6	4	2	9	8
December	1	0	1	1	1	2	2	3	5

Table 4. Distribution of Events Across Time at SmallCap With a Threshold Value of +20%.

Table 4 shows the distribution of months defined as an event among companies listed as SmallCap firms. A month is defined as an event if the price of a stock has increased by 20% or more during one month.

	2010	2011	2012	2013	2014	2015	2016	2017	2018
January		7	15	11	7	9	3	8	9
February		3	10	10	11	18	4	10	1
March	11	2	4	9	0	9	6	2	2
April	6	6	3	3	1	4	6	6	5
May			3	5	6	7	5	3	6
June		1	1	2	2	2	2	5	2
July	2	1	6	6	8	8	14	1	6
August	1	1	3	7	1	1	12	4	10
September	12	2	2	10	5	1	2	3	5
October	1	7	2	7		12	2	4	2
November	4		4	6	7	15	7	3	3
December	12	4	5	2	5	7	6	2	

Studying the distribution of the defined events, one can observe that large price shocks occur more frequently among companies listed at the SmallCap than among LargeCap firms. Furthermore, the events are not evenly distributed across the months and years studied. However, since the largest monthly increase respectively decrease of the index used (OMXPI) is +8,8% and -10,6% throughout the sample period, it does not exceed the threshold value of -20% respectively +20%. Therefore, no months where defined events occur are excluded from the study.

4. Methodology

4.1 Event Study Methodology

When conducting a study of stock market reactions it is appropriate to use the event study methodology introduced by Fama et al. (1969). It examines the short- and long-term economic impact on stock returns of occurrences that could be of interest to investors. The methodology is commonly used in research studying the impact of specific corporate events and decisions the following months after the event has occurred. Studying the abnormal stock returns when the market adjusts to new information can provide an understanding of the effect of corporate policy decisions and to test market efficiency (Barber and Lyon, 1997; Kothari and Warner, 2007). Examples of corporate events studied where other researchers have applied the methodology are initial public offerings (Ibbotson, 1975), mergers and acquisitions (Asquith, 1983), and stock splits (Dharan and Ikenberry, 1995).

The calculated abnormal returns (ARs) are the deviations of the empirically observed values from the estimated normal market values. Normal market values are the estimated values of what the price of each stock should have been if the event had not occurred. These values are estimated by the used models' assumptions of the relation between each stock and the OMXSPI index.

The ARs are measured to establish whether the observed values are systematically different from the expected values. The usual practice when testing the statistical significance of the anomalies is to test the null hypothesis that the mean abnormal return of the sample firms at time t is equal to zero. Testing abnormal returns over a multi-period interval, which is a chosen period following the event, is commonly done by using either cumulative abnormal returns (CARs) or buy-and-hold abnormal returns (BHARs) (Kothari and Warner, 2007). The details of the two methods are explained in section 4.2.

Different time horizons are studied after the event to see how long potential trends last. Some researchers assume that the reaction lag is short-lived, aligned with the theory of random walks, and therefore the observation window for the study only needs to be a few days following the occurrence of the event (Lasfer, Melnik, and Thomas, 2003). Alternative literature suggests that the effect can be seen for several months or even years following the event, contradicting the random walk theory (Benou and Richie, 2003; Ising et al., 2006). When studying longer observation windows it is common to include a period before the event to study potential market effects of investor expectations or information-leakage of the event (MacKinlay, 1997).

However, there are some issues associated with measuring abnormal market returns over longer time horizons. The main concern arises when estimating the normal market conditions. When studying long time horizons it becomes more difficult to make realistic predictions of what the returns would have been in the absence of the event (Kothari and Warner, 2007). This makes the abnormal returns less accurate than when shorter observation windows are studied. In short-term studies, the problem is avoided as the expected returns from day to day are close to zero, making the abnormal returns far more apparent. Therefore, research studying long-term effects tends to have various outcomes and results at different levels of statistical significance. However, this does not imply that the results of long-time studies are directly dismissable. Many research papers establish the presence of either an overreaction or underreaction using various measurement methods and conclude that it is reasonable to believe the found anomalies cannot simply exist by chance (Chopra, Lakonishok, and Rittner, 1992).

4.2 Measurements of Abnormal Returns

More recent studies in the field calculate averages (ARs) or sums (CARs) of the abnormal returns over an observation period when estimating the effects of the event. This method is used rather than calculating the returns of holding the stocks throughout the observation period, so-called buy-and-hold abnormal returns (BHARs). In the BHARs method, the returns over time received from a portfolio of firms that have undergone the event are compared to the returns of a portfolio of benchmark firms which have not undergone the studied event over a chosen observation period. In the CARs method, the abnormal returns are instead compared to each firm's expected normal return over time, which is estimated based on the firm’s historical data, rather than using benchmark firms (Kothari and Warner 2008).

Fama (1998) argues that the BHARs method becomes less reliable when studying long-term horizons of abnormal returns due to the potential correlation among event firms and non-event firms. Barber and Lyon (1997) argued for the BHARs method over CARs in a study where they compare the methods through test statistics. They believe that the CAR method leads to biased predictions of abnormal returns, but acknowledge that BHARs also have some negatively biased test statistics. However, in a follow-up study by Lyon et al. (1997) where they try to improve the BHARs method to correct for the found negative biases, they recognize that it does not provide any particularly more reliable inferences than the CARs method. Therefore, abnormal returns are calculated using the CARs method in this study. The complete model is specified in the section below.

4.3 Estimation Windows to Predict Expected Returns

To estimate normal returns for each firm in our sample after an event has occurred, each company's specific alpha and beta have to be estimated. In the paper by Benou and Richie (2003), it is not explained how the alphas and betas for each firm have been estimated. Therefore, the decision of how to estimate these variables in our study is based on literature in the field. MacKinlay (1997) suggests that the estimation window when performing an event study on a monthly basis should be between 23-120 months. Furthermore, he argues that the estimation period should, when possible, be defined as the period before the event window is taking place and that the estimation period should not contain any occurrences of events.

Figure 1: Design of the Event Study as Suggested by MacKinlay

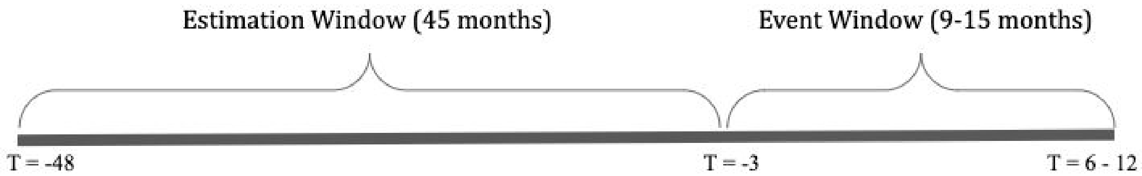

Figure 1 shows how an event study normally is designed. An Estimation Window is defined before and is of a greater length than the Event Window. Moreover, the estimation window does not contain any observation defined as events.

Unlike many other event studies, our defined events, a price change of more than 20% during one month, are not specific external events that affect the stock market. Instead, the events are a part of the usual fluctuations in the stock market. The specific volatility of each stock results in more observed events for some stocks than others. If estimating each firm's alpha and beta using an estimation window where no events occur the results would become biased and not consistent with the purpose of the study since only firms where few events occur would be studied. Furthermore, if event-free estimation windows are used, only a small fraction out of the many events that have occurred at the Swedish stock market could be studied. Therefore, each company's alpha and beta will be estimated based on the whole sample period for each firm.

Figure 2: Event Study Design Used in This Study

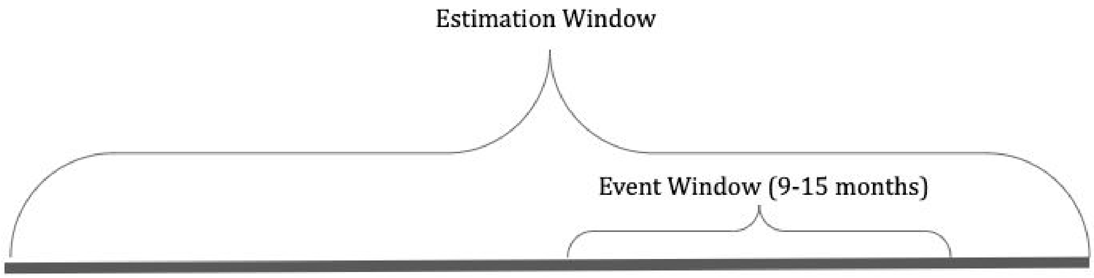

Figure 2 shows the Event Study Design used in this study. The defined Estimation Window has the length of the total time sample period obtained for each stock. Moreover, the Estimation Window allows a month defined events to be included.

It should be stated that other papers studying similar events have to our knowledge not explained how they estimate each company's alpha and beta. Therefore, based on the motivation against the estimation windows used in a classic event study methodology, the conclusion is that our choice of estimation window will result in estimations of the ARs and CARs that are most appropriate for our study and its purpose. Moreover, the method suggested by MacKinlay (1997) will be a part of the Robustness Test of our study.

4.4 The GARCH and EGARCH Models for Estimating Expected Return

To estimate the normal market values, a standard single-factor model using ordinary least squares has traditionally been used when applying the event study methodology. The betas, which are the estimate of systematic risk, and the error terms are assumed to be stationary in the model. However, literature regarding time-series analysis on stock returns suggests that studies that do not take into account that the betas and error terms can vary over time might present results leading to unreliable statistical inferences (Schwert and Seguin, 1990). There is a tendency for volatility clustering in stock returns and therefore it is more realistic to assume the presence of heteroskedasticity. This means that the standard errors are non-constant when modeling expected returns which motivates the usage of the generalized autoregressive conditional heteroskedastic (GARCH) model when estimating the parameters. The model incorporates the variance and error term from the previous periods when estimating the return in the upcoming period (Brockett, Chen and Garven, 1999). The GARCH (1,1) model, where the numbers following the GARCH indicate that it is a single time series using one lagged value of return and one lagged value of volatility to predict the next period's values, is previously used in similar studies conducted at the U.S. stock market (Benou and Richie, 2003) and the German stock market (Ising et al., 2006).

The GARCH model has repeatedly proven to provide more accurate estimations of future stock prices than many of the other well used models, for example, the ordinary least squares (OLS) method (Ising et al., 2006). However, the GARCH model still has some limitations. Nelson (1991) specifies that the GARCH model treats price increases and decreases similarly, which is not always a realistic assumption. Research has shown that the volatility of stock prices tends to increase more after a large price decrease than after a large price increase. This is called the leverage effect (Black, 1976). Nelson introduced an exponential version of the GARCH model, named the EGARCH model. In this model, the natural logarithm (ln) of the past conditional variance is used to estimate future volatility of the stock, incorporating the previously mentioned difference between increases and decreases in the model. Which of the GARCH and EGARCH models that result in the best-fitted estimates under the influence of asymmetric conditional variances varies across studies in the field (Kothari and Warner, 2007). Therefore, this study will use the EGARCH (1,1) model in addition to the GARCH (1,1) model for estimating future expected return to find the best fitting estimates for the used dataset.

The model for GARCH (1,1) and EGARCH (1,1) is specified as:

$$(1) \qquad R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,t}$$

The parameters in the model are estimated using the maximum likelihood technique, which takes the probabilities of the distribution of observations into account when predicting fitting estimates. This is necessary when the density of the observed values varies throughout the dataset.

In contradiction to the standard market model, which assumes strict exogeneity, the error term in the GARCH (1,1) and EGARCH (1,1) method is conditioned on the prior values and follows a distribution with a mean of 0 with a conditional variance of h_t. All information on past errors and variance available at time $t-1$ is given by Ω_{t-1}.

$$(2) \qquad \varepsilon_{j,t} | \Omega_{t-1} \sim N(0, h_t)$$

The conditional variance, h_t, is determined by the squared past errors and the past conditional variance. For the GARCH (1,1) method the variance is specified as:

$$(3) \qquad h_t = \Phi_0 + \Phi_1 \varepsilon_{t-1}^2 + \Phi_2 h_{t-1}$$

For the EGARCH (1,1) method the conditional variance is given by the natural logarithm of the squared past errors and the past conditional variance ln(h_t).

$$(4) \qquad ln\,(h_t) = ln\,(\Phi_0 + \Phi_1 \varepsilon_{t-1}^2 + \Phi_2 h_{t-1})$$

The abnormal returns are then defined as the difference between the observed value and the value estimated by the GARCH (1,1) and EGARCH (1,1) models.

$$(5) \qquad AR_{j,t} = R_{j,t} - (\alpha + \beta_j R_{m,t})$$

To find the cumulative abnormal return (CAR) for a certain period the monthly abnormal return over the chosen event window [*b,e*] across the sample is added. The average of the received CARs is then computed.

$$(6) \quad AR_t = \frac{1}{N} \sum_{j=1}^{N} AR_{j,t}$$

$$(7) \quad CAR_j = \sum_{t=b}^{e} AR_t$$

$$(8) \quad CAR = \frac{1}{N} \sum_{j=1}^{N} CAR_j$$

Different periods are used when calculating the CARs. The significance of the effects is established through statistical hypothesis testing.

4.5 The T-test

When applying the GARCH and EGARCH models for stock return analysis it is often assumed that the estimates follow a student's t-distribution. This distribution is similar to a normal distribution but with heavier tails, which means that there is a greater probability to receive extreme values than when using a normal distribution (Kothari and Warner, 2007). The null hypothesis is that the ARs and CARs equal zero and follow a student's t-distribution which is tested through the t-test specified below. The null hypothesis is rejected if the test statistics (t_{AR} or t_{CAR}) reach the chosen critical values corresponding to p-value 0.1, 0.05, 0.01, or 0.001 significance levels.

$$(9) \quad t_{CAR} = \frac{CAR_j}{\sigma_{CAR_j/\sqrt{N}}}$$

$$(10) \quad t_{AR} = \frac{AR_{j,t}}{\sigma_{AR_j/\sqrt{N}}}$$

CAR_j is the sample average cumulative abnormal return and $\sigma_{CAR_{jt}}$ is the sample standard deviation across the sample collection of *N* events.

A t-test is commonly used when the observations are assumed to follow a normal distribution while the variance is unknown. However, the ARs of each firm in our sample are not assumed to be normally distributed, as they are per definition abnormal. This contradiction does not need to be addressed as Central Limit Theorem explains that if the observations are drawn for independent and finite distributions and the sample is large enough, the ARs will collectively follow a normal distribution. (Baber and Lyon, 1997). Therefore, it is possible to test the statistical significance of the ARs as well.

4.6 Robustness Test

Robustness tests of our study will be conducted to establish the accuracy of the results presented in the section Empirical Results. The objective is to conclude if potential trends only strictly apply when the method and thresholds are set as in the main test. Therefore, both different thresholds used to define events as well as another procedure to estimate the alpha and beta of each company will be examined. The absolute values of the new thresholds will be determined after analyzing the main results, to make the tests with new thresholds as fruitful as possible. If the initial results are significant, the threshold will be set to a lower value in absolute terms to see if significance can be found for smaller price movements as well. This is of interest since a lower threshold leads to more opportunities for investors to base their strategy on if significant values are found. If the results received are not significant, and a clear trend after the defined events are not seen, the threshold will be raised in absolute terms. This is done to see if significant patterns exist when the price movements are more extreme.

Furthermore, the test of robustness will include a section where a different procedure for estimation is used to predict normal stock prices absent of the event. This test is of great importance for our study since it is not known which procedure Benou and Richie (2003) used in their study. The additional procedure tested will be the one suggested by MacKinlay (1997) when conducting event studies. Here only events with event-free estimation windows of 45 months three months before the event will be included in the sample (see Figure 1). As previously stated, this method is not considered to be ideal for our study. However, since the procedure of estimating used in the original study is not stated, it is relevant to include this procedure in our study as well.

5. Empirical Results

The first part of this section will present the results of the replication of the study conducted by Benou and Richie (2003). They study stock returns following a 20% monthly price decrease for large companies to see if a reversal trend exists. Following the replication part, we present our contributions, where it is examined if similar reversal patterns exist for price increases and smaller firms after a price shock has occurred. The tables for the results present average monthly abnormal results or cumulative abnormal returns and their corresponding t-statistic. The ARs and CARs for each test are reported using both the GARCH and the EGARCH model.

5.1 Replication of the Original Study

Table 5 shows the abnormal returns for each separate month surrounding the defined event of a monthly decrease of at least 20% at t=0. What is most striking is that the event month t=0 does not present an abnormal return of at least -20%. This is unexpected since the large price decline at t=0 was the reason why this month was defined as an event in the first place. The fact that the AR at t=0 is statistically insignificant and the value of AR is close to zero could however be due to the large price decrease of 20% being a potential correction following a previously abnormal increase in the stock market. In that scenario the observed value would not deviate too much from expected normal market values and therefore show insignificant abnormal return. This argumentation is supported by the results of studying abnormal returns of the months before the event. For these months the ARs are successively positive. Furthermore, for month t=-1 there is a positive AR of approximately 15%, using both GARCH and EGARCH, which is significant at a 5% level, showing that a large abnormal price increase has occurred before the event at t=0 where the decrease of 20% is taking place. For that reason, this unusual outcome does not necessarily imply errors in the method or dataset, but methodological errors could of course also be a potential explanation for the unanticipated AR at t=0.

The months following the event show significant anomalies at a 10% level at month t=1 and t=5 using both methods. However, the abnormal returns throughout the months move in different directions. This gives no clear indication of predictable monthly patterns for investor reactions to large price declines for the first six months following the event. The significant returns during these two separate months, t=1 and t=5, is most likely attributable to a specific sample firm or a specific occurrence in the stock market, rather than being a general trend over time.

Table 5: Monthly ARs Surrounding an Event (-20%) for Companies Listed at LargeCap

*Table 5 shows the results for the Average Monthly Abnormal returns (ARs) surrounding the event month (t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The ARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = ARs estimated using GARCH (1,1) model, N=78		*Panel B = ARs estimated using the EGARCH (1,1) model, N=85*	
Event Month	**ARs (%)**	**t-statistic**	**ARs (%)**	**t-statistic**
-3	4.34%	0.79	4.1%	0.81
-2	-3.26%	-1.01	-3.11%	-1.07
-1	15.21%	2.35**	13.74%	2.28**
0	-1.04%	-0.08	-3.85%	-0.33
1	16.58%	1.68*	15.01%	1.71*
2	-0.74%	-0.09	-0.56%	-0.08
3	3.35%	0.38	3.17%	0.41
4	-0.81%	-0.15	-1.33%	-0.28
5	-8.38%	-2.04*	-7.77%	-2.13**
6	-11.26%	-1.43	-9.47%	-1.31

Table 6 presents the cumulative abnormal return for different time intervals following the defined event. The CARs estimated using both GARCH and EGARCH shows that a 20% decrease in the stock price for LargeCap companies is followed by continually negative returns when looking at periods up to a year following the event. The negative cumulative abnormal return is statistically insignificant at even a 10% level for an initial six months after the large price decrease, as well as for the scenario when entering the market one month after the event and holding the stock up to twelve months. However, there are significant results at a 10% and 5% level using the GARCH respectively the EGARCH model, for the windows two-to-twelve months, three-to-twelve months as well as six-to-twelve, which are showing continuously negative CARs. This could indicate a potentially protracted underreaction at the market, where the prices continue to decrease a couple of months after the event has taken place. Investors who enter the market two months after a large price decrease earn approximately 30% less than what they would have expected. Moreover, predictions through the EGARCH model show significant results for the one-to-twelve month period as well. Overall, the results show a potential underreaction which is the opposite of what Benou and Richie found in their study.

Table 6: CARs up to One Year Following an Event (-20%) for Companies Listed at LargeCap

*Table 6 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=78		*Panel B = CARs estimated using the EGARCH (1,1) model, N=85*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-1.26%	-0.10	-0.95%	-0.08
1:12	-28.82%	-1.47	-31.72%	-1.77*
2:12	-45.40%	-1.83*	-46.73%	-2.07**
3:12	-44.66%	-1.63*	-46.17%	-1.86*
6:12	-38.82%	-1.70*	-40.24%	-1.94*

Figure 3 graphs the CARs from month one through twelve, estimated through the GARCH method. These are the months of greatest interest for investors since they can not trade upon the information before the event has taken place. The graph clearly shows no evidence of a reversal pattern after the large price decline in the stock market has taken place. The fact that the CARs continue to decline after the large price decrease indicates an underreaction. From an investor's point of view, the optimal strategy would be to enter the market in a short position two to three months after the event, based on the significant CARs presented in Table 6, to earn as much as possible from the arbitrage opportunity.

Figure 3: CARs up to One Year Following an Event (-20%) for Companies Listed at LargeCap

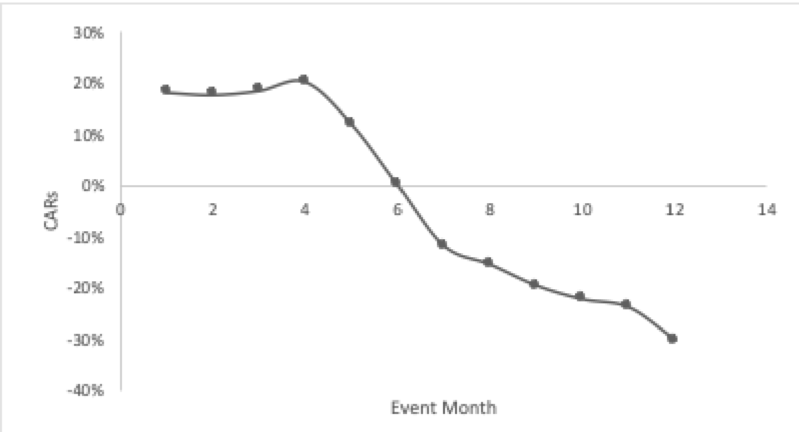

Figure 3 shows the CARs graphed over the following twelve months after the event, defined as a decrease of 20% or more, has taken place among companies listed at LargeCap. Each CAR for the respective month in the graph represents the CAR entering the market right after the event and staying until the respective month. The CARs are estimated through the GARCH method. The estimation window used is the whole time sample period.

When studying the observation windows longer than one year following the large price decrease we still see continuous negative CARs. Table 7 and 8 shows the largest negative earnings when investors enter the market six months after the large price decrease and stay up to two respectively three years. There are however only significant results when estimating through the GARCH model for three years, and only at a 10% level, giving weak support for the inferences. For the rest of the results, all CARs are insignificant.

Table 7: CARs up to Two Years Following an Event (-20%) for Companies Listed at LargeCap

*Table 7 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to two years following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=66		*Panel B = CARs estimated using the EGARCH (1,1) model, N=72*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:24	-46.97%	-1.55	-41.78%	-1.51
6:24	-56.23%	-1.57	-49.79%	-1.55
12:24	-14.83%	-1.05	-10.11%	-0.79

Table 8: CARs up to Three years Following an Event (-20%) for Companies Listed at LargeCap

*Table 8 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to three years following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=59		*Panel B = CARs estimated using the EGARCH (1,1) model, N=65*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:36	-44.80%	-1.58	-38.88%	-1.54
6:36	-57.01%	-1.68*	-48.77%	-1.63
12:36	-9.93%	-0.81	-3.93%	-0.36

5.2 Contribution

5.2.1. Negative Price Shocks for SmallCap Firms

Table 9 presents the monthly average abnormal return for each month surrounding the event of a price decrease for companies listed at the SmallCap. No significant results are observed, except for the event month. The fact that the event month t=0 is significant, which was not the case for LargeCap firms, shows that the events themselves are significant and true in size. The ARs, before and following the event, are moving in both directions and give no indications of potential information leakage before the event, or any predictable patterns following the event. A potential immediate and very short underreaction could be seen since the first two months following the event are continuously negative. However, since the results are not statistically significant we cannot draw such a conclusion.

Table 9: Monthly ARs Surrounding an Event (-20%) for Companies Listed at SmallCap

*Table 9 shows the results for the Average Monthly Abnormal returns (ARs) surrounding the event month (t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The ARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = ARs estimated using GARCH (1,1) model, N=114		*Panel B = ARs estimated using the EGARCH (1,1) model, N=145*	
Event Month	**ARs (%)**	**t-statistic**	**ARs (%)**	**t-statistic**
-3	-6.47%	-1.20	-4.61%	-1.00
-2	-0.06%	-0.01	2.04%	0.29
-1	2.33%	0.70	3.73%	0.87
0	-30.88%	2.49**	-33.80%	-3.59****
1	-8.29%	-1.19	-5.26%	-1.01
2	-2.02%	-0.29	-7.05%	-1.17
3	10.38%	1.55	8.25%	1.70*
4	6.73%	0.87	5.40%	0.90
5	-8.80%	-1.03	-6.61%	-0.97
6	-4.70%	-0.49	-0.08%	-0.01

When studying the CARs for companies listed at SmallCap, positive returns can be seen for the event windows lasting up to a year after the event takes place. This could indicate a protracted overreaction since consecutive positive CARs follow the initial negative ARs for the first two months after the event. This could mean that there potentially is an initial short-term underreaction which is followed by a long-term overreaction. However, as none of the values are significant using either GARCH or EGARCH model, it is difficult to draw any conclusions or inferences from these results.

Table 10: CARs up to One Year Following an Event (-20%) for Companies Listed at SmallCap

*Table 10 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=114		*Panel B = CARs estimated using the EGARCH (1,1) model, N=145*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-6.19%	-0.53	-5.20%	-0.44
1:12	92.77%	1.04	82.91%	1.26
2:12	101.06%	1.09	88.17%	1.30
3:12	103.08%	1.11	95.23%	1.37
6:12	94.77%	1.11	88.19%	1.37

Figure 4 graphs the CARs from month one to month twelve, estimated through the GARCH method. It shows the distinct positive trend that, on average, takes place six months after the event has occurred. However, the trend is statistically insignificant and should rather be seen as an average of the outcome for all events studied among SmallCap companies.

Figure 4: CARs up to a Year Following an Event (-20%) for Companies Listed at SmallCap

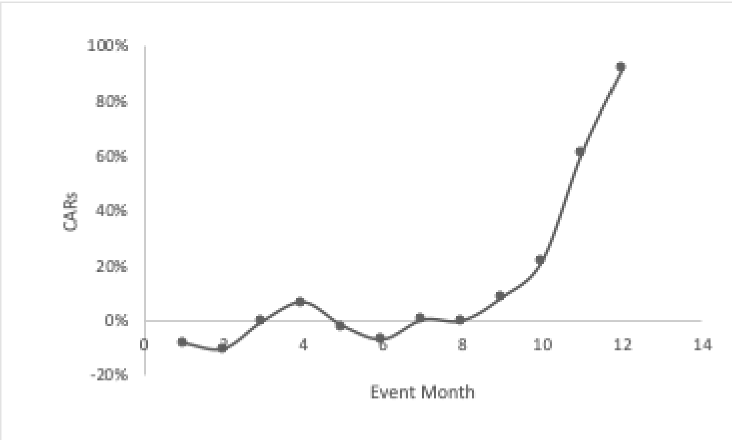

Figure 4 shows the CARs graphed over the following twelve months after the event, defined as a decrease of 20% or more, has taken place among companies listed at SmallCap. Each CAR for the respective month in the graph represents the CAR entering the market right after the event and staying until the respective month. The CARs are estimated through the GARCH method. The estimation window used is the whole time sample period.

5.2.2 Positive Price Shocks for LargeCap firms

Table 11 shows the ARs for the months surrounding an event of a price increase for companies listed as LargeCap. When studying the ARs, no conclusions can be drawn from the results of the studied months before the event. The ARs presented are both positive and negative, and insignificant even at a 10% level. The AR at t=0 is however significant at a 1% level. This is expected and highly reasonable since the price deviation is itself defined as the event. The following months after the event are continuously negative, except for t=4. The results are significant up to a 1% level for the month t=2 and t=5 estimated through both the GARCH and the EGARCH methods. This negative trend following the large price increase at t=0 implies an overreaction from the investors, but it is weakly significant.

Table 11: Monthly ARs Surrounding an Event (+20%) for Companies Listed at LargeCap

*Table 11 shows the results for the Average Monthly Abnormal returns (ARs) surrounding the event month (t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price increases by 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The ARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = ARs estimated using GARCH (1,1) model, N=146		*Panel B = ARs estimated using the EGARCH (1,1) model, N=158*	
Event Month	**ARs (%)**	**t-statistic**	**ARs (%)**	**t-statistic**
-3	1.92%	0.57	0.64%	0.19
-2	0.10%	0.02	-0.29%	-0.06
-1	-8.02%	-1.40	-7.04%	-1.31
0	23.77%	3.24***	25.14%	3.67****
1	-5.72%	-1.52	-5.77%	-1.66*
2	-6.81%	-2.82***	-8.31%	-2.80***
3	-3.34%	-1.02	-1.27%	-0.34
4	6.21%	1.14	6.47%	1.27
5	-7.89%	-2.58**	-8.06%	-2.84***
6	-1.32%	-0.84	-1.86%	-1.27

When analyzing the results presented in Table 12, the conclusion is that the indication of an initial overreaction lasting for six months that was seen earlier (see Table 11) is true. The CARs post-event are negative and significant at a 1% level using both methods. The overreaction is seen strongest for the first six months as the prices continue to fall. Event windows longer than six months do not present the same trend. The negative CARs become smaller in size when holding the stock up to a year. Moreover, statistically significant values are only found for the first six months following the event, which makes us unable to draw any conclusions from the results of studying the full-year period.

Table 12: CARs up to One Year Following an Event (+20%) for Companies Listed at LargeCap

*Table 12 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price increases by 20% or more during that month. Notes *, **, *** & **'* denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=146		*Panel B = CARs estimated using the EGARCH (1,1) model, N=158*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-18.87%	-2.88***	-18.80%	-3.09***
1:12	-10.42%	-1.04	-10.93%	-1.19
2:12	-4.70%	-0.39	-5.16%	-0.48
3:12	2.11%	0.20	3.15%	0.32
6:12	7.13%	1.19	6.02%	1.11

Figure 5 shows the initial reversal pattern for companies listed at LargeCap after a large price increase has taken place. The declining CARs during the first months following the event confirms an initial overreaction. The continuously negative CARs that lasts almost throughout the first six months, except for month t=4, makes it possible for investors to receive positive earnings by entering the market taking a short position during the first month after a large price increase has taken place and holding it for six months. By doing so, investors can earn approximately 18% more than they had expected.

Figure 5: CARs up to One Year Following an Event (+20%) for Companies Listed at LargeCap

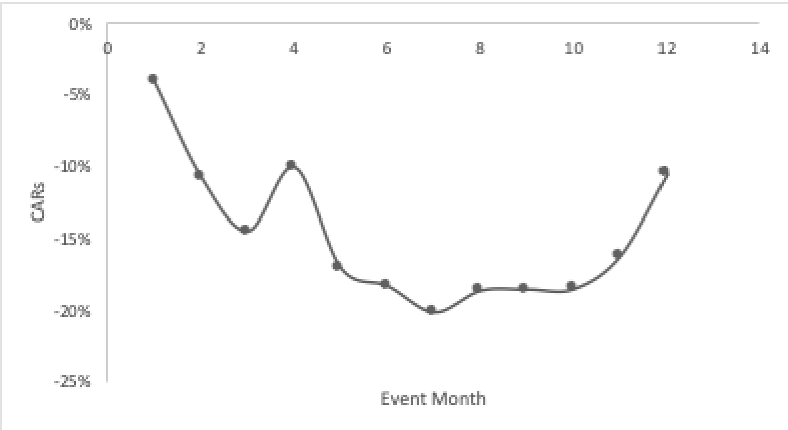

Figure 5 shows the CARs graphed over the following twelve months after the event, defined as an increase of 20% or more, has taken place among companies listed at LargeCap. Each CAR for the respective month in the graph represents the CAR entering the market right after the event and staying until the respective month. The CARs are estimated through the GARCH method. The estimation window used is the whole time sample period.

5.2.3 Positive Price Shocks for SmallCap Firms

Table 13 presents the abnormal returns following a price increase for firms listed at SmallCap. For the months following the event, no predictable patterns of the ARs can be observed, since the ARs are both positive and negative, and also insignificant. The event month is significant for a positive abnormal return at a 1% level using both the GARCH and EGARCH models. The results also show that the defined event, on average, is a much larger price increase than the minimum threshold of 20% since the estimated ARs for both methods is approximately 40%. The two months before the event shows quite large negative ARs that are significant at a 5% level or less. This significant decrease before the event at t=0 could imply that the defined event is a result of a previous overreaction that caused the prices to fall just before the event. However, from an investor's point of view, the results from Table 13 does not show any inferences that could be used in a trading strategy, since investors only are interested in trends that occur after the event has taken place as they normally do not know when an event will occur.

Table 13: Monthly ARs Surrounding an Event (+20%) for Companies Listed at SmallCap

*Table 13 shows the results for the Average Monthly Abnormal returns (ARs) surrounding the event month (t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price increases by 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The ARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = ARs estimated using GARCH (1,1) model, N=187		*Panel B = ARs estimated using the EGARCH (1,1) model, N=227*	
Event Month	**ARs (%)**	**t-statistic**	**ARs (%)**	**t-statistics**
- 3	-0.10%	-0.03	-1.91%	-0.69
-2	-9.62%	-3.08***	-9.63%	-3.37****
-1	-15.32%	-2.72***	-12.64%	-2.50**
0	41.55%	8.28****	40.88%	9.82****
1	6.33%	0.85	4.10%	0.70
2	-4.97%	-1.47	-3.56%	-1.42
3	-4.92%	-1.04	-6.52%	-1.56
4	-2.97%	-0.79	-2.82%	-1.12
5	2.39%	0.44	2.88%	0.66
6	-0.57%	-0.11	1.40%	0.32

When looking at the CARs for companies listed at SmallCap, positive returns are found for the event windows lasting up to a year after the event. However, initially, there is a period up to six months after the event has occurred that presents a negative CAR. This indicates an initial overreaction to the event. When investors stay in the market for more than six months, positive CARs can be earned up to a year following the event. This is the same trend that was observed for companies listed at SmallCap when price decreases of -20% were studied. However, as none of the values are significant using either the GARCH or EGARCH model, it is difficult to draw any conclusions or inferences from these results.

Table 14: CARs up to One Year Following an Event (+20%) for Companies Listed at SmallCap

*Table 14 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price increases by 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=187		*Panel B = CARs estimated using the EGARCH (1,1) model, N=227*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-4.71%	-0.42	-4.52%	-0.52
1:12	37.02%	0.83	25.91%	0.77
2:12	30.69%	0.81	21.81%	0.77
3:12	35.66%	0.88	25.36%	0.86
6:12	41.17%	1.21	31.83%	1.22

Figure 6 graphs the CARs from month one through twelve, estimated through the GARCH method. The negative returns the seven months following the event at t=0 indicates an overreaction to the large positive price change. The results are, however, statistically insignificant.

Figure 6: CARs up to One Year Following an Event (+20%) for Companies Listed at SmallCap

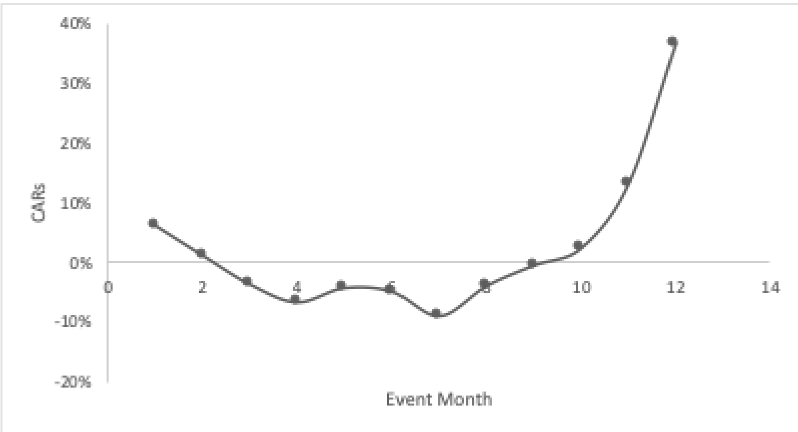

Figure 6 shows the CARs graphed over the following twelve months after the event, defined as an increase of 20% or more, has taken place among companies listed at SmallCap. Each CAR for the respective month in the graph represents the CAR entering the market right after the event and staying until the respective month. The CARs are estimated through the GARCH method. The estimation window used is the whole time sample period.

5.3 Summary of the Results

The results present some significant statistical CARs following a large price movement among stocks that are listed at LargeCap. When a large price decrease has occurred during one month, CARs observed up to a year after the event are negative. This suggests that the momentarian investment strategy would be preferable. Shorting the stock after a large decrease in the stock price has occurred would lead to larger positive earnings in comparison to what was expected. In contrast, when a large price increase occurred during one month among larger firms, one could see that the CAR up to six months after the event presented evidence for a reversal in the stock price. These results would suggest the usage of the contrarian investment strategy. Investors entering the market in a short position the month after a large price increase has occurred and holding it for six months will earn approximately 20% more than expected. Since all CARs from the tests conducted at the companies listed at SmallCap were insignificant, no statistical inference can be drawn from the results.

6. Robustness Check

To test the robustness of our results, new absolute levels of thresholds were set to see if the previous results were strictly dependent on the previous threshold of 20%. For the large companies which showed significant CARs when the threshold was set to 20%, the threshold in the robustness test was lowered to 17.5%. For the companies listed at SmallCap, which did not show any significant CARs when the threshold was set at 20%, the threshold was instead raised to 30%.

While it is customary to apply similar robustness tests to all samples, we argue that it is of relevance for our research to use different thresholds for the robustness check for the SmallCap and LargeCap sample since the data differ in terms of volatility. In the data set for SmallCap firms, almost all events far exceeded the 20% threshold. Therefore it would not contribute to our research significantly to only increase the threshold to 22.5% to mirror the lowered threshold by 2.5% applied to LargeCap firms. However, lowering the threshold for LargeCap firms by 10%, to mirror the raised threshold for SmallCap firms, causes trouble in terms of methodology as the benchmark index would exceed the threshold for some sample months. The large increase of the threshold for SmallCap firms was chosen to see if more distinct price shocks were more likely to be followed by predictable patterns or trends over time. All the tables presenting the CARs for respective tests are found in Appendix B.

6.1 Using New Thresholds

6.1.1 Results for LargeCap Firms

For decreases of at least 17.5%, the CARs following the event are similar to when the threshold was set to 20%, only less significant. Investors entering the market two, three respectively six months after a large price decrease occurred will during the year following the event earn about 30% less than they would have expected. These results are significant at a 10% level. The CARs are consistently smaller in absolute values using the lower threshold than the CARs for the same event windows when the threshold was set to 20%. Furthermore, the estimations through the EGARCH model was less significant when the threshold was 17.5%. The conclusion is that the results when studying the CARs with the new threshold are similar but less significant.

For an increase of at least 17.5% during one month for Large Cap firms, significant results are only found for the first six months following the event, which are negative and significant at a 5% level using both the GARCH and EGARCH model. Buying the stock one month after the event and holding it for six months, the investor will earn approximately 14% less than expected. Significant trends lasting for more than six months cannot be seen using any of the models. These results show a trend consistent with what we found when using a 20% threshold, but once again, the CARs are less negative. Moreover, the CARs estimated using the EGARCH method for price increases are as significant as the previously tested threshold of 20%.

Given the results of the tests using the new threshold that is lowered to 17.5%, we conclude that the results presented in the main result section are robust for a lowered smaller price shock for firms listed at LargeCap. However, the trends seen are less distinct.

6.1.2 Results for SmallCap Firms

Results for large price decreases for companies listed at SmallCap show positive CARs for all observation windows studied when using a threshold of 30%. The difference from when the threshold was set at 20% is that even the shortest event window studied, entering the market one month after the event and holding up to six months, results in positive cumulative abnormal returns. When the threshold was set to 20% the CARs were negative for the initial six months after the event. However, none of the CARs are statistically significant when studying SmallCap companies.

When raising the threshold to 30% for price increases, we still see no significant trends following the event among SmallCap firms. However, even though the CARs are not significant, they point in the same direction as the CARs observed when studying the threshold of 20% as the price continues to increase after a positive price shock. Our results using a raised threshold further supports the findings of the lower threshold for a positive price shock.

6.2 Using a New Estimation Method

Benou and Richie (2003) do not describe which method they use to predict the normal returns needed to calculate the ARs and CAR in their paper. Therefore, to further test if the previously presented results with certainty apply to the Swedish market, a second procedure for estimating the normal returns is used. Only events with an event-free estimation period of 48 months before the event are studied. The procedure is described in section 4.3.

6.2.1 Results for LargeCap Firms

When estimating CARs after a large price decrease among companies listed at LargeCap using an event-free estimation window, almost all results are positive. These findings are the opposite of what was seen when using the previous method on the same sample when almost all calculated CARs were negative, which indicated a potential underreaction. Furthermore, these new results align with the ones found by Benou and Richie (2003) in their paper. A potential explanation for the deviating results from the

ones when using the original estimation method is that the results received from this estimation method are more or less biased. This is due to the sample only consisting of stocks that have had no events within four years before the event we chose to study.
Since the sample stocks have not experienced a price decrease of 20% before there might be an overreaction when the stock price suddenly falls at t=0. A potential overreaction occurring at t=0 would support the results received with this new estimation window, where the CARs are continuously positive after the event. Furthermore, when CARs are estimated for large firms after a large price increase, the results are quite similar to when the CARs were estimated through the previously used procedure. However, as none of the CARs estimated through this method are significant, no statistically confirmed conclusions can be made. The insignificant results might partly be explained by the small sample studied, due to the required event-free estimation window.

6.2.2 Results for SmallCap Firms

Interestingly, using the new estimation procedure results in the only CARs significant for SmallCap firms. Investors entering the market one, two respectively three months after the event of a price decrease will earn a negative return of approximately 60% less than what is expected. This is significant for all the CARs within these observation windows at a 5% level, regardless if they were estimated through the GARCH or the EGARCH model. Moreover, the sample of events is still rather small due to the alternative method of estimation. Furthermore, the CARs are strictly negative for all of these observation windows. When using the previous procedure of estimating the normal returns the CARs were strictly positive, but insignificant. However, this sample is partially biased since it only consists of events where the estimation period before the event does not consist of any events. This bias might explain these results. For SmallCap firms that have not previously experienced large price decreases, investors might underestimate the magnitude of initial negative price decrease occurring at t=0. This could result in a continuous price decline lasting for many months, up to a year, rather than a severe price fall at t=0.

Furthermore, no significant CARs are found when following the same procedure for price increases of at least 20% applied at companies listed at the SmallCap. Additionally, all of the CARs are negative, which is the opposite of what was found using the other method. A reasonable explanation for this could not be found, and the results might depend on the very small sample (N=11, N=15).

6.2.3 Comments on the New Estimation Method

It is important to acknowledge that the sample becomes fairly small when the alternative procedure of estimation is used. This could be one reason for the less significant results for the large companies. Furthermore, the sample used does not consist of all the events occurring during the sample period as a consequence of the set estimation window. Due to the biased results, the findings with this procedure do not apply to the full population.

The results from this test of robustness did not consequently confirm or reject the previous findings for potential trends after large price movements. For negative price shocks among LargeCap firms, the results using this estimation procedure were instead similar to the findings of Benou and Richie (2003). Large price decreases are followed by positive CARs the year after the event. The similarities between the results could potentially indicate that Benou and Richie used event-free estimation windows in their study. However, it is more likely that the similarities are a coincidence since almost all of our findings are insignificant even at a 10% level. Moreover, using the new estimation procedure does not give results applicable to the full population.

7. Discussion

7.1 Discussion of the Results

Stock market reactions is a topic frequently studied in financial research. If significant trends are found after a defined event has taken place, the information can be incorporated into an investment strategy. The results of our study, where an event was defined as a monthly change of the stock price by 20% or more, show contradicting implications of behavior among traders compared to the results of Benou and Richie (2003). Their paper concluded that investors in the U.S market have a tendency to overreact, which means that large price decreases often are followed by an abnormal positive increase in the stock price. In contrast, we conclude that underreactions among investors occur more frequently at the Swedish stock market for LargeCap companies. This results in further decreases in the stock price after a negative price shock has occurred, significantly lasting up to a year. Furthermore, our findings support that positive price shocks for companies listed at the LargeCap also are followed by statistically significant negative abnormal returns, lasting up to six months after the event. This shows a tendency for overreactions among investors to positive price shocks.

The results for the SmallCap firms are in line with what was anticipated in our hypothesis based on the size effect theory. Over time, returns among SmallCap firms are generally positive. We could observe positive CARs when the stocks were held for a year following the event, regardless of the price shock was positive or negative. However, apart from some ARs for a few individual months, all results were statistically insignificant at a 10% level. Therefore, no statistical inference can be drawn from the results for SmallCap companies. Furthermore, these results can not be compared with similar studies conducted at other geographical stock markets, since research on the topic is limited. The insignificant results for the sample consisting of firms with lower market values might explain why this has not been researched as much as larger firms. One explanation for the insignificant results might be that large price movements occur much more frequently among smaller firms. Therefore, price shocks might not receive the same attention or cause as large reactions among investors.

Benou and Richie (2003) concluded in their study that the pronounced indication of overreactions in the U.S. stock market gives investors reason to consider these effects when constructing their portfolios. This could be done by going long in sectors that show tendencies for overreactions to large price declines, as they discovered in their robustness check that the effect differed across sectors. In this paper, different sectors or other categorizations were not studied due to the already limited amount of events in the sample. Instead, our focus was to study price shocks in both directions while segmenting the sample in regards to the market value of the companies. Furthermore, longer periods than one year were not included in our contribution, as neither us nor Benou or Richie found evidence for significant trends lasting for longer than a year.

Interestingly, the results of our study on the LargeCap companies instead align very well with the ones of Ising et al. (2006). They also conducted a study replicating the paper of Benou and Richie at the German stock market. Their findings indicate that the German stock market is consistently overly optimistic, as investors tend to overreact to large price increases and underreact to large price decreases. The findings of our study indicate a similar behavior among investors in the Swedish stock market. As the Swedish market has more in common with the German market than the U.S. market, in regards to legislation, culture, and the European Union membership, similar trading behaviors among the investors seem logical. Furthermore, the resembling results give some support for the implication of overreactions and underreactions we find at the Swedish market, even though we did not find statistically significant support for all of our results.

7.2 Discussion of the Methodology

The literature on financial volatility is indecisive of the appropriateness of the different versions of the GARCH model. Therefore, the EGARCH model was implemented throughout our study as well. The results from the two different models were shown to be quite similar when estimating the size of the ARs and CARs, but with some distinctions. For some samples, the EGARCH model gave less significant results than the GARCH model, and sometimes more significant results. However, as the results of the ARs and the CARs estimated with the two models were rather similar, it was not relevant to research this further. If the results had differed distinctly it would have been of interest to compare the assumptions incorporated in the models and analyze how these assumptions affect the calculated ARs and CARs.

For our specific research question of studying long-term reactions to large price changes, the GARCH and EGARCH models are well suited since they both consider volatility clustering when estimating the normal market values. The usage of the ARs and CARs method was also well suited, as it has become standard in the event study methodology field due to its advantages compared to the BHARs method. We believe that the chosen method had the best potential to provide as close to realistic inferences of the stock market as possible, out of the selections of methods available for usage. However, some factors complicate the significance of the presented results.

The sample of data used consists of monthly returns for each firm that had been listed at the Nasdaq Stockholm stock exchange as a LargeCap or SmallCap company at any point between the years 2010-2019. The data sample used is extended, in comparison to the original study, to include all LargeCap and SmallCap firms within our chosen period, rather than using a sample from an equivalent of the S&P 100 index as done by Benou and Richie (2003). While more evident patterns could potentially have been seen if we had used a more limited and narrowly selected sample, this would potentially present a biased view of the effect for the full population. The Swedish stock exchange is rather small in size and some particular firms have a large influence on the overall market. Including or excluding those firms in the limited sample could affect the inferences from the results. Furthermore, as the purpose of the study was to present results applicable to the full population, all companies listed at LargeCap respectively SmallCap were included.

We also consider it a potential problem that we decided to not further study the reasons why the price shocks occur. It is realistic to assume that potential trends after large stock price movements are different depending on the reason behind the price shock. Examples of news that could cause a stock to increase or decrease more than 20% could be profit warnings, product launches, and annual report releases. Various company news could generate different reactions among the investors and therefore deviating trends following the event. There could also be a few, very distinct events that heavily influence the results. Furthermore, our study does not acknowledge if the price shock occurred during a few hours or weeks, as long as the stock price during the specific month increased or decreased by 20% or more. These aspects could further affect the potential trends of the stock price in the following months.

We acknowledge that there is a distinct trend deviation at t=4 (see Figures 4, 5, and 6) in several of our results presented for the different samples. We speculate that this is a consequence of the timing of the events. When looking at the distribution of events (see Table 1-4) one can observe the clustering of events in August and September. Four months following the event is the time approaching the year-end when investors commonly tend to restructure their portfolios and realize returns. This might be an explanation for these unusual outcomes in the graphs, however, we cannot be certain. For realistic statistical inferences, the ideal experiment would involve an even distribution of events to avoid potential seasonal effects.

7.3 Limitations of the Study

When predicting the normal market values for SmallCap firms it was not always possible to find the fitted estimates needed. This problem might have emerged due to the long estimation window used. In our sample, the SmallCap firms experienced several more large price movements (see Table 1-4) than the LargeCap firms. The large price deviations occurring more frequently might have been the reason for the difficulties that emerged when trying to find the desired relation between the stock and the index. The sample stocks where no estimates were found had to be eliminated. Furthermore, there is a clear disadvantage of estimating future normal stock returns based on the whole sample period since the estimation becomes less specific. Using a set of consecutive months right before the event as an estimation window, rather than the whole sample period, results in estimations with a closer correlation with the market at a specific point in time. However, as discussed in the methodology section, this procedure for estimation rather than using a shorter estimation window was still superior for our study.

Moreover, companies listed as SmallCap are often younger firms than the ones listed as LargeCap. Therefore, they often have a more unpredictable growth path since very few investors know whether the company will be able to generate future positive cash flows or not. Furthermore, structural changes in the businesses occur more often which could cause price shocks to occur more frequently among SmallCap firms. Overall, the conclusion is that it is difficult to predict behavioral patterns for these stocks regardless of the amount and quality of historical data. These concerns were known when initiating the study as well. Regardless, the purpose was to see if it was possible to find any predictable trends for smaller companies despite all of the above-mentioned concerns since it then could be incorporated in an investment strategy. Unfortunately, no significant results were reached when studying SmallCap firms. The results further support the theory about small firms having more unpredictable stock price movements. The above-mentioned characteristics of the smaller firm give some explanation for the insignificant results found.

Furthermore, it is important to acknowledge that the sample used, consisting of 90 LargeCap firms and 92 SmallCap firms, is fairly limited. Even though each firm could undergo several events, hence resulting in more events than the number of firms, a larger firm sample could potentially have resulted in more evident results. In order to extend the sample, and thereby reduce this shortfall, the full Nordic market could be studied instead. This might be relevant due to the close cooperation between the countries and the reasonable assumption that there are similarities in investor behaviors as well as firm characteristics at the Nordic markets. However, including all the Nordic countries would lead to less relevant and specific results since the implications would not be ensured to apply to each specific country's market. Therefore, we decided that the Swedish market was appropriate for our study, even though we encourage future research in different geographical markets.

Our study would further have benefited from testing the robustness of the time sample. Studying the results when the time sample was changed to exclude certain periods, it would have been possible to see if our results were influenced by some specific months or years included in our sample. It is reasonable to assume that some years influence the results more than others due to macroeconomic trends affecting the overall market. This test of robustness could further have supported our results, or provided important knowledge about investors' anticipation over time, depending on the results from this potential test of robustness.

While the results from our study, as well as the ones of Benou and Richie, indicate that arbitrage opportunities exist after a large price movement has occurred, these trends are not evident or predictable enough to be fully exploitable. There is still a need for an amount of speculation by the investor, which enables the arbitrage opportunity to prevail. If the arbitrage were more evident it is assumed that the effect would be exploited until it almost disappears, as some argue has happened with other found trends, for example, the January effect. Furthermore, the results mostly show statistical significance at only a 5% level when studying the LargeCap firms, and insignificance for SmallCap firms. If the trends following an event were evident, a higher level of significance would have been reached.

Moreover, the results presented for the companies listed at LargeCap show that investors need to take a short position in the market after a large price movement has occurred to benefit from the existing arbitrage opportunity. This could further explain why potential arbitrage opportunities after a large price movement have not fully been exploited. Even though it is often assumed that investors can take short positions in stocks as easily as taking long ones, this is not always a realistic assumption. Shorting stocks often involve higher transaction costs and risk, since the shorter is forced to buy back the stock regardless of how much the stock has risen or fallen during the period of shortage. These two factors limit the number of investors engaged in this type of trading. A limited number of traders could potentially be an explanation for the partly inefficient market and explain why some of these arbitrary trades possible to conduct are not exploited.

It is also important to acknowledge that all inferences are based on historical data and therefore they are not perfect predictions of the future. There will always be unforeseen events affecting the future stock price movements in unpredictable ways. Evidence of the overreaction and underreaction hypothesis based on historical data can give indications on how to place your money as an investor, but strategizing in stock purchases always involves some amount of risk-taking.

To present results perfectly illustrating potential abnormal returns after a large price movement has occurred, the ideal experiment would involve knowing what the exact stock price would have been in the absence of the event. This information would eliminate the uncertainty of estimating the normal stock price, which is needed to analyze the difference defined as the abnormal returns. By all means, this cannot be done. The normal stock price cannot be observed, only estimated, and this is done based on historical data. Furthermore, even if history could predict the future perfectly, the predictions are estimated using different models. All of these include a set of assumptions about the real world. Moreover, these assumptions result in predictions deviating more or less, based on the assumptions made, from the actual future price of the stock. Therefore, the predictions based on estimations can never fully reflect the true future price movements of the stock.

There is also a concern of the prior knowledge investors have about the specific sample firms which might affect their behavior in regards to events. The financial history of a firm might influence how an investor values the news and chooses to react upon it. These valuations will reasonably differ across sample firms. An investor might overreact to news regarding Firm A but underreact to news of Firm B, based on what the investor remembers about how previous events evolved. The ideal experiment for our research question would, therefore, involve incorporating the firm-specific biases.

7.4 Further Research

For a deeper knowledge regarding potential trends following a large price movement, further research on the topic is encouraged. It would be of interest to thoroughly analyze the specific events that cause the stock price to fall or rise for one month. Moreover, segmenting the sample on possible causes for the price shock, other potential trends following the event might be shown that could also perhaps be more statistically significant and thereby give stronger indications for potential investment strategies. Another approach would be to look further into potential seasonal effects, as we acknowledged that most events occur in August and September, to investigate if the distribution of events affects the results. Moreover, it could be of interest to further research companies listed at SmallCap. Studies on these companies have not been done as widely as studies on larger firms. While there are difficulties finding predictable patterns among smaller firms, significant results might be found in these firms would be segmented based on industry or periods. It is also of great interest to further conduct similar research across other geographical stock markets to find national trends as they seem to vary, based on the indications of our research as well as the related literature studied.

8. Conclusion

We conclude that a tendency for underreactions among investors in the Swedish stock market to negative price shocks of 20% or more exists for firms listed as LargeCap companies. These results are in contrast to the findings of the study by Benou and Richie (2003). Moreover, a tendency for overreactions to positive price shocks of 20% or more is found. Our results do not support the contrarian strategy for large price decreases, only for price increases. Instead, for price decreases, we see evidence in favor of the momentum strategy. No particular inferences can be drawn from the results regarding the stock market behavior before any defined event. Furthermore, we were unable to find statistically significant results for firms listed at SmallCap. Therefore we are unable to draw any conclusions regarding trends following a price shock for these firms. Our results further highlight the relevance of studying investor reactions across different geographical stock markets as all markets do not show similar trends.

9. References

9.1 Published Sources

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, Journal of Financial Economics, Volume 17, Issue 2, Pages 223-249.

Asquith, Paul, Robert F. Bruner, and David W. Mullins, 1983, The gains to bidding firms from merger, Journal of Financial Economics, Volume 11, Issues 1–4, Pages 121-139.

Barber, Brad M., and John D. Lyon, 1997, Detecting long-run abnormal stock returns: The empirical power and specification of test statistics, Journal of Financial Economics, Volume 43, Issue 3, Pages 341-372.

Barber, Brad M., and Chih-Ling Tsai, 1999, Improved Methods for Tests of Long-Run Abnormal Stock Returns, The Journal of Finance, Volume 54, Issue 1, Pages 165-201.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, Journal of Financial Economics, Volume 9, Issue 1, Pages 3-18.

Benou, Georgina, and Nivine Richie, 2003, The Reversal of Large Stock Price Declines: The Case of Large Firms. Journal of Economics and Finance, Volume 27, Issue 1, Pages 19-38.

Berg, Eric, and Alfred Bergström, 2015, Overreaction on the Stockholm Stock Exchange: Evidence from Sweden, Master Thesis, Linköping University.

Black, Fisher, 1976, The pricing of commodity contracts, Journal of Financial Economics, Volume 3, Issues 1–2, Pages 167-179.

Brockett, Patrick L., Hwei-Mei Chen, and James R. Garven, 1999, A new stochastically flexible event methodology with application to Proposition 103, Insurance: Mathematics and Economics, Volume 25, Issue 2, Pages 197-217,

Chan, Ka-keung C., Yasushi Hamao, and Josef Lakonishok, 1991, Fundamentals and Stock Returns in Japan, Journal of Finance, Volume 46, Issue 5, Pages. 1739-64,

Chan, Ka-keung C., 1988, On the Contrarian Investment Strategy, The Journal of Business Volume 61, Issue 2, Pages 147-63.

Chopra, Navin, Josef Lakonishok and Jay R. Ritter, 1992, Measuring abnormal performance: Do stocks overreact?, Journal of Financial Economics, Volume 31, Issue 2, Pages 235-268.

Clare, Andrew, and Stephen Thomas, 2006, The overreaction hypothesis, and the UK stock market, Journal of Business Finance & Accounting, Volume 22, Pages 961 - 973.

Da Costa, Newton, 1994, Overreaction in the Brazilian stock market, Journal of Banking and Finance, Volume. 18, Issue 4, Pages 633-642

De Bondt, Werner F. M., and Richard Thaler, 1985, Does the Stock Market Overreact?, The Journal of Finance, Volume 40, Issue. 3, Pages 793-805.

Dharan, Bala G., and David L. Ikenberry, 1995, The Long-Run Negative Drift of Post-Listing Stock Returns, Journal of Finance, Volume 50, Issue 5, Pages 1547-1574.

Elton, Edwin J., and Martin J. Gruber, 1997, Modern portfolio theory, 1950 to date, Journal of Banking and Finance, Volume 21, Issues 11–12, Pages 1743-1759.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, The Journal of Finance, Volume 47 Issue 2, Pages 427-465.

Fama, Eugene F., and Kenneth R. French, 1986, Common factors in the serial correlation of stock returns, UCLA: Finance.

Fama, Eugene F., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, The Journal of Finance, Volume *25*, Issue 2, Pages 383-417.

Fama, Eugene F., et al, 1969, The Adjustment of Stock Prices to New Information, International Economic Review, Volume 10, Issue 1, Pages 1-21.

Gaunt, Clive, 2000, Overreaction in the Australian Equity Market, Pacific-Basin Finance Journal. Volume 8, Pages 375-398.

Hansen Klungland, Martin, and Peter Sollie Klokk, 2018, Overreaction Effect in Nordic Stock Markets: A Quantitative Analysis of a Contrarian Investment Strategy, Master Thesis, BI Norwegian Business School.

Ibbotson, Roger G., 1975, Price performance of common stock new issues, Journal of Financial Economics, Volume 2, Issue 3, Pages 235-272.

Ising, Jan, Dirk Schiereck, Marc W.Simpson, and Thomas W. Thomas, 2006, Stock returns following large 1-month declines and jumps: Evidence of overoptimism in the German market, The Quarterly Review of Economics and Finance, Volume 46, Issue 4, Pages 598-619.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, Journal of Finance, Volume 48, Issue 1, Pages 65-91.

Kahneman, Daniel, and Amos Tversky, 1982, Judgment Under Uncertainty: Heuristics and Biases, (Cambridge University Press).

Kothari, S.P., and Jerold B. Warner, 2007, Econometrics of Event Studies, Chapter 1, Handbook of Empirical Corporate Finance, (Elsevier).

Lansdorp, Simon, and Willem Jellema, 2013, Momentum from underreaction (white paper), Robeco.

Lasfer, Ameziane M., Arie Melnik, and Dylan C. Thomas, 2003, Short-term reaction of stock markets in stressful circumstances, Journal of Banking and Finance, Volume 27, Issue 10, Pages 1959-1977.

Malkiel, Burton, G., 2003, The Efficient Market Hypothesis and Its Critics, Journal of Economic Perspectives, Volume 17, Issue 1, Pages 59-82.

Molnár, Peter, 2016, High-low range in garch models of stock return volatility, Applied Economics, Volume 48, Issue 51, Pages 4977–4991.

Nelson, Daniel B., 1991, Conditional Heteroskedasticity in Asset Returns: A New Approach, Econometrica, Volume 59, Issue 2, Pages 347-370.

Rozeff, Michael S., and William Kinney, 1976, Capital market seasonality: The case of stock returns, Journal of Financial Economics, Volume 3, Issue 4, Pages 379-402.

Zarowin, Paul, 1990, Size, Seasonality, and Stock Market Overreaction, Journal of Financial and Quantitative Analysis, Volume 25, Issue 1, Pages 113-125.

Wäneryd, Karl-Erik, 2001, Stock-market psychology: How people value and trade stocks. (Edward Elgar Publishing).

9.2 Electronic Sources

Avanza Bank, 2020, Börsvärde.
https://www.avanza.se/aktier/aktiegeneratorn/aktiegeneratorn-foerdjupning/borsvarde.html, (Accessed 2 April, 2020)

Nasdaq OMX Nordic, 2020, Vad är ett aktieindex?
http://www.nasdaqomxnordic.com/utbildning/aktier/vadaraktieindex?languageId=3, (Accessed 5 April, 2020)

10. Appendices

10.1 Appendix A: List of All Companies Used in Each Sample

10.1.1 List of LargeCap Firms

AAK
ABB
Addtech
Ahlstrom-Munksjö
Alfa Laval
Assa Abloy
AstraZeneca
Atlas Copco
Atrium Ljungberg
Attendo
Autoliv
Avanza Bank Holding
Axfood
Balder
Beijer Ref
Betsson
BillerudKorsnäs
Boliden
Bonava
Bravida Holding
Castellum
Dometic Group
Electrolux
Elekta
Ericsson
Evolution Gaming Group
Fabege
Fastpartner
Fenix Outdoor International
Getinge
H&M
Handelsbanken
Hexagon
Hexpol
Holmen
Hufvudstaden
Husqvarna
ICA Gruppen
Industrivärden
Indutrade
Intrum
Investor
JM
Kindred Group
Kinnevik
Klövern
Kungsleden
Latour
Lifco
Loomis
Lundberg-
företagen
Lundin Mining
Lundin Petroleum
Millicom
MTG
Mycronic
NCC
Nibe Industrier
Nobia
Nolato
Nordea
Pandox
Peab
Ratos
Resurs Holding
Saab
Sagax
Samhällsbyggnadsbolaget i
Norden
Sandvik
SCA
SEB
Securitas
Skanska
SKF
SSAB
Stora Enso
Sweco
Swedbank
Swedish Match
Swedish Orphan Biovitrum
Tele2
Telia Company
Thule Group
TietoEVRY
Trelleborg
Vitrolife
Volvo
Wallenstam
Wihlborgs
ÅF Pöyry

10.1.2 List of SmallCap Firms

A3 Allmänna IT- och Telekomaktiebolaget
Active BioTech
Agromino
Anoto Group
Arctic Paper
Arise
B3 Consulting Group
Bactiguard Holding
BE Group
Beijer Electronics
Bergs Timber
BioInvent International
Björn Borg
Bong
Boule Diagnostics
Brinova Fastigheter
Cantagria
Christian Berner Tech Trade
Concordia Maritime
Consilium
C-RAD
Dedicare
Doro
Duroc
Edgeware
Electra Gruppen
Elos Medtech
Empir Group
Endomines
Eniro
Episurf Medical
Etrion
eWork Group
Feelgood Svenska
FormPipe Software
Gaming Innovation Group
GHP Speciality Care
HANZA Holding
Havsfrun Investment
ICTA
KABE Group
Karolinska Development
Lammhults Design Group
Magnolia Bostad
Malmbergs Elektriska
MedCap
Medivir
Micro Systemation
Midway
Moberg Pharma
Moment Group
MQ
multiQ International
NAXS
Net Insight
NeuroVive Pharmaceutical
NGS Group
Nilörngruppen
Note
Novotek
Odd Molly
Ortivus
Oscar Properties
PledPharma
Poolia
Precise Biometrics
Prevas
Pricer
ProfilGruppen
Railcare Group
Rejlers
RNB Retail and Brands
Saniona
Semcon
Sensys Gatso Group
Serneke Group
Sintercast
Softronic
Sportamore
Starbreeze
Stockwik Förvaltning
Strax
Studsvik
Svedbergs
TradeDoubler
Trention
Venue Retail Group
Vicore Pharma Holding
Viking Supply Ships
Wise Group
Xbrane Biopharma
ZetaDisplay

10.2 Appendix B: Additional Tables

Table 15: CARs up to One Year Following an Event (-17.5%) for Companies Listed at LargeCap

*Table 15 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price decreases 17.5% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=127		*Panel B = CARs estimated using the EGARCH (1,1) model, N=126*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	0.89%	0.10	1.35%	0.16
1:12	-19.26%	-1.34	-17.13%	-1.31
2:12	-31.92%	-1.81*	-28.55%	-1.78*
3:12	-31.81%	-1.66*	-28.35%	-1.63*
6:12	-26.33%	-1.66*	-21.71%	-1.67*

Table 16: CARs up to One Year following an event (+17.5%) for Companies Listed at LargeCap

*Table 16 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price increases 17.5% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=200		*Panel B = CARs estimated using the EGARCH (1,1) model, N=215*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-14.16%	-2.61***	-13.51%	- 2.68 ***
1:12	-9.60%	-1.21	-9.65%	-1.34
2:12	-4.37%	-0.47	-5.47%	-0.66
3:12	-0.48%	-0.06	-0.27%	-0.04
6:12	3.97%	0.84	2.95%	0.69

Table 17: CARs up to One Year Following an Event (-30%) for Companies Listed at SmallCap

*Table 17 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price decreases 30% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=41		*Panel B = CARs estimated using the EGARCH (1,1) model, N=54*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	32.79%	1.10	22.60%	1.10
1:12	99.71%	1.06	41.91%	1.02
2:12	77.20%	0.94	33.73%	0.92
3:12	66.69%	1.04	35.56%	1.29
6:12	83.72%	1.22	35.63%	1.19

Table 18: CARs up to One Year Following an Event (+30%) for Companies Listed at SmallCap

*Table 18 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price increases 30% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). The estimation window used is the whole time sample period.*

	Panel A = CARs estimated using GARCH (1,1) model, N=108		*Panel B = CARs estimated using the EGARCH (1,1) model, N=125*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	8.22%	0.46	4.61%	0.33
1:12	72.90%	0.95	56.70%	0.94
2:12	60.68%	0.93	47.44%	0.93
3:12	67.34%	0.97	53.80%	1.01
6:12	59.99%	1.05	50.17%	1.10

Table 19: CARs up to One Year following an Event (-20%) for Companies Listed at LargeCap

*Table 19 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price decreases 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). An estimation window of 45 months three months before each event is taken place is used.*

	Panel A = CARs estimated using GARCH (1,1) model, N=14		*Panel B = CARs estimated using the EGARCH (1,1) model, N=21*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	3.98%	0.38	6.32%	0.89
1:12	13.35%	0.78	8.19%	0.69
2:12	11.85%	0.72	5.60%	0.49
3:12	4.52%	0.32	-1.10%	-0.11
6:12	9.70%	0.80	2.47%	0.29

Table 20: CARs up to One Year Following an Event (+20%) for Companies Listed at LargeCap ‘

*Table 20 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at LargeCap. A specific month is defined as an event if the stock price increases by 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). An estimation window of 45 months three months before each event is taken place is used.*

	Panel A = CARs estimated using GARCH (1,1) model, N=21		*Panel B = CARs estimated using the EGARCH (1,1) model, N=24*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-1.78%	-0.46	-1.04%	-0.30
1:12	1.02%	0.13	1.79%	0.26
2:12	4.55%	0.61	4.66%	0.72
3:12	4.06%	0.51	4.19%	0.61
6:12	3.75%	0.60	3.50%	0.65

Table 21: CARs up to One Year Following an Event (-20%) for Companies Listed at SmallCap

*Table 21 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price decreases by 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). An estimation window of 45 months three months before each event is taken place is used.*

	Panel A = CARs estimated using GARCH (1,1) model, N=19		*Panel B = CARs estimated using the EGARCH (1,1) model, N=23*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-16.21%	-1.26	-14.66%	-1.31
1:12	-65.78%	-2.39**	-55.80%	-2.30**
2:12	-67.39%	-2.47**	-56.90%	-2.36**
3:12	-64.93%	-2.39**	-54.32%	-2.27**
6:12	-43.96%	-1.72*	-36.08%	-1.64

Table 22: CARs up to One Year Following an Event (+20%) for Companies Listed at SmallCap

*Table 22 shows the results for the Cumulative Abnormal Returns (CARs) for different event windows lasting up to a year following the event (occurring at t=0) for companies listed at SmallCap. A specific month is defined as an event if the stock price increases by 20% or more during that month. Notes *, **, *** & **** denote the statistical significance at the 10%, 5%, 1% respectively 0,1%. The CARs are estimated both through the GARCH (1,1) (Panel A) and the EGARCH (1,1) method (Panel B). An estimation window of 45 months three months before each event is taken place is used.*

	Panel A = CARs estimated using GARCH (1,1) model, N=11		*Panel B = CARs estimated using the EGARCH (1,1) model, N=15*	
Event window	**CARs (%)**	**t-statistic**	**CARs (%)**	**t-statistic**
1:6	-67.76%	-1.39	-55.71%	-1.57
1:12	-70.21%	1.10	-52.26%	-1.13
2:12	-56.50%	-0.97	-38.30%	-0.90
3:12	-68.12%	-1.20	-46.82%	-1.11
6:12	-40.15%	-0.87	-24.44%	-0.73