Mergers and Acquisitions in UK: a study for Abnormal Returns and Trading

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Abstract

This thesis examines Mergers and Acquisitions that took place in United Kingdom during 1990-2011. Actually, it is examined only the firms that are listed in London Stock Exchange in that period. Focusing on what is referred in bibliography as “market cleanliness” when there are corporate announcements and if there is market efficiency after an M&A announcement. The sample is being tested for abnormal returns and abnormal trading volume with the program that created for this purpose in Matlab software.
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List of Abbreviations

AR      Abnormal Returns
AC      Abnormal Volume
CAR     Cumulative Abnormal Returns
CAV     Cumulative Abnormal Volume
ACAR    Average Cumulative Abnormal Returns
ACAV    Average Cumulative Abnormal Volume
M&A     Merger and Acquisition
1. Introduction

The current thesis aims to study if market remains efficient and what is referred in bibliography as “market cleanliness” when there are corporate announcements, focusing on the case of Mergers and Acquisitions (M&As). By this study we are concentrated on United Kingdom and especially on the listed firms on London Stock Exchange which have been involved in a Merger or Acquisition Event, either as a Target or as an Acquirer, and the benefits that may require from that event. To investigate whether there is information asymmetry in the market we are going to use a certain methodology to examine abnormal activity in the stock market. In many studies that have been carried out in the past, researchers have employed different types of methodologies to evaluate M&A event’s performance. Most known categories of these methodologies are the event study methodology, the accounting method or survey but in our case we are going to use the event study methodology.

As the literature has indicated so far, there are many examples around M&A announcements which have shown positive returns to shareholders of the target and negative or zero and in some cases small positive returns for the acquirer. Of course that depends on many other factors such as type of methodology used for evaluation etc. As Spyrou & Siougle (2010) claimed there are many cases of former examination, on how investors react to new information. Some of them may overreact while some others may react slowly with smoother moves. Depending on the type of behavior that an investor may have the results may be not consistent with Market Efficient Hypothesis (EMH).

Another issue that arises has to do with the location, meaning where the M&A takes place, is it local or cross-border. The reason that it is examined in many studies is because returns after a Merger or Acquisition are different. As Doukas & Travlos(1988) supported in their study cross-border Mergers and Acquisitions on US particularly had positive, significant abnormal returns. Their result based upon other studies performed previously. On the contrary, Manzon, et al., (1994) claimed that abnormal returns derives from differences of international taxation and Bjorvatn, (2004) supported that M&As which different countries being involved based on “economic integration”.

Regarding the Efficient Market Hypothesis according to Beechey, et al., (2002) and Samuelson, (1965) investors faces the new market information and depending on their rationale may react normally or overreact in some cases as well as under react. As they claimed in their investigation, in order investors to have a net effect should have a normal
reaction which is more spontaneous than extreme and follows what is called normal distribution pattern.

Another factor that is critical is insider information. Many prior studies have been carried out to test information efficiency around the announcement of corporate events such as Mergers and Acquisitions in our case. Although early studies have shown that abnormal returns may have been produced from M&As and are associated with insider trading. Arnold, et al., (2000). Insider trading appears when a part of the market participants possess information that has an effect on share prices of its own firm and this information is used to profit from trading. More specifically, superior information is used by insiders to produce abnormal returns by selling for example shares before there is a decrease to their price or the opposite. Moreover in the literature there is also another view which is supported. Abnormal returns may be created not necessarily from inside information but from insiders’ potential ability to However, as a certain stream in the literature argues, those abnormal returns could also be explained by insiders’ ability to detect temporary mispricing of the firm’s stock, rather than by their possession of inside information.

There are two opinions supported around insider trading. First there are economist who support that insider trading is positive for an economy because as they claimed it leads to development of efficient market that have a more informational character. According to Meulbroek, (1992), Aktas, et al., (2007) Leland, (1992) studies in case of insider trading if information is revealed on the market early the fundamental value of the firm will be reflected on share prices. In this case investors will make their decision facing a lower risk. Second, the managers’ role in trading activity of the company’s shares is a more proper way for them to be compensated. (Dye, 1984 & Manne 1966) The reason why this view is supported is because managers’ performance is reflected in share prices and that has a double positive effect for managers and shareholders.

On the contrary to these supporters mentioned above, there are strong believers of the opposite point of view. Shin, (1996) suggested that insider trading increase the losses during trading activity coming from liquidity traders. This kind of traders, originally, faces the disadvantage of not having information. In addition, Ausubel, (1990) states that market efficiency will be disturbed if outsiders know that insiders have more information because investment activity will be reduced. Leland, (1992) is one of these supporters that claimed insider trading creates an information asymmetric market. Concluding, according to Leland
investors in this kind of situation are exposed to higher risk regarding the cost that is taking into account and the market lacks of liquidity. A previous study by Bhattacharya & Daouk, (2002) suggests that enforcement, rather than the existence of rules alone is required for regulation to improve market cleanliness. The abnormal return on a given day is the difference between the expected return from our model and the actual return. By adding together abnormal returns over time we calculate cumulative abnormal returns (CARs). A positive abnormal price movement occurs before the announcement of good news (a “positive pre-announcement CAR”). This could indicate that the positive news in the announcement had been traded on before it had been made public, in breach of FSMA. Movements in the right direction are more likely to be the result of genuinely informed (and possibly insider) trading than those in the wrong direction. Even if insider trading is taking place, it may account only for a very small proportion of trading in a share, particularly for very liquid stocks, and fail to move the price. It may be possible for insiders to trade in a way which minimizes the price impact. In addition, where stocks are volatile, the impact of insider trading will be hard to spot through prices alone. For this reason, market abuse detection systems consider more variables than just a stock’s price. They may also look at volumes and the proportion of trading in the hands of each intermediary over time (see e.g. Minenna, (2003)). Meulbroek, (1992) identifies large price run-ups ahead of mergers and acquisition announcements where insider trading occurs.

1.1 Objectives
The main target of this thesis is to examine whether there are abnormal returns around Merger and Acquisition announcements in the UK concerning firms, either target or acquirer, which are listed on London Stock Exchange. We are going to examine a long period starting from the begging of the year 1990 up to the end of 2011. Also we are going to investigate the trading volume around M&A announcements which indicates as the previous researches have shown abnormal market activity.
1.2 Significance
This assignment provides further study in investigation around M&A announcements and the existence of abnormal returns and abnormal trading volume. Of course many researchers have focused on this subject before but the current thesis investigates a very large period of time covering nearly 25 years of announcements. We are testing the efficiency of the UK market by using the event study methodology. Based on other studies the subject that varies is the event window study. Bradley, et al., (1988) & Doukas, et al., (2002) used a window event of \([-5, 5]\) days, while Jarrell & Poulsen, (1989) used a window of \([-20, 10]\) days. Later Smith & Kim, (1994) in their study used a smaller event window of \([-5, 5]\) as our first case and \([-1, 0]\) and Houston, et al., (2001) used a window of \([-4, 1]\) days and Moeller, et al., (2003) used a window event of \([-1, 1]\). In our dissertation we used three event windows \([-1, 1]\], \([-5, 5]\) as the previous studies have done and we added \([-10, 10]\) event window. All event windows refer to days.

1.3 Limitations
In this dissertation in order to apply the event study methodology we have to collect all the data required from the methodology. Bloomberg database could not provide all the essential information because we are looking information for the companies nearly 25 years before which may not be available any more. In our case this happens for some firms which information about stock prices and trading volume was not available in the Bloomberg Database. Of course if we had information for all the firms of our sample that participated in M&A deals we could produce more accurate results of the listed firms in London Stock Exchange.
2. Literature Review

2.1 Mergers and Acquisitions

In the literature the sector that is more affected in Europe from Merger and Acquisitions (M&As) is the banking sector. This happens because the rationale behind the M&A event is to efficiently reduce the cost between banks such as operating costs, transaction cost and so on.

Another reason is that mergers generate value because allow banks to improve the position that already have in the market.

At first we will observe how firms that are involved in M&A announcements react. Many studies have been carried out analyzing different markets, such as US or European, and especially they focused on the banking sector. These studies are measuring the performance of share prices before and after an M&A announcement. What they try to achieve is to observe whether there are excess returns, relating to the announcement, for the shareholders and to correlate this with the announcement as an event. Houston & Ryngaert, 1994) examined a part of domestic mergers that occurred in the US and found that generally value for shareholders is not created through a merger. Although they found that there is a positive correlation in value created from a merger and the performance of the firm before being acquired. What they concluded is that in general more profitable firms acquire less profitable firms. Pilloff (1996) in his study states that economic efficiencies include gains which are correlated to abnormal returns. This means that mergers in US which are more likely to have reduced costs have higher returns after the M&A event. On the contrary Berger states (2000) and Hughes, et al. (1999) suggested that the revenues which arise through diversification of assets are more efficient relating to an M&A event. Finally, Kane (2000) is the last reference to US who said that M&As are more likely to create value when the target in a Merger is large firm (bank) and both target and acquirer have their headquarters in US is an indicator of higher increase in market penetration.

This dissertation is focused on Europe and particularly in UK and as Beitel, et al., (2004) did in his study we will examine European events. Beitel, et al., (2004) focused on 98 large banks from Europe that have been participated in an M&A event through the period of 1985 to 2000 to examine what impelled those firms and their excess returns. There were many motives that boosted the merging of those institutions spanning from firm size to increase of profitability. Campa & Hernando, (2004) also were involved with European mergers but they were focused not only in financial but also in non-financial mergers and reported that the value that
is higher is mostly created by industries that are regulated meaning the firms should be from the same country. But this situation may be optimal from the perspective of the market because it indicated more market power but on the other hand is quite painful for the customers because it implies higher prices.

Campa & Hernando, (2006) stated that the majority of gains which were being estimated coming from the possibility of cost reduction, which caused by “eliminating overlapping operations and consolidating backroom operations”. They also claimed that abnormal stock returns before or after an M&A announcement date are positively correlated costs that are estimated to be saved from the event.

Speaking about the country that an M&A may takes place Hopkins, (1999) talked about domestic M&As and cross border M&As. The motives of domestic M&As are divided into four categories strategic, market, economic and personal motives. When he referred to cross-border M&As he claimed that in the global market what is considered as an advantage is the differentiation of nationalities, economies of scale and scope. In addition to that cross-border motives depend on achieving efficiency in firms’ operations, management of risk etc.

The study of Keown & J.M., (1981) has proved that market begins to react to mergers which are intended to occur before even they are announced to public. They support that the trading before the announcement is based on inside, illegal, information. Additionally, they characterized inside information as “poorly held secrets” meaning that there is distribution of the pending merger announcement. The results of their study supported the semi-strong efficiency form that we are going to analyze below, since the reaction that comes from the market related with new, public information is fulfilled the following trading day after the announcement date.
2.2 Efficient Market Hypothesis

Efficient market hypothesis and the phrase “random walk” are totally associated in finance. With the phrase “random walk”, is described the random change in shares’ prices regarding the prices of the previous day. The term random walk basically refers to the impact of new information to the price of the stock. If we consider that news is unpredictable then the same must happen with the change in the shares price which must be unpredictable too.

Originally, the efficient market hypothesis was introduced by Eugene Fama in the early 1960s when he tried to develop an academic concept in his Ph.D thesis. It was widely accepted from most of the economists until 1990 but after that period new theories introduced to world. (Fox, 2002)

Many analysts have found problems while they were applying efficient market hypothesis. The problem was found especially on stocks that have low price to earnings ratio and outperform other shares. (Basu 1977 & Fama E 1992) On the other hand, there were theories that believe “cognitive biases cause these inefficiencies” Fox (2002) aiming to push investors purchase stocks with overpriced growth and not valuable stocks. Beechey, et al., (2002) observed much inefficiency that make efficient market hypothesis controversial but apart from that still is consider being a great starting point.

As we mentioned above in the middle 1960s Eugene Fama introduced the meaning of random walk hypothesis through his Ph.D thesis Fama (1965) while in the same period Samuelson published a proof for a version of this hypothesis Samuelson, (1965). Based in that particular paper which went a step further by refining the initial theory, we now have the three types that characterize the market efficiency: Strong, semi-strong and weak. We are going to analyze them below.

Samuelson (1965) also asserted that efficient market hypothesis fits best in individual stocks than in the stock market as a whole. Of course what he claimed is fully based on researched and proved with the right regressions and diagrams which support what he said about stock market whether “micro” or “macro” is efficient.

For the case of UK market which is under investigation, according to efficient market hypothesis types UK stock market is weak form efficient as many studies have shown while other studies support that is semi strong efficient. For instance Khan (1986) supported that is semi strong efficient because after releasing lots of important information, from the trader’s view, in the grain future market he concluded that belongs to this category. Also Firth with his studies Firth (1976, 1979, 1980) over takeover announcements supported that after the announcements share prices adjusted fully to the relevant levels. Concluding that the UK market is semi strong efficient. Although the market responded quickly to those changes,
which were of short-term, kind does not necessarily mean that belong to the semi strong category. A better indicator I order to characterize a market efficient is the long term performance and not an immediate response to an event.

Efficient market hypothesis states that when some investors come up with new information may have two possible extreme reactions, either overreact or underreact. In order to have a net effect on market prices that is not exploit to return an abnormal profit the investors should have spontaneous and normal reactions, meaning reactions that follow the normal distribution pattern. (Beechey, et al., 2002 & Samuelson, 1965)

There is a categorization of the market efficiency depending on different implications for the functionality of the market. That is the weak, semi-strong and strong efficient markets.
In the first case of weak efficient markets, we cannot predict future prices of a stock based on past prices. So investors cannot earn excess returns based on past stock prices or data. In that sense, share prices follow what is called a random walk and market participants will not be able to gain profits from an inefficient market. Saad, et al., (1998)

When a market belongs to semi-strong efficiency category the share prices follow the public new information instantly in a way that investors cannot profit by trading using this particular information. (Malkiel, 1987) As we are informed from theory, according to strong-form efficient market hypothesis public and private information is reflected in share prices and no one can benefit to earn excess returns. In a strong efficient market we can observe two categories of investors, those who are lucky and those who are not, but in any case we will not find any superior investors who can constantly beat the market. (Brealey, et al., 2011)
2.3 Insider Trading

Many event studies about deals’ announcements, such as mergers and acquisitions, suggest that an important amount of information is released around these announcements Chae, (2005). An extensive previous literature exists that shows an increase in the volume and price of a target firm before the first public announcement of a merger or acquisition. These studies provide evidence on these increases and show that they are a result of insider trading. Insider trading can be defined as the unaccepted selling or buying of a firm’s securities, by individuals or firms, which possess valuable information about the firm’s movements; information which has not yet been announced to the public (Meulbroek, 1992). Thus, these studies prove that the increases are a result of direct or indirect trading on non-public information Arnold, et al., (2000).

It is generally accepted that the study of insider trading has risen in importance after the 2007 financial crisis and has become a matter of public concern and interest Barnes, (2011). Previous studies have attempted to measure the extent of insider trading at the time of a merger announcement. For example, the FSA examined the changes in the prices of stocks, which were above the changes in the market as a whole, by using two trading days prior to the day of announcement as the pre-announcement window and the day of announcement and the next trading day as the post-announcement window. Given these data Dubow & Monteiro, (2006) found significant evidence of price changes right before the announcement of a deal. They interpreted this pre-announcement abnormal performance as a result of insider trading. However, their study window was too small to measure for price changes before a merger or acquisition deal.

Barnes (1996& 2009) conducted a similar study, as well, although he used a wider window. By employing a pre-announcement window of two months, he found an increase equal to 31% in the target firm’s stock prices two months before the announcement to one month afterwards and an increase equal to 23% before the announcement. His results are consistent with Bulkley & Herreras (2002) and Bulkley, et al. (2002) who found high levels of abnormal stock price performance during the five days before the deal announcement and Meulbroek (1992), who reports large stock price increases “ahead of mergers and acquisition announcements where insider trading occurs”.

However, according to Dubow & Monteiro (2006) “Even if insider trading is taking place, it may account only for a very small proportion of trading in a stock, particularly for very liquid stocks, and fail to move the price or volume”. The predictions about trading volume before a merger or acquisition announcement are ambiguous in finance theory Chae (2005). For
example, Kyle (1985) finds that liquidity trading is exogenous and inelastic to stock price. This means that there is an increase of information asymmetry in the trading volume and occurs because the traders that possess private information try to take advantage of these information. On the other hand, Admati & Pfleiderer (1988) and Foster & Viswanathan, (1990), find that “liquidity traders have timing discretion”. This means that information asymmetry is decreased in the trading volume. According to Chae (2005)“in these models, when discretionary liquidity traders receive exogenous trade demands prior to announcements, they will postpone trading until the announcement is made and the information asymmetry is resolved”. Thus, we can observe a decrease in total volume before the announcement and a correspondingly increase afterwards.
### 2.4 Event study methodology

As it is referred previously, the event study methodology is commonly used in order to find the impact on stock prices that an announcement of a Merger and Acquisition may have on the firms. Basically, an event study is a statistical method that measures the value that an event can create or destroy, for two business entities that take part in an event. The main idea created by an event study is to find the abnormal return caused by a Merger or Acquisition deal and has an impact to the market as a whole. Anyone can understand simply by studying, any of the event studies that have been done over the past 30 years that the logic behind the statistical implementation of event studies has not changed over time. Even nowadays, the majority of the event studies are based on the model introduced by Fama, et al., (1969). There are not significant changes in the main methodology, meaning that still there is calculation of the mean, the abnormal and cumulative abnormal returns of the securities. However, we cannot ignore that daily observations and sometimes intraday, instead of monthly observations are now used in order to have more precise results. Also the methodology that is followed in order to estimate the abnormal returns has been improved with more sophisticated procedures that are mostly important for what is referred in a few paragraphs below as long horizon studies.

The mechanism of how event study methodology is applied, especially on Mergers and Acquisitions, has been referred by Warren-Boulton & Dalkir, (2001). In financial markets, investors bet on whether an M&A will raise or lower prices. Especially Mergers, on which the price has been raised, both business entities will benefit from the event because the prices will be raised for all their shares. In that sense, people would expect the efficiencies from the merger to have a down side trend for the prices but as the possibility of the merger grows the share price of the participants to the deal falls. Thus, when an important event, relating to a Merger, occurs, market price effects can be predicted with the help of evidence from financial markets.

Also, Warren-Boulton & Dalkir, (2001) use an “event-probability methodology”, which initially was introduced by McGuckin et al. (1992), to be applied to merger analysis. This particular methodology involves “ex-ante calculation of the financial markets’ assessment of the probability that the merger will indeed take place in the future.” Warren-Boulton & Dalkir, (2001)

An overview of event study methodology is also given through the studies of Mac Kinlay, (1997), who also documented the origins and breadth of them. Moreover, he mentioned the
use of event studies in many applications such as accounting, finance research and “economy wide events”, such as Mergers and Acquisitions, and issuing of new equity or debt. In addition, as Mitchell & Netter, (1994) referred, event study is a method that was “developed and refined by financial economists” that used it to reveal securities fraud cases. They pointed the significance of the event study technique to reveal the changes in stock prices when they are related to release of new information.

In the case of Fama, et al., (1969) there was evidence from the market which shows that the announcement of an event, such as a split, makes the market to reevaluate the volume of the income coming from the shares. It is claimed that the results of the event study shows the market efficiency through the rapid adjustment of the new information to stock prices.

There is also variation through short-horizon event studies and long horizon event studies. It is said that short-horizon studies are more reliable than long-horizon as the second one have much more limitations. However, Kothari & Warner (2005) were able to refine long-horizon studies to improve the results and reliability of long time periods under investigation. While progress has been observed in long-horizon methods still there are serious limitations of those methods. Although, results from those methodologies have to be meticulously analyzed, since, as Lyon, et al. (1999) mentioned, “The analysis of long-run abnormal returns is treacherous”. Of course, those reports make long-horizon methods more reliable and they eliminate the previous warnings about the accuracy of the results of this method Brown & Warner (1980). There is a lot of discussion around the accuracy of long-horizon methods against the results of short-horizon ones since they are non-problematic and more or less straightforward. As Fama (1991) claimed, short-horizon tests represent the “cleanest evidence we have on efficiency”.

In the reports of Blume (1971) and Gonedes (1973) they made two modifications of the Fama, et al. (1969) methodology Firstly, event studies that use monthly observations have a date horizon between five and seven years of data. Second, depending on whether the event period belongs in the period that is used to estimate the market model parameters or not the results defer. As Fama, et al. (1969) and Ball & Brown (1968) have pointed out “the coefficient estimates are biased because the disturbances are not mean zero”. This should not be considered as a problem but since the time period of estimation becomes longer, five to seven years, and so does the bias of the data. A later study by Scholes (1972) indicated that estimations referring to data prior to event period and estimation of the abnormal returns of the market model in the period of investigation produce coefficients that are constant.
2.5 Hypotheses Formation

After concluding the chapter which includes the literature review, we form the hypotheses set for further investigation in the current dissertation. These are:

The first set:
\( H_0: \) There is abnormal share returns during 1990-2011 before the event

\( H_1: \) There is no abnormal share returns during 1990-2011 before the event

The second set:
\( H_0: \) There is abnormal share trading volume during 1990-2011 before the event

\( H_1: \) There is no abnormal share trading volume during 1990-2011 before the event
3. Methodology and Data

3.1 Data selection procedure

Our sample period spans 1990 to 2011. Our dataset is limited to public firms listed in the London Stock Exchange that have participated in a number of mergers or acquisition deals. The source of our market data is Bloomberg database. To be included, a firm must have taken part in a merger or acquisition deal that has been completed. We additionally require the acquirer firms to possess more than 50% of the target firm after the deal, to focus on significant M&A deals. Firms with unavailable data relating to a merger or acquisition deal and firms with incomplete deals have been excluded from the sample. We have also reviewed our data for inconsistencies by comparing the acquirer firm data and the target firm data. This procedure has produced an initial sample of 1980 deals but we are able to provide results for 1892 M&A announcements that took part in the period under investigation. This happens because data were unavailable to Bloomberg database.

For every firm either as a target or an acquirer we have to collect daily data from January 1988 to September 2012. Closing price and the trading volume will provide as the data we need before and after an M&A announcement. We also collect the same data for the index FTSE 100 that includes 100 companies listed on the London Stock Exchange with the highest market capitalization. “It is one of the most widely used stock indices and is seen as a gauge of business prosperity.”

Stock returns are calculated through the closing prices. Actually stock returns are the first differences of log price levels. The closing prices are also collected from Bloomberg database.

In many cases, the announcement of an event occurs during a weekend or during a holiday. For this specific reason, we are examine the next trading day, not more than three days after the announcement date, in order to derive information for stock closing prices and volume traded. This is depicted also in the program produced in Matlab and is shown on Appendix.

1 [www.investopedia.com](http://www.investopedia.com)
3.2 Methodology

3.2.1 Returns
We followed the event study methodology to estimate the Cumulative Abnormal Returns (CAR) over \([-\lambda, +\lambda]\) days around the M&A announcement, which is day zero (0) for every target and acquirer of our sample. We used a period of \([-k,-30]\) days prior to announcement date, for every firm to calculate the daily returns for that specific estimation period. The market model regression that we performed is the following:

\[ R_{i,t} = a_i + b_i R_{m,t} \]

This regression refers to every single firm of our sample \((i)\) that participates in an M&A deal with the \(R_{i,t}\) return of the firm (target of acquirer) on day \(t\), as well as to the return of the FTSE100 index on the same day. This regression also produces the estimates \(\hat{a}_t, \hat{b}_t\) of each of the firms under investigation, so with these results we can calculate the abnormal returns of the firm and also the cumulative abnormal returns.

\[ AR_{i,t} = R_{i,t} - (\hat{a}_t + \hat{b}_t R_{m,t}) \]

Cumulative abnormal returns are calculated by summing the abnormal returns for each firm across time.

\[ CAR_t = \sum_{t=-\lambda}^{+\lambda} AR_t \]

We also calculated the Average Cumulative Abnormal Returns by adding all the individual CARs related to a specific period \([-\lambda, +\lambda]\) for all the events under investigation.

\[ ACAR^{-k,\lambda} = \frac{1}{N} \sum_{i=1}^{N} CAR_{i}^{-k,\lambda} \]
3.2.2 Volume traded

As we are concerned, there is a lot of discussion around trading volume prior to any announcement and especially those of Mergers and Acquisitions. As (Kyle, 1985) suggested the trading volume increases when there is information asymmetry. As he claimed this is caused when “liquidity is exogenous and inelastic to price”. Actually this is happening because traders who have been informed privately want to share the information.

Based on the theory above we are trying to examine whether there is abnormal stock trading volume prior to a Mergers and Acquisitions announcement for the firms of our sample. In order to configure that the statement above holds, we have to take the average trading volume for each firm’s stock prior to the event and compare it with an average of a benchmark period.

The price of the volume traded varies a lot, for this reason we are going to use the natural logarithm in the formula:

\[ V_{i,t} = \ln(1 + Volume\ traded\ in\ day\ t\ of\ firm\ i) \]

We followed the very same methodology as we did with the returns to estimate the Cumulative Abnormal Volumes (CAV). Again, for \([-\lambda, +\lambda]\) days around the M&A announcement, which is the day zero (0) we calculated the abnormal volumes traded for every target and acquirer of our sample. We used a period of \([-k, -30]\) days prior to announcement date, for every firm to calculate the daily volume traded for that specific estimation period. The market model regression that we performed is the following:

\[ V_{i,t} = a_i + b_i V_{m,t} \]

This regression refers to every single firm of our sample (i) that participates in an M&A deal with the \(V_{i,t}\) trading volume of the firm (target of acquirer) on day t, as well as to the trading volume of the FTSE100 index on the same day. This regression also produces the estimates \(\hat{a}_i, \hat{b}_i\) of each of the firms under investigation, so with these results we can calculate the abnormal volume of the firm and also the cumulative abnormal volume.

\[ AV_{i,t} = V_{i,t} - (\hat{a}_i + \hat{b}_i V_{m,t}) \]

Cumulative abnormal volumes are calculated by summing the abnormal volumes of each firm across time.
We also calculated the Average Cumulative Abnormal Volumes by adding all the individual CAVs related to a specific period \([-\lambda, \lambda]\) for all the events under investigation.

\[
CAV_t = \sum_{t=-\lambda}^{+\lambda} AV_t
\]

To calculate and derive all the results we used the software Matlab (developed by MathWorks) which is a numerical computing environment and fourth-generation programming language. We used the Matlab R2012b edition in order to have all the latest and fastest procedures available.

We have developed from the begging an algorithm that calculates the all the equations given above, AR, CAR, ACAR, AV, CAV, ACAV. The import of the data that were previously downloaded from Bloomberg database in a couple of Microsoft Excel files was done to Matlab software. We formed our database through this very useful tool in order to be able to manage the large volume of data. The program is able to manage many deals and a lot of data through iterative processes. The full program is available on the appendix.
4. Data analysis & Discussion

As we said above our sample period spans 1990 to 2011. Our dataset is limited to public firms listed in the London Stock Exchange that have participated to a number of mergers or acquisition deals. We are going to provide a diagram that depicts the number of the listed firms in London Stock Exchange that participated in Mergers and Acquisitions each year from 1990 to 2011.

![M&A announcements](image)

**Figure1:** Firms that are listed in London Stock Exchange and are involved in a Merger and Acquisition event during 1990-2011.

Then we will illustrate some statistical results for the sample. We separate the sample in returns of stock prices and trading volumes of shares.
### Descriptive Statistics

<table>
<thead>
<tr>
<th>Descriptive Statistics</th>
<th>[-100,-30]</th>
<th>Acquirer Returns</th>
<th>Target Returns</th>
<th>Acquirer/Target Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>-1.6002</td>
<td>-6.9386</td>
<td>-6.9386</td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>2.9957</td>
<td>5.0106</td>
<td>5.0106</td>
<td></td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0325</td>
<td>0.0565</td>
<td>0.0457</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>10.7893</td>
<td>-12.8672</td>
<td>-9.7641</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1601,2000</td>
<td>4366,2000</td>
<td>5132,8000</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Descriptive Statistics</th>
<th>[-150,-30]</th>
<th>Acquirer Returns</th>
<th>Target Returns</th>
<th>Acquirer/Target Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>-2.128</td>
<td>-6.9386</td>
<td>-6.9386</td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>4.6517</td>
<td>6.2146</td>
<td>6.2146</td>
<td></td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.035</td>
<td>0.0564</td>
<td>0.0466</td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>18.9977</td>
<td>-2.2408</td>
<td>2.1931</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2834,0000</td>
<td>4677,5000</td>
<td>5326,7000</td>
<td></td>
</tr>
</tbody>
</table>

**Table A: Descriptive Statistics for Returns of Stock Prices**

In table A, are presented the descriptive statistics of the vectors that include for every M&A event the returns that refers to Acquirer or Target or Both of them. These statistics were calculated for the period of 1990-2011. Calculation of mean, median, standard deviation, minimum, maximum, skewness and kurtosis also refer to the period of 2007-2011, for market participants. In the calculations of every descriptive statistic not available values are not taken into account. As we see for event window of [-100, -30] daily observations the mean for acquirer target and for both of them is almost zero. The median is centered in zero for the three cases. The maximum daily return is 5.0106 and belongs to the Target’s vector while the minimum is -6.9386 and belong to target too. As we can see standard deviation for the three cases is very low and that is a sign that implies the data is very close to the mean. Acquirer’s Return distribution shows large skewness a fatter right tail and obviously a very large kurtosis that shows a huge peak above normal distribution. Target’s Returns distribution show a large skewness, a fatter left tail, and the same is for the returns that refer to both target and acquirer. Also it can be observed the extremely large kurtosis in that case too. For event window we have more or less the same statistical results with very small variations.
In table B, are presented the descriptive statistics of the vectors that include for every M&A event the Trading Volume that refers to Acquirer or Target or Both of them. These statistics were calculated for the period of 1990-2011. Calculation of mean, median, standard deviation, minimum, maximum, skewness and kurtosis also refer to the period of 2007-2011, for market participants. In the calculations of every descriptive statistic not available values are not taken into account. As we see for event window of [-100, -30] daily observations the mean for acquirer target and for both of them are significant different from zero they are quite big and positive. The median is not centered in zero for the three cases. The maximum daily volume traded is 20.4136 (in first log differences) and belongs to the Target’s vector while the minimum is 0 and belongs to the three vectors simultaneously. As we can see standard deviation for the three cases is not very low and that is a sign that implies the data are spread out over a large range of values. Skewness in all the cases is small negative implying a relative fatter left tail in the distribution. Kurtosis is not very large for the three vectors, meaning that we have a small peak above normal distribution. The same results with minor differences we have also in the case of [-150, -30] event window.
In this section of the dissertation will be represented the results of the cumulative abnormal returns (CAR), Cumulative Abnormal Volumes (CAV) and the Average Cumulative Abnormal Returns (ACAR) as well as the Average Cumulative Abnormal Volumes (ACAV) for all the firms that participated in an Merger and Acquisition announcement either is a target or acquirer. We separate our sample in two categories according to the days chosen before the announcement. One case has to do with 100 days prior to announcement until 30 days prior to announcement date. The former selection creates the event-date window, which is [-100,-30] days before an announcement. The second case refers to more days prior the announcement, actually 150 days, up to 30 days before the announcement and that creates an event window of [-150, -30] days. We applied the same time range in both target and acquirer return prices and volume trading prices.

Before starting annotate the results for ACAR, ACAV in each case we have to mention the number of observations that we have in each vector of Cumulative Abnormal Returns or Cumulative Abnormal Volumes and are used to produce the Average Cumulative Abnormal Returns or Average Cumulative Abnormal Volumes. As we have mentioned before we did not have data for all the firms that participated in M&A events since they are not available from the Bloomberg Database. Some of the firms may have data but not for all the days during the investigation period. Using the Matlab we can exclude the unavailable values and report how many observations create a vector of CAR or CAV and produce an Average CAR or Average CAV.

First we checked the period [-100,-30] for the returns of stocks. The acquirer’s vector includes 1707 out of the 1892 observations of the sample that refers to all the deals occurred during the period 1990-2011. The target’s vector includes 1604 out of the 1892 observations of the sample and the vector that refers to both of them 1419 observations. This is for each case the multitude that we use to calculate the each ACAR. We should not forget to clarify that each of these amounts, refer to all three event window periods that created by different values of $\lambda$ around the date of announcement, remains the same.

For period [-150, -30], the acquirer’s vector includes 1706 out of the 1892 observations of the sample while the target’s vector includes 1597 out of the 1892 observations of the sample and the vector that refers to both of them 1411 observations.

Regarding the trading volume, for period [-100,-30] days we have the acquirer’s vector which includes 1707 out of the 1892 observations of the sample while the target’s vector includes
1685 out of the 1892 observations of the sample and the vector that refers to both of them 1409 observations.

Concluding, the event period [-150, -30] for trading volume has the acquirer’s vector which includes 1705 out of the 1892 observations of the sample while the target’s vector includes 1586 out of the 1892 observations of the sample and the vector that refers to both of them 1399 observations.

In order to evaluate whether our results are statistically significant or not we used the t statistic. Actually t-statistic is a ratio which shows the variation of the estimation of a parameter from its actual value and it includes also the standard error. 2 Matlab produces for data that user demands a value for t-statistic automatically by using the appropriate statistical equations. We use the t-statistic for checking our two main hypotheses.

<table>
<thead>
<tr>
<th></th>
<th>RETURNS</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACAR Acquirer</td>
<td>λ</td>
</tr>
<tr>
<td>[-100, -30]</td>
<td>0.0013</td>
</tr>
<tr>
<td>t -statistic</td>
<td>0.89</td>
</tr>
<tr>
<td>[-150, -30]</td>
<td>0.0004</td>
</tr>
<tr>
<td>t -statistic</td>
<td>0.30</td>
</tr>
</tbody>
</table>

Table 1: Average Cumulative Abnormal Returns (ACAR) of share prices for all acquirer firms that have participated in Merger & Acquisition announcement and are listed in London Stock Exchange.

In table 1 above are presented the Average Cumulative Abnormal Returns (ACAR) for all the acquirers that participated in a Merger or in an Acquisition event. Calculation of ACAR for different [-λ, +λ] period around the event date, day zero, concern the period 1990 to 2011. In first case of event window 100 days prior to event up to 30 day before the event day we observe that Average Cumulative abnormal returns for Acquirers are statistically insignificant for all the cases of the length of the event period around the day zero even in 1% significance level except from the second case that are statistically significant for 10%. So the null hypothesis of the first set of hypotheses is accepted in the two out of three cases, there are abnormal returns but not in the case of [-5, 5] days around day zero. In the case of [-150, -30]...

2 After an estimation of a coefficient, the t-statistic for that coefficient is the ratio of the coefficient to its standard error. That can be tested against a t distribution to determine how probable it is that the true value of the coefficient is really zero. Source: (http://economics.about.com/od/economicsglossary/g/tstat.htm)
30] days prior to announcement date, we have also, statistically insignificant results for all the lengths around the announcement day for the three ACAR results. The null hypothesis of first set is accepted for the Acquirers for all period lengths around announcement date. There are abnormal returns for the stock prices of Acquirers.

<table>
<thead>
<tr>
<th>ACAR Target</th>
<th>λ</th>
<th>[-1,1]</th>
<th>[-5,5]</th>
<th>[-10,10]</th>
</tr>
</thead>
<tbody>
<tr>
<td>[-100, -30]</td>
<td>-0.0026</td>
<td>-0.0080</td>
<td>-0.0184</td>
<td></td>
</tr>
<tr>
<td>t -statistic</td>
<td>-1.63</td>
<td>-1.78</td>
<td>-2.05</td>
<td></td>
</tr>
<tr>
<td>[-150, -30]</td>
<td>-0.0022</td>
<td>-0.0058</td>
<td>-0.0141</td>
<td></td>
</tr>
<tr>
<td>t -statistic</td>
<td>-1.62</td>
<td>-1.82</td>
<td>-2.30</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Average Cumulative Abnormal Returns (ACAR) of share prices for all target firms that have participated in Merger & Acquisition announcement and are listed in London Stock Exchange.

In table 2 above are presented the Average Cumulative Abnormal Returns (ACAR) for all the targets that participated in a Merger or Acquisition event. Calculation of ACAR for different [-λ, +λ] period around the event date concern the period 1990 to 2011. In first case of event window 100 days prior to event up to 30 day before the event day we observe that Average Cumulative Abnormal Returns for targets are statistically significant in event period [-1, 1] for 10% significance level, so we reject the null hypothesis for significance level of 10%. For [-5, 5] event period the sample is statistically significant for 5% significance level and we should not accept the null hypothesis of the first hypothesis set at 5% level. On the other hand, for the event period of [-10, 10] we reject the null hypothesis for 5% significance level since for that level we have statistically significant results. In the second case of [-150, -30] event period the results of ACAR in absolute values are significant in the first case of [-1, 1] for 10% significance level, so we reject the null hypothesis for that level. For the case of [-5, 5] results are significant in 5% significance level and so are for the event period of [-10, 10] days around event date. The null hypothesis is not accepted for this significance level.
Table 3: Average Cumulative Abnormal Volumes (ACA\textsuperscript{V}) of share prices for all acquirer firms that have participated in Merger & Acquisition announcement and are listed in London Stock Exchange.

In table 3, presented the Average Cumulative Abnormal Volumes (ACA\textsuperscript{V}) for all the acquirers that participated in a Merger or Acquisition event. In this table is depicted the ACA\textsuperscript{V} for the trading volume of the shares for different [-\(\lambda\), +\(\lambda\)] period around the event date, day zero (0), during 1990-2011. In the first case of event window [-100, -30] days we observe that Average Cumulative Abnormal Volume for Acquirers are statistically insignificant for all the three cases of the length of the event period around the day zero. For this reason we accept the null hypothesis of second hypothesis set, we have abnormal volume trading. In the case of [-150, -30] days prior to announcement date, we have also, statistically insignificant results for all the lengths around the announcement day for the three ACA\textsuperscript{V} results. The null hypothesis of the second set is not rejected even in 1% significance level for the Acquirers for all period lengths around announcement date.

Table 4: Average Cumulative Abnormal Volume (ACA\textsuperscript{V}) of share prices for all target firms that have participated in Merger & Acquisition announcement and are listed in London Stock Exchange.
In Table 4 are depicted the Average Cumulative Abnormal Volumes (ACAV) of trading volumes for all the targets that participated in a Merger or Acquisition event. Calculation of ACAV for different \([-\lambda, +\lambda]\) period around the event date, day zero, during 1990-2011. In first case of event window \([-100, -30]\) in absolute values, we observe that Average Cumulative Abnormal Volumes for Targets are statistically significant in event period \([-1, 1]\) for 10% significance level, so we reject the null hypothesis for significance level of 10%. For \([-5, 5]\) event period the sample is statistically significant for 1% significance level and we should reject the null hypothesis of second set hypotheses even at 1% level. Moreover in the event period of \([-10, 10]\) we also reject the null hypothesis for 1% significance level since for that level we have statistically significant results. In the second case of \([-150, -30]\) event period the results of ACAV in absolute values are statistically insignificant in the first case of \([-1, 1]\), so we accept the null hypothesis even for 10%. For the case of \([-5, 5]\) results are significant in 5% significance level and so are for the event period of \([-10, 10]\) days around event date. The null hypothesis is not accepted for this 5% significance level.

<table>
<thead>
<tr>
<th>RETURNS</th>
<th>ACAR Acquirer/Target</th>
<th>(\lambda)</th>
<th>([-1,1])</th>
<th>([-5,5])</th>
<th>([-10,10])</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>[-100, -30]</td>
<td>-0.0006</td>
<td>-0.0007</td>
<td>-0.0076</td>
<td></td>
</tr>
<tr>
<td></td>
<td>t -statistic</td>
<td>-0.54</td>
<td>-0.20</td>
<td>-1.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[-150, -30]</td>
<td>-0.0009</td>
<td>-0.0014</td>
<td>-0.0095</td>
<td></td>
</tr>
<tr>
<td></td>
<td>t -statistic</td>
<td>-0.97</td>
<td>-0.56</td>
<td>-2.32</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Average Cumulative Abnormal Returns (ACAR) of share prices for acquirer and target firms that have participated in Merger & Acquisition announcement and are listed in London Stock Exchange.

In Table 5 above we summarized the data we have already collected for both Acquirers and Targets in order to create a new vector that includes all the prices that returns of firms produced. What we applied in this part does not differ from the previous calculations of ACAR results but now the new vector that refers to Cumulative Abnormal Returns includes returns for all the firms that participated in an event, meaning both target and acquirer.

The Average Cumulative Abnormal Returns (ACAR) of stock returns for all targets and acquirers that participated in a Merger or Acquisition event is illustrated in Table 5. Again calculation of ACAR for different \([-\lambda, +\lambda]\) period around the event date, day zero, concern the
period 1990 to 2011. In first case of event window [-100, -30] in absolute values, we can see that Average Cumulative Abnormal Returns for both Acquirers and Targets are statistically insignificant in event period [-1, 1] even for 10% significance level, so we accept the null hypothesis even for 10% significance level. For [-5, 5] event period the sample is again statistically insignificant for all the three significance levels and we accept the null hypothesis of the first hypothesis set. Although in the event period of [-10, 10] we reject the null hypothesis for 10% significance level since for that level we have statistically significant results. In the second case of [-150, -30] event period the results of ACAR in absolute values are statistically insignificant in the case of [-1, 1] and [-5, 5] even for 10% significance level, so we accept the null hypothesis for 10% level. For the case of [-10, 10] results are significant in 5% significance level for the event period of days around event date. The null hypothesis is not accepted for this 5% significance level.

<table>
<thead>
<tr>
<th>VOLUME</th>
<th>ACAV Acquirer/Target</th>
<th>λ</th>
<th>[-1,1]</th>
<th>[-5,5]</th>
<th>[-10,10]</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>[-100, -30]</td>
<td>-0.0329</td>
<td>-0.2575</td>
<td>-0.4475</td>
<td></td>
</tr>
<tr>
<td>t -statistic</td>
<td>[-100, -30]</td>
<td>-0.73</td>
<td>-1.81</td>
<td>-1.79</td>
<td></td>
</tr>
<tr>
<td>[-150, -30]</td>
<td>-0.0108</td>
<td>-0.1649</td>
<td>-0.2872</td>
<td></td>
<td></td>
</tr>
<tr>
<td>t -statistic</td>
<td>[-150, -30]</td>
<td>-0.24</td>
<td>-1.15</td>
<td>-1.13</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Average Cumulative Abnormal Volumes (ACAV) of share prices for both acquirer and target firms that have participated in Merger & Acquisition announcement and are listed in London Stock Exchange.

In Table 6 above we follow the same procedure and we summarized the data we have already collected for both Acquirers and Targets in order to create a new vector that includes all the values that trading volumes of firms produced. We apply exactly the same formulas and steps in order to derive ACAV results but now the new vector that refers to Cumulative Abnormal Volumes includes the volume traded for both target and acquirer of all firms.

The Average Cumulative Abnormal Volumes (ACAV) of all targets and acquirers that participated in a Merger or Acquisition event is depicted in table 6 above. We repeat the calculation of ACAV for different [-λ, +λ] periods around the event date, day zero, concern the period 1990 to 2011. When K takes the value 100 creates the event window of [-100, -30], and in absolute values, we can see that Average Cumulative Abnormal Volumes for both
Acquirers and Targets are statistically insignificant in event period [-1, 1] even for 10% significance level, so we accept the null hypothesis for any significance level below 10%. For [-5, 5] event period the sample is statistically significant at 5% significance level and we reject the null hypothesis for that level. The same observation for the event period of [-10, 10] and that makes us to reject the null hypothesis for 5% significance level since for that level we have statistically significant results. In the second case of [-150, -30] event period the results of ACAV in absolute values are statistically insignificant for all the three cases of the length of the event period around the day zero and the null hypothesis is not rejected even for 10% significance level.
5. Conclusion and Recommendations

In this dissertation has been discussed the subject of Mergers and Acquisitions that took place in United Kingdom during 1990-2011. Actually, we examined in our sample only the firms that are listed in London Stock Exchange in that period. Our sample included daily share prices and trading volume of firms beginning from 1988 up to September 2012. The Bloomberg database, which used to find all that information, did not include information for all the companies that participated in an M&A deal. This happens because the sample contains companies from the very past and these values possibly are not available anymore.

With the available data we created a database in order to process the information provided. We used the Matlab software for implementing an algorithm that helps us to imitate the Event Study Methodology. This useful tool produced for all the firms, either is a Target or an Acquirer, the vectors of Abnormal Returns, Abnormal Volumes, Cumulative Abnormal Returns, Cumulative Abnormal Volumes, Average Cumulative Abnormal Returns, Average Cumulative Abnormal Volumes. For the last two vectors we used different event windows depending on the date that the Merger or Acquisition was announced. We examined the results that ACAR and ACAV produced for statistical significance through the t statistic test for significance levels of 10%, 5% and 1%. These results helps us to decide either to reject or accept the null or alternative hypothesis for the two categories in hypotheses formation mentioned in chapter 2 paragraph 2.5 above.

The results examine whether there are or not abnormal returns and abnormal volume traded around M&A announcements for three different event windows. For event window [-1, 1], referred to the Acquirers as whole, seems that [-100, -30] days before the announcement of the M&A event there are abnormal returns since the results are statistical insignificant for the three significance levels and that force us to accept the null hypothesis. For [-5, 5] days event window we have statistically significant results and not abnormal returns for 10% level. Exactly the same goes with the event window of [-10, 10] days and the null hypothesis of abnormal returns is accepted too. Changing the period prior to announcement of the event we took a sample of [-150, -30] days for acquirers. For event window of [-1, 1] still there are not statistically significant results for the ACAR value and the null hypothesis is accepted, we have abnormal returns. The very same result of abnormal returns for acquirers is observed in the event window of [-5, 5] days and also in [-10, 10] days.

Then we examined the ACAR results for targets with the same rationale. First we took a sample for each firm [-100, -30] days prior to the announcement. Using the same significance levels we examine the ACAR for [-1, 1] days event window. Results of t test showed...
statistical significance in different levels either 10% 5% or 1% so there are not abnormal returns. In the second case of [-150, -30] event window the results of ACAR in absolute values are significant so there are not abnormal returns in that case too.

We applied the same rational to calculate ACAV for Acquirers. In first case of [-100, -30] days as well as in the case of [-150, -30] days prior to announcement date, we have also, statistically insignificant results for all the lengths around the announcement day for the three ACAV results. The null hypothesis of the second set is not rejected even in 1% significance level for the Acquirers and there is abnormal trading volume.

In event window [-100, -30] in absolute values, we observe that ACAV for Targets have statistically significant results and the same happens in case of [-150, -30] event period and there is not abnormal activity. Except from the first case of [-1, 1], in which we accept the null hypothesis for abnormal trading volume.

Using the same logic, we applied the same technic for the vector containing returns for both target and acquirer. In event window [-100, -30] in absolute values, ACAR is statistically insignificant apart for the event period of [-10, 10] that there are not abnormal returns for 10% level. In the second case of [-150, -30] event period we accept that there are abnormal returns. For the case of [-10, 10] results are significant in 5% so there are not abnormal returns for that level.

In conclusion, ACAV of all targets and acquirers in [-100, -30] and [-150, -30] event periods in absolute values are statistically insignificant for all the length of the event period around the day zero and the null hypothesis is not rejected even for 1% significance level so there is abnormal volume traded. Only in first case for event window [-5, 5] & [-10, 10] we have not abnormal returns for 10% significance level.

It is obvious that depending the event window and the days prior to an event announcement there is abnormal activity either we refer to return of stocks or to volume traded. In case of Acquirers usually we have abnormal activity while in case of Target we do not have except from one event window. In case that we combine these two participants we mostly have abnormal activity either we refer to returns or volume.

This research can be extended in the future by using different event windows and maybe a smaller sample in order to derive more accurate results because in our case we have the limitation of the absence of some values.
List of References


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Firth, M., 1976. Share Prices and Mergers. s.l.:Farnborough: SaxonHouse/Lexington Books..


Fox, J., 2002. . Is The Market Rational? No, say the experts. But neither are you--so don't go thinking you can outsmart it. Fortune..


Appendix
In this section is presented the Matlab program as it is developed for the needs of this thesis. First is presented the code of Return Calculations and then the code of Trading Volume Calculations.

```matlab
clear all;
load('final_Price.mat')
[m,n] = size(dealsdates);
k = input('Please enter desired k value:
#> ');
lamda1 = 1;
lamda5 = 5;
lamda10 = 10;
AcqReturns=zeros((k-30)*m,3);
TargetReturns=zeros((k-30)*m,3);
ACQ_FTSEReturns=zeros((k-30)*m,3);
TARGET_FTSEReturns=zeros((k-30)*m,3);
Acq_Rit1 = zeros(m*(2*lamda1+1),2);
Acq_Rit5 = zeros(m*(2*lamda5+1),2);
Acq_Rit10 = zeros(m*(2*lamda10+1),2);
Acq_Rmt1= zeros(m*(2*lamda1+1),2);
Acq_Rmt5= zeros(m*(2*lamda5+1),2);
Acq_Rmt10= zeros(m*(2*lamda10+1),2);
Target_Rit1 = zeros(m*(2*lamda1+1),2);
Target_Rit5 = zeros(m*(2*lamda5+1),2);
Target_Rit10 = zeros(m*(2*lamda10+1),2);
Target_Rmt1= zeros(m*(2*lamda1+1),2);
Target_Rmt5= zeros(m*(2*lamda5+1),2);
Target_Rmt10= zeros(m*(2*lamda10+1),2);
X=zeros((k-30),2);
Y=zeros((k-30),2);
Acq_AB=zeros(m,3);
Target_AB=zeros(m,3);
Acq_ARt1= zeros (m*(2*lamda1+1),2);
Target_ARt1= zeros (m*(2*lamda1+1),2);
Acq_CAR1 = zeros(m,1);
Target_CAR1=zeros(m,1);
Acq_ARt5= zeros (m*(2*lamda5+1),2);
Target_ARt5 = zeros (m*(2*lamda5+1),2);
Acq_CAR5 = zeros(m,1);
Target_CAR5=zeros(m,1);
Acq_ARt10= zeros (m*(2*lamda10+1),2);
Target_ARt10 = zeros (m*(2*lamda10+1),2);
Acq_CAR10 = zeros(m,1);
Target_CAR10=zeros(m,1);

error2 =0;
error=0;

for z=0:m-1
    acqGoToNextz=0; % Variables that we use for checking the availability of data in the vectors of Acquirer and Target. In case of unavailable data it goes to the next z. Next repetition.
```
targetGoToNextZ=0; % Tha variables that we initialise here, take values in lines 73,80 kai 174,181

date = dealsdates(z+1);
dealDatesRow = z+1;

acqTicker = dealsAcqTxt(dealDatesRow); % Finds the Name of the Firm (Acquirer) according to the date of announcement as it is given in the vector that includes the announcement dates

acqColumn = find(ismember(acqTxt, acqTicker)==1); % finds the column in the database with the Acquirers data which matches with the firm that we are searching

targetTicker = dealsTargetTxt(dealDatesRow);

targetColumn = find(ismember(targetTxt, targetTicker)==1); % finds the column in the database with the Targets which matches with the firm that we are searching

acqId = find(ismember(acqIDTxt, acqTicker)==1); % Finds the Id of the firm in the database of Acquirer Returns

targetId = find(ismember(targetIDTxt, targetTicker)==1); % Finds the Id of the firm in the database of Target Returns

% Acquirer Price

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Search for row in the matrix with the prices for the Acquirer according to the date of the event. If it is not found then searches for the next day or even two days after the initial date.

if any(acq(:,acqColumn)==date)
    acqRow = find(ismember(acq(:,acqColumn), date)==1);
    acqdate=date;
elseif any(acq(:,acqColumn)==date+1)
    acqRow = find(ismember(acq(:,acqColumn), date+1)==1);
    disp('Next date in acqColumn');
    acqdate=date+1;
elseif any(acq(:,acqColumn)==date+2)
    acqRow = find(ismember(acq(:,acqColumn), date+2)==1);
    disp('The day after next date in acqColumn');
    acqdate=date+2;
elseif any(acq(:,acqColumn)==date+3)
    acqRow = find(ismember(acq(:,acqColumn), date+3)==1);
    disp('Three days after the initial date in acqColumn');
    acqdate=date+3;
else disp('There is no such date in acquirers matrix');
    acqGoToNextZ=1;
end

% Saving the data of the Acquirer's price to
if acqGoToNextZ ==0
    if (acqRow-30)<=0
        fprintf('There are not enough data for the firm:''%s'n',acqTicker{:});
        acqGoToNextZ=2;
    elseif (acqRow-k)<=0
        l=(acqRow-30)-1;
        acqRange = acqRow -1;
        fprintf('There are less than required data for the firm:''%s'' in loop number :%d'n',acqTicker{:},z);
        for i=1:l
            x=z*(k-30)+i;
            AcqReturns(x,1)=acqId;
            AcqReturns(x,2)=acq(acqRange+i,acqColumn);
            AcqReturns(x,3)=acq(acqRange+i,acqColumn+2);
        end
        for i=1:k-l
            y=z*(k-30)+l+i;
            AcqReturns(y,1)=acqId;
            AcqReturns(y,2)=NaN;
            AcqReturns(y,3)=NaN;
        end
    elseif (acqRow-k)>0
        acqRange = acqRow-k;
        for i=1:k-30
            x=z*(k-30)+i;
            AcqReturns(x,1)=acqId;
            AcqReturns(x,2)=acq(acqRange+i,acqColumn);
            AcqReturns(x,3)=acq(acqRange+i,acqColumn+2);
        end
    end
end
end

if acqGoToNextZ ==0
    if any(FTSE(:,1)==acqdate)% Find the date in the vector that contains all the dates for the deals and returns the position of the particular date
        ftseRow = find(ismember(FTSE(:,1), acqdate)==1); % Finds the row in the vector of FTSE dates that is the same with the date from acquirer above
    else disp('There is not this date in the FTSE100 matrix')
        error=error+1;
    end
end
Saving the Returns For Acquirer
for ë=1,5,10

\[ f = (2^\lambda_1) + 1; \]
for i=1:f
\[ Acq\_Rit1 \left((z*f) + i, 1\right) = dealDatesRow; \]
\[ Acq\_Rit1 \left((z*f) + i, 2\right) = acq(acqRow - \lambda_1 - 1 + i, acqColumn + 2); \]
end

\[ f = (2^\lambda_5) + 1; \]
for i=1:f
\[ Acq\_Rit5 \left((z*f) + i, 1\right) = dealDatesRow; \]
\[ Acq\_Rit5 \left((z*f) + i, 2\right) = acq(acqRow - \lambda_5 - 1 + i, acqColumn + 2); \]
end

\[ f = (2^\lambda_{10}) + 1; \]
for i=1:f
\[ Acq\_Rit10 \left((z*f) + i, 1\right) = dealDatesRow; \]
\[ Acq\_Rit10 \left((z*f) + i, 2\right) = acq(acqRow - \lambda_{10} - 1 + i, acqColumn + 2); \]
end

Saving the Returns of the Market for corresponding dates
for ë=1,5,10

\[ f = (2^\lambda_1) + 1; \]
for i=1:f
\[ Acq\_Rmt1 \left((z*f) + i, 1\right) = dealDatesRow; \]
\[ Acq\_Rmt1 \left((z*f) + i, 2\right) = FTSE(ftseRow - \lambda_1 - 1 + i, 2); \]
end

\[ f = (2^\lambda_5) + 1; \]
for i=1:f
\[ Acq\_Rmt5 \left((z*f) + i, 1\right) = dealDatesRow; \]
\[ Acq\_Rmt5 \left((z*f) + i, 2\right) = FTSE(ftseRow - \lambda_5 - 1 + i, 2); \]
end

\[ f = (2^\lambda_{10}) + 1; \]
for i=1:f
\[ Acq\_Rmt10 \left((z*f) + i, 1\right) = dealDatesRow; \]
\[ Acq\_Rmt10 \left((z*f) + i, 2\right) = FTSE(ftseRow - \lambda_{10} - 1 + i, 2); \]
end

% Saving the data of the FTSE 100 to the vector ACQ_FTSERetorns
if (ftseRow-30)<=0
fprintf('There is not enough data from FTSE 100 for the
firm:'%s',acqTicker{:});
elseif (ftseRow-k)<=0
l=(ftseRow-30)-1;
ftseRange = ftseRow - l;
fprintf('There are less FTSE 100 data for the firm:'%s''in loop
number:%d',acqTicker{:},z);
    for i=1:l
        x=z*(k-30)+i;
        ACQ_FTSEReturns(x,1)= acqId;
        ACQ_FTSEReturns(x,2)= FTSE(ftseRange+i,1);
        ACQ_FTSEReturns(x,3)= FTSE(ftseRange+i,2);
    end
    for i=1:k-l
        y=z*(k-30)+l+i;
        ACQ_FTSEReturns(y,1)= acqId;
        ACQ_FTSEReturns(y,2)=NaN;
        ACQ_FTSEReturns(y,3)=NaN;
    end
elseif (ftseRow-k)>0
    ftseRange = ftseRow-k;
    for i=1:k-30
        x=z*(k-30)+i;
        ACQ_FTSEReturns(x,1)= acqId;
        ACQ_FTSEReturns(x,2)= FTSE(ftseRange+i,1);
        ACQ_FTSEReturns(x,3)= FTSE(ftseRange+i,2);
    end
end
else fprintf('Data of the FTSE 100 Returns will not be saved to vector ACQ_FTSEReturns
for loop number z=%d because there are not corresponding data
to Acquirer returns',z);
end

%Target Price

if any(target(:,targetColumn)==date)
    targetRow = find(ismember(target(:,targetColumn), date)==1);
    targetdate=date;
elseif any(target(:,targetColumn)==date+1)
    targetRow = find(ismember(target(:,targetColumn), date+1)==1);
    disp('Next Date in targetColumn');
    targetdate=date+1;
elseif any(target(:,targetColumn)==date+2)
    targetRow = find(ismember(target(:,targetColumn), date+2)==1);
    disp('The day after next date in targetColumn');
    targetdate=date+2;
else any(target(:,targetColumn)==date+2)
targetRow = find(ismember(target(:,targetColumn), date+3)==1);
disp('Three days after the initial date in targetColumn');
targetdate=date+3;
else   disp('There is no such date in targets matrix');
targetGoToNextZ=1;
end

if targetGoToNextZ ==0
    % Saving the data of the Target's price to the matrix
    TargetReturns
    if (targetRow-30)<=0
        fprintf('There are not enough data of the target prices for the
        firm:' '%s',targetTicker{:});
        for i=1:k-30
            x=z*(k-30)+i;
            TargetReturns(x,1)=targetId;
            TargetReturns(x,2)=NaN;
            TargetReturns(x,3)=NaN;
        end
        targetGoToNextZ=2;
    elseif (targetRow-k)<=0
        l=(targetRow-30)-1;
        targetRange = targetRow -l;
        fprintf('There are less FTSE 100 data for the firm:' '%s' in loop
        number :%d',targetTicker{:},z);
        for i=1:l
            x=z*(k-30)+i;
            TargetReturns(x,1)=targetId;
            TargetReturns(x,2)=target(targetRange+i,targetColumn);
            TargetReturns(x,3)=target(targetRange+i,targetColumn+2);
        end
        for i=1:k-l
            y=z*(k-30)+l+i;
            TargetReturns(y,1)=targetId;
            TargetReturns(y,2)=NaN;
            TargetReturns(y,3)=NaN;
        end
    elseif (targetRow-k)>0
        targetRange = targetRow-k;
        for i=1:k-30
            x=z*(k-30)+i;
            TargetReturns(x,1)=targetId;
            TargetReturns(x,2)=target(targetRange+i,targetColumn);
            TargetReturns(x,3)=target(targetRange+i,targetColumn+2);
        end
    end

end

if any(FTSE(:,1)==targetdate)% Finds the date in the vector that contains
    all the dates for the deals and returns the position of the particular date
ftseRow = find(ismember(FTSE(:,1), targetdate)==1); %Finds the row in the vector of FTSE dates that is the same with the date from Target above
else disp('There is not this date in the FTSE100 matrix')
   error2=error2+1;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%   Saving the Returns For Target
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  for ë=1,5,10
f= (2*lamda1)+1;
for i=1:f
   Target_Rit1 ((z*f)+i,1)= dealDatesRow;
   Target_Rit1 ((z*f)+i,2)=target(targetRow-lamda1-1+i, targetColumn+2);
end

f= (2*lamda5)+1;
for i=1:f
   Target_Rit5 ((z*f)+i,1)= dealDatesRow;
   Target_Rit5 ((z*f)+i,2)=target(targetRow-lamda5-1+i, targetColumn+2);
end

f= (2*lamda10)+1;
for i=1:f
   Target_Rit10 ((z*f)+i,1)= dealDatesRow;
   Target_Rit10 ((z*f)+i,2)=target(targetRow-lamda10-1+i, targetColumn+2);
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Saving the Returns of the Market for corresponding dates
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% for ë=1,5,10
f= (2*lamda1)+1;
for i=1:f
   Target_Rmt1 ((z*f)+i,1)= dealDatesRow;
   Target_Rmt1 ((z*f)+i,2)=FTSE(ftseRow-lamda1-1+i,2);
end

f= (2*lamda5)+1;
for i=1:f
   Target_Rmt5 ((z*f)+i,1)= dealDatesRow;
   Target_Rmt5 ((z*f)+i,2)=FTSE(ftseRow-lamda5-1+i,2);
end

f= (2*lamda10)+1;
for i=1:f
   Target_Rmt10 ((z*f)+i,1)= dealDatesRow;
   Target_Rmt10 ((z*f)+i,2)=FTSE(ftseRow-lamda10-1+i,2);
end
%Saving the data of the FTSE 100 to the vector TARGET_FTSEReturns
if (ftseRow-30)<=0
    fprintf('There are not enough data of the FTSE100 prices for the firm:'"%s"
    targetTicker{:});
elseif (ftseRow-k)<=0
    l=(ftseRow-30)-1;
    ftseRange = ftseRow -l;
    fprintf('There are less FTSE 100 data for the firm:'"%s"' in loop number :%d
    targetTicker{:},z);
    for i=1:l
        x=z*(k-30)+i;
        TARGET_FTSEReturns(x,1)= targetId;
        TARGET_FTSEReturns(x,2)= FTSE(ftseRange+i,1);
        TARGET_FTSEReturns(x,3)= FTSE(ftseRange+i,2);
    end
    for i=1:k-l
        y=z*(k-30)+i+1;
        TARGET_FTSEReturns(x,1)= targetId;
        TARGET_FTSEReturns(x,2)= NaN;
        TARGET_FTSEReturns(x,3)= NaN;
    end
elseif (ftseRow-k)>0
    ftseRange = ftseRow-k;
    for i=1:k-30
        x=z*(k-30)+i;
        TARGET_FTSEReturns(x,1)= targetId;
        TARGET_FTSEReturns(x,2)= FTSE(ftseRange+i,1);
        TARGET_FTSEReturns(x,3)= FTSE(ftseRange+i,2);
    end
    else fprintf('Data of FTSE100 are not saved to Target_FTSEReturns for the z=%d
    because there are not corresponding data in target matrix
    targetTicker{:},z);
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%Running the regression to calculate a,b(weighted) for the acquirer%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

for i=1:(k-30)
    if AcqReturns(i+(k-30)*z,2)==0||isnan(AcqReturns(i+(k-30)*z,2))
        Y(i,1)=NaN;
        Y(i,2)=NaN;
    else
        Y(i,1)= AcqReturns(i+(k-30)*z,1);
        Y(i,2)=AcqReturns(i+(k-30)*z,3);
for i=1:(k-30)
    if ACQ_FTSEReturns(i+(k-30)*z,2)==0||isnan(ACQ_FTSEReturns(i+(k-30)*z,2))
        X(i,1)=NaN;
        X(i,2)=NaN;
    else
        X(i,1)= ACQ_FTSEReturns(i+(k-30)*z,1);
        X(i,2)=ACQ_FTSEReturns(i+(k-30)*z,3);
    end
end
if ~isnan(Y(:,;))
    if ~isnan(X(:,;))
        b(1,:)=regress(Y(:,2),[ones(length(X),1) X(:,2)]);
        Acq_AB(z+1,1)=b(1,1);
        Acq_AB(z+1,2)=b(1,2);
        Acq_AB(z+1,3)=X(1,1);
    else
        Acq_AB(z+1,1)=NaN;
        Acq_AB(z+1,2)=NaN;
        Acq_AB(z+1,3)=X(1,1);
    end
else
    Acq_AB(z+1,1)=NaN;
    Acq_AB(z+1,2)=NaN;
    Acq_AB(z+1,3)=X(1,1);
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Running the regression to %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% calculate a,b(weighted) for the %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Target

for i=1:(k-30)
    if TargetReturns(i+(k-30)*z,2)==0||isnan(TargetReturns(i+(k-30)*z,2))
        Y(i,1)=NaN;
        Y(i,2)=NaN;
    else
        Y(i,1)= TargetReturns(i+(k-30)*z,1);
        Y(i,2)=TargetReturns(i+(k-30)*z,3);
    end
end
for i=1:(k-30)
    if TARGET_FTSEReturns(i+(k-30)*z,2)==0||isnan(TARGET_FTSEReturns(i+(k-30)*z,2))
        X(i,1)=NaN;
        X(i,2)=NaN;
    else
        X(i,1)= TARGET_FTSEReturns(i+(k-30)*z,1);
        X(i,2)=TARGET_FTSEReturns(i+(k-30)*z,3);
    end
end
if ~isnan(Y(:,:))
  if ~isnan(X(:,:))
    b(1,:) = regress(Y(:,2),[ones(length(X),1) X(:,2)]);
    Target_AB(z+1,1)=b(1,1);
    Target_AB(z+1,2)=b(1,2);
    Target_AB(z+1,3)=X(1,1);
  else
    Target_AB(z+1,1)=NaN;
    Target_AB(z+1,2)=NaN;
    Target_AB(z+1,3)=X(1,1);
  end
else
  Target_AB(z+1,1)=NaN;
  Target_AB(z+1,2)=NaN;
  Target_AB(z+1,3)=X(1,1);
end

%%%%%%%%%%%%%%%%%%%%%%% Calculations of the Abnormal Returns of Acquirer and Target based
on the equation: %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%ARt = Rit - (â*+â*Rmt)

%%ë=1
AcqART1 = Acq_Rit1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2) -
(Acq_AB(z+1,1)+Acq_AB(z+1,2)*Acq_Rmt1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));
Acq_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),1)= z+1;
Acq_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2)= AcqART1(1:2*lamda1+1,1);
Acq_CAR1(z+1,1) = sum(Acq_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));

TargetART1 = Target_Rit1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2) -
(Target_AB(z+1,1)+Target_AB(z+1,2)*Target_Rmt1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));
Target_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),1)= z+1;
Target_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2)= TargetART1(1:2*lamda1+1,1);
Target_CAR1(z+1,1) = sum(Target_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));

%%ë=5
AcqART5 = Acq_Rit5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2) -
(Acq_AB(z+1,1)+Acq_AB(z+1,2)*Acq_Rmt5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));
Acq_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),1)= z+1;
Acq_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2)= AcqART5(1:2*lamda5+1,1);
Acq_CAR5(z+1,1) = sum(Acq_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));

TargetART5 = Target_Rit5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2) -
(Target_AB(z+1,1)+Target_AB(z+1,2)*Target_Rmt5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));
Target_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),1)= z+1;
Target_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2)= TargetART5(1:2*lamda5+1,1);
Target_CAR5(z+1,1) = sum(Target_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));

%%ë=10
\[ AcqARt10 = Acq\_Rit10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2) - \\
(Acq\_AB(z+1,1)+Acq\_AB(z+1,2)*Acq\_Rmt10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2)); \]
\[ Acq\_ART10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),1) = z+1; \]
\[ Acq\_ART10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2) = AcqARt10(1:2*\text{lamda10}+1,1); \]
\[ Acq\_CAR10(z+1,1) = \text{sum}(Acq\_ART10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2)); \]

\[ Target\_ARt10 = Target\_Rit10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2) - \\
(Target\_AB(z+1,1)+Target\_AB(z+1,2)*Target\_Rmt10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2)); \]
\[ Target\_ART10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),1) = z+1; \]
\[ Target\_ART10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2) = TargetART10(1:2*\text{lamda10}+1,1); \]
\[ Target\_CAR10(z+1,1) = \text{sum}(Target\_ART10(z*(2*\text{lamda10}+1)+1:(z+1)*(2*\text{lamda10}+1),2)); \]

\[ \text{end} \]
\[ Acq\_ACAR1 = \text{nanmean}(Acq\_CAR1); \]
\[ Acq\_ACAR5 = \text{nanmean}(Acq\_CAR5); \]
\[ Acq\_ACAR10 = \text{nanmean}(Acq\_CAR10); \]
\[ Target\_ACAR1 = \text{nanmean}(Target\_CAR1); \]
\[ Target\_ACAR5 = \text{nanmean}(Target\_CAR5); \]
\[ Target\_ACAR10 = \text{nanmean}(Target\_CAR10); \]

%Creation of ACQ_TARGET CAR
\[ AcqTarget\_CAR1 = \text{vertcat}(Acq\_CAR1,Target\_CAR1); \]
\[ AcqTarget\_CAR5 = \text{vertcat}(Acq\_CAR5,Target\_CAR5); \]
\[ AcqTarget\_CAR10 = \text{vertcat}(Acq\_CAR10,Target\_CAR10); \]

%Creation of ACAR for Acquirer kai Target
\[ AcqTarget\_ACAR1 = \text{nanmean}(AcqTarget\_CAR1); \]
\[ AcqTarget\_ACAR5 = \text{nanmean}(AcqTarget\_CAR5); \]
\[ AcqTarget\_ACAR10 = \text{nanmean}(AcqTarget\_CAR10); \]

\[ [H,P,CI,\text{Stats\_Acq\_ACAR1}] = \text{ttest}(Acq\_CAR1); \]
\[ [H,P,CI,\text{Stats\_Acq\_ACAR5}] = \text{ttest}(Acq\_CAR5); \]
\[ [H,P,CI,\text{Stats\_Acq\_ACAR10}] = \text{ttest}(Acq\_CAR10); \]
\[ [H,P,CI,\text{Stats\_Target\_ACAR1}] = \text{ttest}(Target\_CAR1); \]
\[ [H,P,CI,\text{Stats\_Target\_ACAR5}] = \text{ttest}(Target\_CAR5); \]
\[ [H,P,CI,\text{Stats\_Target\_ACAR10}] = \text{ttest}(Target\_CAR10); \]
\[ [H,P,CI,\text{Stats\_AcqTarget\_ACAR1}] = \text{ttest}(AcqTarget\_CAR1); \]
\[ [H,P,CI,\text{Stats\_AcqTarget\_ACAR5}] = \text{ttest}(AcqTarget\_CAR5); \]
\[ [H,P,CI,\text{Stats\_AcqTarget\_ACAR10}] = \text{ttest}(AcqTarget\_CAR10); \]

fprintf('%Acquirer ACAR for ë=1, k=%d: %d
',k,Acq\_ACAR1 );
fprintf('%Acquirer ACAR for ë=5, k=%d: %d
',k,Acq\_ACAR5 );
fprintf('%Acquirer ACAR for ë=10, k=%d: %d
',k,Acq\_ACAR10 );
fprintf('%Target ACAR for ë=1, k=%d: %d
',k,Target\_ACAR1 );
fprintf('%Target ACAR for ë=5, k=%d: %d
',k,Target\_ACAR5 );
fprintf('%Target ACAR for ë=10, k=%d: %d
',k,Target\_ACAR10 );
fprintf('%Acquirer&Target ACAR for ë=1, k=%d: %d
',k,AcqTarget\_ACAR1 );
fprintf('%Acquirer&Target ACAR for ë=5, k=%d: %d
',k,AcqTarget\_ACAR5 );
fprintf('%Acquirer&Target ACAR for ë=10, k=%d: %d
',k,AcqTarget\_ACAR10 );
fprintf('Acquirer ACAR T stat for ê=1, k=%d:         %d
',k,getfield(Stats_Acq_ACAR1, 'tstat'));
fprintf('Acquirer ACAR T stat for ê=5, k=%d:         %d
',k,getfield(Stats_Acq_ACAR5, 'tstat'));
fprintf('Acquirer ACAR T stat for ê=10, k=%d:        %d
',k,getfield(Stats_Acq_ACAR10, 'tstat'));
fprintf('Target ACAR T stat for ê=1, k=%d:         %d
',k,getfield(Stats_Target_ACAR1, 'tstat'));
fprintf('Target ACAR T stat for ê=5, k=%d:         %d
',k,getfield(Stats_Target_ACAR5, 'tstat'));
fprintf('Target ACAR T stat for ê=10, k=%d:        %d
',k,getfield(Stats_Target_ACAR10, 'tstat'));
fprintf('Acquirer&Target ACAR T stat for ê=1, k=%d:         %d
',k,getfield(Stats_AcqTarget_ACAR1, 'tstat'));
fprintf('Acquirer&Target ACAR T stat for ê=5, k=%d:         %d
',k,getfield(Stats_AcqTarget_ACAR5, 'tstat'));
fprintf('Acquirer&Target ACAR T stat for ê=10, k=%d:        %d
',k,getfield(Stats_AcqTarget_ACAR10, 'tstat'));

clear all;
load('final_Volume.mat')
[m,n] = size(dealsdates);
k = input('plz enter desired k value:
 #>');
lamda1 = 1;
lamda5= 5;
lamda10 = 10;
AcqVolReturns=zeros((k-30)*m,3); %Initialization of the vectors according to k value
TargetVolReturns=zeros((k-30)*m,3);
ACQVol_FTSEReturns=zeros((k-30)*m,3);
TARGETVol_FTSEReturns=zeros((k-30)*m,3);
AcqVol_Rit1 = zeros(m*(2*lamda1+1),2);
AcqVol_Rit5 = zeros(m*(2*lamda5+1),2);
AcqVol_Rit10 = zeros(m*(2*lamda10+1),2);
AcqVol_Rmt1= zeros(m*(2*lamda1+1),2);
AcqVol_Rmt5= zeros(m*(2*lamda5+1),2);
AcqVol_Rmt10= zeros(m*(2*lamda10+1),2);
TargetVol_Rit1 = zeros(m*(2*lamda1+1),2);
TargetVol_Rit5 = zeros(m*(2*lamda5+1),2);
TargetVol_Rit10 = zeros(m*(2*lamda10+1),2);
TargetVol_Rmt1= zeros(m*(2*lamda1+1),2);
TargetVol_Rmt5= zeros(m*(2*lamda5+1),2);
TargetVol_Rmt10= zeros(m*(2*lamda10+1),2);
x=zeros((k-30),2);
y=zeros((k-30),2);
AcqVol_AB=zeros(m,3);
TargetVol_AB=zeros(m,3);
AcqVol_ARt1= zeros (m*(2*lamda1+1),2);
TargetVol_ARt1= zeros (m*(2*lamda1+1),2);
AcqVol_CAR1 = zeros(m,1);
TargetVol_CAR1=zeros(m,1);
AcqVol_ARt5= zeros (m*(2*lamda5+1),2);
TargetVol_ARt5 = zeros (m*(2*lamda5+1),2);
AcqVol_CAR5 = zeros(m,1);
TargetVol_CAR5=zeros(m,1);
AcqVol_ARt10= zeros (m*(2*lamda10+1),2);
TargetVol_ARt10 = zeros (m*(2*lamda10+1),2);
AcqVol_CAR10 = zeros(m,1);
TargetVol_CAR10=zeros(m,1);

error2 =0;
error=0;

for z=0:m-1
    acqGoToNextZ=0;         % Variables that we use for checking the availability of data in
                          % the vectors of acqVol,targetVol respectively
    targetGoToNextZ=0;      % Tha variables that we initialise here, take values in lines
                          % 73,80 kai 174,181

    date = dealsdates(z+1);
    dealDatesRow = z+1;

    acqVolTicker = dealsAcqTxt(dealDatesRow);% Finds the Name of the Firm (Acquirer)
        %according to the date of
        %announcement as it is given in the
        %vector that includes the announcement dates
    acqVolColumn = find(ismember(acqVolTxt, acqVolTicker)==1);%finds the column in the
        %database with the Acquirers data which matches with the firm that we are searching acqVol

    targetVolTicker = dealsTargetTxt(dealDatesRow);

    targetVolColumn = find(ismember(targetVolTxt, targetVolTicker)==1); %finds the column in
        %the database with the Targets which matches with the firm that we are searching targetVol

    acqVolId = find(ismember(acqIDTxt, acqVolTicker)==1); % Finds the Id of the firm in the
        %database of Acquirer Volume
    targetVolId = find(ismember(targetIDTxt, targetVolTicker)==1); % Finds the Id of the firm in
        %the database of Target Volume

    %Acquirer Price

    % Search for row in the matrix with the prices of volume traded for the Acquirer
% according to the date of the event. If it is not found then searches for
the next day or even two days after the initial date.

if any(acqVol(:,acqVolColumn)==date)
    acqVolRow = find(ismember(acqVol(:,acqVolColumn), date)==1);
    acqVolDate=date;
elseif any(acqVol(:,acqVolColumn)==date+1)
    acqVolRow = find(ismember(acqVol(:,acqVolColumn), date+1)==1);
    disp('Next date in acqColumn');
    acqVolDate=date+1;
elseif any(acqVol(:,acqVolColumn)==date+2)
    acqVolRow = find(ismember(acqVol(:,acqVolColumn), date+2)==1);
    disp('The day after next date in acqColumn');
    acqVolDate=date+2;
elseif any(acqVol(:,acqVolColumn)==date+3)
    acqVolRow = find(ismember(acqVol(:,acqVolColumn), date+3)==1);
    disp('Three days after the initial date in acqColumn');
    acqVolDate=date+3;
else disp('There is no such date in acquirers matrix');
    acqGoToNextZ=1;
end

    %Saving the data of the Acquirer's price to
    %the matrix AcqReturns

if acqGoToNextZ ==0
    if (acqVolRow-30)<=0
        fprintf('There are not enough data in acqVol for the firm:''%s''\n',acqVolTicker{:});
        acqGoToNextZ=2;
    elseif (acqVolRow-k)<=0
        l=(acqVolRow-30)-1;
        acqRange = acqVolRow-1;
        fprintf('There are less than requiered data for the firm:''%s'' in loop number:%d\n',acqVolTicker{:},z);
        for i=1:l
            x=z*(k-30)+i;
            AcqVolReturns(x,1)=acqVolId;
            AcqVolReturns(x,2)=acqVol(acqRange+i,acqVolColumn);
            AcqVolReturns(x,3)=acqVol(acqRange+i,acqVolColumn+2);
        end
        for i=1:k-l
            y=z*(k-30)+l+i;
            AcqVolReturns(y,1)=acqVolId;
            AcqVolReturns(y,2)=NaN;
            AcqVolReturns(y,3)=NaN;
        end
    elseif (acqVolRow-k)>0
        acqRange = acqVolRow-k;
        for i=1:k-30
            x=z*(k-30)+i;
            AcqVolReturns(x,1)=acqVolId;
            AcqVolReturns(x,2)=acqVol(acqRange+i,acqVolColumn);
            AcqVolReturns(x,3)=acqVol(acqRange+i,acqVolColumn+2);
        end
    end
if acqGoToNextZ ==0

if any(FTSEVol(:,1)==acqVoldate)% Find the date in the vector that contains all
the dates for the deals and returns the position of the particular date
    ftseVolRow = find(ismember(FTSEVol(:,1), acqVoldate)==1); %Finds the row in
    the vector of FTSE100 containing the volumes that is the same with the date from acquirer
    above
    else disp('There is not this date in the FTSE100 with volumes matrix')
        error=error+1;
    end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  Saving the Volumes For
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  Acquirer
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  for ë=1,5,10
f= (2*lamda1)+1;
for i=1:f
    AcqVol_Rit1 ((z*f)+i,1)= dealDatesRow;
    AcqVol_Rit1 ((z*f)+i,2)=acqVol(acqVolRow-lamda1-1+i, acqVolColumn+2);
end

f= (2*lamda5)+1;
for i=1:f
    AcqVol_Rit5 ((z*f)+i,1)= dealDatesRow;
    AcqVol_Rit5 ((z*f)+i,2)=acqVol(acqVolRow-lamda5-1+i, acqVolColumn+2);
end

f= (2*lamda10)+1;
for i=1:f
    AcqVol_Rit10 ((z*f)+i,1)= dealDatesRow;
    AcqVol_Rit10 ((z*f)+i,2)=acqVol(acqVolRow-lamda10-1+i, acqVolColumn+2);
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  Saving the Volumes of the Market for
corresponding dates
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% for ë=1,5,10
f= (2*lamda1)+1;
for i=1:f
    AcqVol_Rmt1 ((z*f)+i,1)= dealDatesRow;
end
AcqVol_Rmt1 ((z*f)+i,2)=FTSEVol(ftseVolRow-lamda1-1+i,2);
end

f= (2*lamda5)+1;
for i=1:f
    AcqVol_Rmt5 ((z*f)+i,1)= dealDatesRow;
    AcqVol_Rmt5 ((z*f)+i,2)=FTSEVol(ftseVolRow-lamda5-1+i,2);
end

f= (2*lamda10)+1;
for i=1:f
    AcqVol_Rmt10 ((z*f)+i,1)= dealDatesRow;
    AcqVol_Rmt10 ((z*f)+i,2)=FTSEVol(ftseVolRow-lamda10-1+i,2);
end

%Saving the data of the FTSE 100 volume to the vector ACQ_FTSEVolume
if (ftseVolRow-30)<=0
    fprintf('There is not enough data from FTSE 100 for the
    firm:'%s'\n',acqVolTicker{:});
elseif (ftseVolRow-k)<=0
    l=(ftseVolRow-30)-1;
    ftseRange = ftseVolRow-l;
    fprintf('There are less FTSE 100 data for the firm:'%s''in loop
    number:%d\n',acqVolTicker{:},z);
    for i=1:l
        x=z*(k-30)+i;
        ACQVol_FTSEReturns(x,1)= acqVolId;
        ACQVol_FTSEReturns(x,2)= FTSEVol(ftseRange+i,1);
        ACQVol_FTSEReturns(x,3)= FTSEVol(ftseRange+i,2);
    end
    for i=1:k-l
        y=z*(k-30)+l+i;
        ACQVol_FTSEReturns(x,1)= acqVolId;
        ACQVol_FTSEReturns(y,2)=NaN;
        ACQVol_FTSEReturns(y,3)=NaN;
    end
elseif (ftseVolRow-k)>0
    ftseRange = ftseVolRow-k;
    for i=1:k-30
        x=z*(k-30)+i;
        ACQVol_FTSEReturns(x,1)= acqVolId;
        ACQVol_FTSEReturns(x,2)= FTSEVol(ftseRange+i,1);
        ACQVol_FTSEReturns(x,3)= FTSEVol(ftseRange+i,2);
    end
else
    fprintf('Data of the FTSE 100 Returns will not be saved to vector ACQ_FTSEReturns

else
for loop number gia tin epanalipsi z=%d \n because there are not corresponding data to Acquirer Volume',z);

end

%Target Price

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

if any(targetVol(:,targetVolColumn)==date)
targetVolRow = find(ismember(targetVol(:,targetVolColumn), date)==1);
targetVoldate=date;
elseif any(targetVol(:,targetVolColumn)==date+1)
targetVolRow = find(ismember(targetVol(:,targetVolColumn),
date+1)==1);
disp('Next Date in targetColumn');
targetVoldate=date+1;
elseif any(targetVol(:,targetVolColumn)==date+2)
targetVolRow = find(ismember(targetVol(:,targetVolColumn),
date+2)==1);
disp('The day after next date in targetColumn');
targetVoldate=date+2;
elseif any(targetVol(:,targetVolColumn)==date+3)
targetVolRow = find(ismember(targetVol(:,targetVolColumn),
date+3)==1);
disp('Three days after the initial date in targetColumn');
targetVoldate=date+3;
else disp('den uparxei to date sto targetVol');
targetGoToNextZ=1;
end

if targetGoToNextZ ==0
%Saving the data of the Target's Volume price to the matrix TargetReturns

if (targetVolRow-30)<=0
fprintf('dThere are not enough data of the target volume prices for the firm:''%s'\n',targetVolTicker{:});
for i=1:k-30
x=z*(k-30)+i;
TargetVolReturns(x,1)=targetVolId;
TargetVolReturns(x,2)=NaN;
TargetVolReturns(x,3)=NaN;
end
targetGoToNextZ=2;
elseif (targetVolRow-k)<=0
l=(targetVolRow-30)-1;
targetRange = targetVolRow -1;
fprintf('There are less FTSE 100 data for the firm''%s''in loop number:%d\n',targetVolTicker{:},z);
for i=1:l
x=z*(k-30)+i;
TargetVolReturns(x,1)=targetVolId;
end
end
TargetVolReturns(x,2)=targetVol(targetRange+i,targetVolColumn);

TargetVolReturns(x,3)=targetVol(targetRange+i,targetVolColumn+2);
end

for i=1:k-l
    y=z*(k-30)+l+i;
    TargetVolReturns(y,1)=targetVolId;
    TargetVolReturns(y,2)=NaN;
    TargetVolReturns(y,3)=NaN;
end

elseif (targetVolRow-k)>0
    targetRange = targetVolRow-k;
    for i=1:k-30
        x=z*(k-30)+i;
        TargetVolReturns(x,1)=targetVolId;
    end

    TargetVolReturns(x,2)=targetVol(targetRange+i,targetVolColumn);
    TargetVolReturns(x,3)=targetVol(targetRange+i,targetVolColumn+2);
end

end

if any(FTSEVol(:,1)==targetVoldate)% Finds the date in the vector that contains all the dates for the deals and returns the position of the particular date
    ftseVolRow = find(ismember(FTSEVol(:,1),targetVoldate)==1); %Finds the row in the vector of FTSE Vol dates that is the same with the date from Target above
else disp('There is not this date in the FTSEVol matrix ')
    error2=error2+1;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  Saving the Returns For Target Volume
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  for e=1,5,10
    f= (2*lamda1)+1;
    for i=1:f
        TargetVol_Rit1 ((z*f)+i,1)= dealDatesRow;
        TargetVol_Rit1 ((z*f)+i,2)=targetVol(targetVolRow-lamda1-1+i,targetVolColumn+2);
    end

    f= (2*lamda5)+1;
    for i=1:f
        TargetVol_Rit5 ((z*f)+i,1)= dealDatesRow;
        TargetVol_Rit5 ((z*f)+i,2)=targetVol(targetVolRow-lamda5-1+i,targetVolColumn+2);
    end
f = (2*lamda10)+1;
for i=1:f
    TargetVol_Rit10 ((z*f)+i,1)= dealDatesRow;
    TargetVol_Rit10 ((z*f)+i,2)=targetVol(targetVolRow-lamda10-1+i,
targetVolColumn+2);
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  Saving the Volumes of the Market for
corresponding dates
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%  for ë=1,5,10

f = (2*lamda1)+1;
for i=1:f
    TargetVol_Rmt1 ((z*f)+i,1)= dealDatesRow;
    TargetVol_Rmt1 ((z*f)+i,2)=FTSEVol(ftseVolRow-lamda1+i,2);
end

f = (2*lamda5)+1;
for i=1:f
    TargetVol_Rmt5 ((z*f)+i,1)= dealDatesRow;
    TargetVol_Rmt5 ((z*f)+i,2)=FTSEVol(ftseVolRow-lamda5-1+i,2);
end

f = (2*lamda10)+1;
for i=1:f
    TargetVol_Rmt10 ((z*f)+i,1)= dealDatesRow;
    TargetVol_Rmt10 ((z*f)+i,2)=FTSEVol(ftseVolRow-lamda10-1+i,2);
end

%Saving the data of the FTSE 100 to the vector TARGET_FTSEReturns

if (ftseVolRow-30)<=0
    fprintf('There are not enough data of the FTSE100 prices for the
firm:','%s
',targetVolTicker{:});
elseif (ftseVolRow-k)<=0
    l=(ftseVolRow-30)-1;
    ftseRange = ftseVolRow -l;
    fprintf('There are less FTSE 100 data for the firm:','%s
'\in loop
number:%d
',targetVolTicker{:},z);
    for i=1:l
        x=z*(k-30)+i;
        TARGETVol_FTSEReturns(x,1)= targetVolId;
        TARGETVol_FTSEReturns(x,2)= FTSEVol(ftseRange+i,1);
        TARGETVol_FTSEReturns(x,3)= FTSEVol(ftseRange+i,2);
    end
    for i=1:k-l
        y=z*(k-30)+l+i;
        TARGETVol_FTSEReturns(x,1)= targetVolId;
end

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TARGETVol_FTSEReturns(y,2)=NaN;
TARGETVol_FTSEReturns(y,3)=NaN;
end

elseif (ftseVolRow-k)>0
    ftseRange = ftseVolRow-k;
    for i=1:k-30
        x=z*(k-30)+i;
        TARGETVol_FTSEReturns(x,1)= targetVolId;
        TARGETVol_FTSEReturns(x,2)= FTSEVol(ftseRange+i,1);
        TARGETVol_FTSEReturns(x,3)= FTSEVol(ftseRange+i,2);
    end
end
else
    fprintf('Data of FTSE 100 are not being saved to TARGETVol_FTSEReturns for the 
    z=%d \n loop because there are not corresponding data in targetVol matrix\n',z);
end

%%%%%%%%%%%%%%%%%% Running the regression to calculate
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% a,b(weighted) for the acquirer
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% volume

for i=1:(k-30)
    if AcqVolReturns(i+(k-30)^z,2)==0||isnan(AcqVolReturns(i+(k-30)^z,2))
        Y(i,1)=NaN;
        Y(i,2)=NaN;
    else
        Y(i,1)= AcqVolReturns(i+(k-30)^z,1);
        Y(i,2)=AcqVolReturns(i+(k-30)^z,3);
    end
end

for i=1:(k-30)
    if ACQVol_FTSEReturns(i+(k-30)^z,2)==0||isnan(ACQVol_FTSEReturns(i+(k-30)^z,2))
        X(i,1)=NaN;
        X(i,2)=NaN;
    else
        X(i,1)= ACQVol_FTSEReturns(i+(k-30)^z,1);
        X(i,2)=ACQVol_FTSEReturns(i+(k-30)^z,3);
    end
end
if ~isnan(Y(:,:))
    if ~isnan(X(:,:))
        b(1,:)=regress(Y(:,2),[ones(length(X),1) X(:,2)]);
        AcqVol_AB(z+1,1)=b(1,1);
        AcqVol_AB(z+1,2)=b(1,2);
        AcqVol_AB(z+1,3)=X(1,1);
        else
            AcqVol_AB(z+1,1)=NaN;
            AcqVol_AB(z+1,2)=NaN;
            AcqVol_AB(z+1,3)=X(1,1);
    end
else
    AcqVol_AB(z+1,1)=NaN;
    AcqVol_AB(z+1,2)=NaN;
    AcqVol_AB(z+1,3)=X(1,1);
end

%%%%%%%%%%%%%%%%%% Running the regression to calculate
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% a,b(weighted) for the target
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% volume

for i=1:(k-30)
    if TargetVolReturns(i+(k-30)*z,2)==0||isnan(TargetVolReturns(i+(k-30)*z,2))
        Y(i,1)=NaN;
        Y(i,2)=NaN;
    else
        Y(i,1)= TargetVolReturns(i+(k-30)*z,1);
        Y(i,2)=TargetVolReturns(i+(k-30)*z,3);
    end
end

for i=1:(k-30)
    if TARGETVol_FTSEReturns(i+(k-30)*z,2)==0||isnan(TARGETVol_FTSEReturns(i+(k-30)*z,2))
        X(i,1)=NaN;
        X(i,2)=NaN;
    else
        X(i,1)= TARGETVol_FTSEReturns(i+(k-30)*z,1);
        X(i,2)=TARGETVol_FTSEReturns(i+(k-30)*z,3);
    end
end
if ~isnan(Y(:,:))
    if ~isnan(X(:,:))
        b(1,:)=regress(Y(:,2),[ones(length(X),1) X(:,2)]);
        TargetVol_AB(z+1,1)=b(1,1);
        TargetVol_AB(z+1,2)=b(1,2);
        TargetVol_AB(z+1,3)=X(1,1);
    else
        TargetVol_AB(z+1,1)=NaN;
        TargetVol_AB(z+1,2)=NaN;
        TargetVol_AB(z+1,3)=X(1,1);
    end
else
    TargetVol_AB(z+1,1)=NaN;
    TargetVol_AB(z+1,2)=NaN;
    TargetVol_AB(z+1,3)=X(1,1);
end
Calculations of the Abnormal Returns of Acquirer and Target Volumes based on the equation: %ARt = Rit – (â+a*Rmt)

%é=1
AcqArt1 = AcqVol_Rit1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2) - (AcqVol_AB(z+1,1)+AcqVol_AB(z+1,2)*AcqVol_Rmt1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));
AcqVol_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),1)= z+1;
AcqVol_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2)= AcqArt1(1:2*lamda1+1,1);
AcqVol_CAR1(z+1,1) = sum(AcqVol_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));

TargetArt1 = TargetVol_Rit1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2) - (TargetVol_AB(z+1,1)+TargetVol_AB(z+1,2)*TargetVol_Rmt1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));
TargetVol_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),1)= z+1;
TargetVol_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2)= TargetArt1(1:2*lamda1+1,1);
TargetVol_CAR1(z+1,1) = sum(TargetVol_ART1(z*(2*lamda1+1)+1:(z+1)*(2*lamda1+1),2));

%é=5
AcqArt5 = AcqVol_Rit5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2) - (AcqVol_AB(z+1,1)+AcqVol_AB(z+1,2)*AcqVol_Rmt5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));
AcqVol_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),1)= z+1;
AcqVol_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2)= AcqArt5(1:2*lamda5+1,1);
AcqVol_CAR5(z+1,1) = sum(AcqVol_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));

TargetArt5 = TargetVol_Rit5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2) - (TargetVol_AB(z+1,1)+TargetVol_AB(z+1,2)*TargetVol_Rmt5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));
TargetVol_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),1)= z+1;
TargetVol_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2)= TargetArt5(1:2*lamda5+1,1);
TargetVol_CAR5(z+1,1) = sum(TargetVol_ART5(z*(2*lamda5+1)+1:(z+1)*(2*lamda5+1),2));

%é=10
AcqArt10 = AcqVol_Rit10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2) - (AcqVol_AB(z+1,1)+AcqVol_AB(z+1,2)*AcqVol_Rmt10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2));
AcqVol_ART10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),1)= z+1;
AcqVol_ART10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2)= AcqArt10(1:2*lamda10+1,1);
AcqVol_CAR10(z+1,1) = sum(AcqVol_ART10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2));

TargetArt10 = TargetVol_Rit10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2) - (TargetVol_AB(z+1,1)+TargetVol_AB(z+1,2)*TargetVol_Rmt10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2));
TargetVol_ART10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),1)= z+1;
TargetVol_ART10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2)= TargetArt10(1:2*lamda10+1,1);
TargetVol_CAR10(z+1,1) = sum(TargetVol_ART10(z*(2*lamda10+1)+1:(z+1)*(2*lamda10+1),2));

end
AcqVol_ACAR1= nanmean(AcqVol_CAR1);
AcqVol_ACAR5= nanmean(AcqVol_CAR5);
AcqVol_ACAR10= nanmean(AcqVol_CAR10);
TargetVol_ACAR1 = nanmean(TargetVol_CAR1);
TargetVol_ACAR5 = nanmean(TargetVol_CAR5);
TargetVol_ACAR10 = nanmean(TargetVol_CAR10);

% Creation of ACQ_TARGET CAR
AcqTargetVol_CAR1 = vertcat(AcqVol_CAR1, TargetVol_CAR1);
AcqTargetVol_CAR5 = vertcat(AcqVol_CAR5, TargetVol_CAR5);
AcqTargetVol_CAR10 = vertcat(AcqVol_CAR10, TargetVol_CAR10);

% Creation of ACAR for Acquirer kai Target
AcqTargetVol_ACAR1 = nanmean(AcqTargetVol_CAR1);
AcqTargetVol_ACAR5 = nanmean(AcqTargetVol_CAR5);
AcqTargetVol_ACAR10 = nanmean(AcqTargetVol_CAR10);

[H, P, CI, Stats_AcqVol_ACAR1] = ttest(AcqVol_CAR1);
[H, P, CI, Stats_AcqVol_ACAR5] = ttest(AcqVol_CAR5);
[H, P, CI, Stats_AcqVol_ACAR10] = ttest(AcqVol_CAR10);

fprintf(' Acquirer Volume aCAR for \( \varepsilon = 1 \), \( k=%d \): %d
', k, AcqVol_ACAR1);
fprintf(' Acquirer Volume aCAR for \( \varepsilon = 5 \), \( k=%d \): %d
', k, AcqVol_ACAR5);
fprintf(' Acquirer Volume aCAR for \( \varepsilon = 10 \), \( k=%d \): %d
', k, AcqVol_ACAR10);

fprintf(' Target Volume aCAR for \( \varepsilon = 1 \), \( k=%d \): %d
', k, TargetVol_ACAR1);
fprintf(' Target Volume aCAR for \( \varepsilon = 5 \), \( k=%d \): %d
', k, TargetVol_ACAR5);
fprintf(' Target Volume aCAR for \( \varepsilon = 10 \), \( k=%d \): %d
', k, TargetVol_ACAR10);

fprintf(' Acquirer\&Target Volume ACAR for \( \varepsilon = 1 \), \( k=%d \): %d
', k, AcqTargetVol_ACAR1);
fprintf(' Acquirer\&Target Volume ACAR for \( \varepsilon = 5 \), \( k=%d \): %d
', k, AcqTargetVol_ACAR5);
fprintf(' Acquirer\&Target Volume ACAR for \( \varepsilon = 10 \), \( k=%d \): %d
', k, AcqTargetVol_ACAR10);

fprintf(' Acquirer Volume ACAR \( T \) stat for \( \varepsilon = 1 \), \( k=%d \): %d
', k, getfield(Stats_AcqVol_ACAR1, 'tstat'));
fprintf(' Acquirer Volume ACAR \( T \) stat for \( \varepsilon = 5 \), \( k=%d \): %d
', k, getfield(Stats_AcqVol_ACAR5, 'tstat'));
fprintf(' Acquirer Volume ACAR \( T \) stat for \( \varepsilon = 10 \), \( k=%d \): %d
', k, getfield(Stats_AcqVol_ACAR10, 'tstat'));

fprintf(' Target Volume ACAR \( T \) stat for \( \varepsilon = 1 \), \( k=%d \): %d
', k, getfield(Stats_TargetVol_ACAR1, 'tstat'));
fprintf(' Target Volume ACAR \( T \) stat for \( \varepsilon = 5 \), \( k=%d \): %d
', k, getfield(Stats_TargetVol_ACAR5, 'tstat'));
fprintf(' Target Volume ACAR \( T \) stat for \( \varepsilon = 10 \), \( k=%d \): %d
', k, getfield(Stats_TargetVol_ACAR10, 'tstat'));

fprintf(' Acquirer\&Target Volume ACAR \( T \) stat for \( \varepsilon = 1 \), \( k=%d \): %d
', k, getfield(Stats_AcqTargetVol_ACAR1, 'tstat'));
fprintf(' Acquirer\&Target Volume ACAR \( T \) stat for \( \varepsilon = 5 \), \( k=%d \): %d
', k, getfield(Stats_AcqTargetVol_ACAR5, 'tstat'));
fprintf(' Acquirer\&Target Volume ACAR \( T \) stat for \( \varepsilon = 10 \), \( k=%d \): %d
', k, getfield(Stats_AcqTargetVol_ACAR10, 'tstat'));
fprintf('
Acquirer&Target Volume ACAR T stat for \( \epsilon = 5 \), \( k = %d \):
\n', k, getfield(Stats_AcqTargetVol_ACAR1, 'tstat'));
fprintf('
Acquirer&Target Volume ACAR T stat for \( \epsilon = 10 \), \( k = %d \):
\n', k, getfield(Stats_AcqTargetVol_ACAR10, 'tstat'));