The Effect of Unforeseen Crashes on Security Returns of Airline Operators

Bsc - International Bachelor of Economics & Business Economics

Bachelor Thesis

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Executive Summary

This thesis focuses on analyzing how aircraft crashes effect the stock returns of the involved airline operator. Aside from examining the reaction of the stock price, this thesis dives further into this question, to examine if the parameters of the crash influence how returns vary between separate events. The parameters, which are discussed, are the number of fatalities, whether the company has experienced multiple crashes in the span of the year, and whether the airline operator was responsible for the crash. This thesis examines this concept on a global level, accounting for all crashes involving fatalities that have occurred since 2004.

The purpose of this thesis is to provide investors with a guide as how to react when an unforeseen event such as an aircraft crash occurs, and what the statistically most profitable course of action is, despite the damaging news. With current oil prices reaching extreme lows, airline operators have profited from this tremendously, increasing profits, and in turn stock prices have risen. The majority of airline indexes have hit all time highs within the previous quarter, demonstrating how lucrative this market currently is. This naturally attracts investors, and these investors should be prepared for shocks that could hit unexpectedly.

As anticipated, the findings of this thesis show a clear negative correlation between the occurrence of an aircraft crash and the respective stock price in the following days. The afore mentioned parameters play a significant role in determining the abnormal returns, and have negative coefficients. Investors should not overlook the parameters in the event that a crash occurs. All things considered, this thesis also discovers an almost complete reversal in the negative abnormal returns over the successive 60 trading days, once the shock has occurred. This knowledge can be used to achieve profitable trading strategies.

Aircraft crashes receive major media attention across the world, bringing negative abnormal returns to the securities of respective airline operators, thus traders should be informed on the significance of these irregularities, and the crash's independent variables that influence the direction and magnitude of the abnormal returns.

1. Introduction

This thesis is an analytical paper, discussing the effect that aircraft crashes have on security returns of the respective commercial airline operators. It provides a model elaborating on independent variables such as: number of fatalities, repetition of events and operator culpability, which would significantly influence the direction and magnitude of the abnormal returns across multiple time periods. Specifically, it brings forth information on events solely involving fatalities and that have occurred in the previous 13 years.

In recent years, the quantity of airline crashes has significantly decreased; yet higher profile cases such as Malaysia Airlines, Trans Asia Airlines & German Wings have brought wide attention to the sector putting pressure on all Airline Operators to improve safety standards or risk loosing customers. This thesis provides insight on how the stock price reacts after such occasions, bringing forth evidence with statistical backing on the probable course the stocks returns will take in the post-event window. The goal is to provide investors with a model that can be used to make educated decisions, on when to purchase or sell the respective airline operator stocks in the event of such unforeseen incidents.

To best bring forth this issue and to properly quantify it, this thesis introduces the following Research Question:

"How do the incidence of airline crashes and the crash's nature, affect the stock returns in the Short Term?"

This paper will be approaching this question on a global level and taking into consideration all aircraft crashes that have occurred from the period of 2004 to 2017, totaling 20 individual events concerning 15 companies.

This research will build on prior research by elaborating on the fundamentals that have been discussed. Namely, the research is extended to a wider domain, over a shorter time frame. Prior research has focused on specific countries and areas, primarily the United States and Europe, while extending the time horizon of incidents far past 30 years. Contrastingly, this thesis researches every crash of publicly traded operators on a global level in a shorter time frame. This allows for more congruent information, analyzing the industry on a global scale (which is in line with the nature of the business), where the stock returns would not change over time due to advancements in technology.

More over, prior literature has focused largely on predicting stock returns of airline operators in general, using independent variables such as oil prices and passengers carried to calculate the stock returns. Normal and lagged dummy variables are afterwards introduced for the days of the crashes. Testing the statistical significance of the dummy variables allowed examining whether the incidents are correlated with a negative coefficient. This thesis uses the approach of event studies, and substitutes the conventional stock split or dividend increase, with the occurrence of the aircraft crash. Then, it tests the significance of the cumulative abnormal returns as well as the underlying parameters of the crash, through multiple time periods. Subsequently, a model is created providing insights on how the characteristics of the crashes play a role in the abnormal returns. Independent variables such as the number of fatalities, repetition of events and operator culpability are all used to predict how cumulative abnormal returns behave in the days following such an incident.

This is a big task to perform, and limitations to this research do exist. Namely, the percentage of incidents with publicly traded companies being responsible is rather small, meaning that a very large portion of events goes unaccounted for. Only focusing on the days following the crash also limits the number of observations that can be used. Focusing on a global level implies that for developing countries, a majority of the firms were privately or governmentally owned. Unintentionally, this gives a stronger weight to developed countries. These limitations are discussed in further sections, with insights being provided on how future researchers can supplement this study.

2. Literature Review

2.1. Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH), a well renowned theory, sheds light on how all-available information is always efficiently processed by markets so that prices consistently reflect the true value behind the underlying assets *(Fama, 1970)*. The logic comes from the idea that any information, as soon as it becomes accessible to all involved parties on the market, it is instantly processed by well-informed rationally behaving traders, hence mispricing ceases to exist. The occurrence of any event concerning a commodity, good or bad, should be instantly taken into consideration, altering the price of the respective asset. Logically speaking, for a tradable commodity such as company stocks, any emerging new information concerning unforeseen events should be instantly processed by the market, readjusting the value to take the news into account.

Fama went on to describe three forms of the efficient market hypothesis, each pertaining to its own set of conditions. The “strong form”, claims that all collectively accessible information (including insider information) is reflected by the prices on markets. The “semi-strong form”, relaxes this assumption to only publicly accessible information. While the “weak” form, explains that prices only reflect all historical prices and returns *(Fama, 1970).* An unforeseen event, such as an aviation crash, would appropriately match the semi-strong form as all commercial airline crashes are instantly publicized with detail.

Fama’s theories were not met without confrontation, with many arguments originating from the behavioral train of thought. A famed argument was the distinction between value and glamour stocks, which demonstrated that systematic mispricing occurs. “Value stocks” constitute stocks in which the price is too low for the respective potential earnings, while “glamour stocks” are those where the potential earnings are being overvalued. The central idea is that historically well performing stocks are in high demand and that these “glamour stocks” are overvalued *(Lakonishok et al. 1994).* Another conflicting topic with the EMH is the concept of calendar anomalies. For instance, the January effect, demonstrates positive abnormal returns in the month of January due to investors tax loss selling

(Haug & Hirschey 2006). This being said, the idea that value stocks are mispriced has been discredited by claiming that the value premium is brought about through a higher volatility, which is not conflicting with the Efficient Market Hypothesis *(Fama & French, 2012)*. Further more, the behavioral anomalies of over or underreacting to news was not deemed as sufficiently disturbing to the EMH, as they are chance results and additionally disappeared depending on the manner of measurement *(Fama, 1998).*

The purpose of this thesis is to analyze how the appearance of publically available information of a fatal aircraft crash affects the underlying company. Following the logic of the semi-strong form of the Efficient Market Hypothesis, it is expected that the effect of the crash will be transposed into the price of the respective tradable asset, i.e. share price, instantly on the day of the event.

2.2. Event Studies

The first case of event studies could be attributed to James Dolley, whose study from 1933 documented how stock splits affect the respective nominal prices *(MacKinley, 1997 p.13)*. Since the early 20th century, many developments have occurred in the sector, with event study methodology being extended from financial analysis to accounting and other domains of economics *(Binder 1998).* One of the most iconic and revolutionary developments in the field, has to be attributed to the research done by Fama, Fisher, Jensen and Roll in 1969 being cited countless times by further researchers (Binder 1998, p. 111). These researchers' methodology is used to this day as the standard approach to analyzing how security price returns react to the presence of events or announcements (Binder 1998). This section explains Fama, Fisher, Jensen, and Roll's research, which is applicable for the purpose of this thesis. Hence forth, these economists are collectively referred to as "FFJR".

FFJR's research focused on finding if "unusual" behavior in stock returns occurred in the presence of a security split in the months surrounding the splits, and if the behavior can be explained by alterations in other independent variables *(Fama et al. 1969 p. 1-2).* FFJR initially examine the market model as a source of explaining the returns for each stock i in the sample. Monthly data from the previous 29 months and post 30 months of stock trading data are used *(Fama et al. 1969).*

$$R_{it} = \alpha_i + \beta_i R_{mt} + u_{it}$$

Equation 1: Market Model,

The average abnormal returns are calculated for each month across the sample of all the individual firms with announcements. This allows examining the average abnormal returns of every month surrounding the event month s, defined as AAR_s. FFJR went further to sum the effect of the announcements across multiple months by cumulating the averages into a Cumulative Average Abnormal Return $CAAR_{S1,S2}$, in-between two specified months *(Fama et al, 1969).* Slight alterations to this standard model have been made to achieve a higher validity, by FFJR and Ball & Brown *(Binder, 1998)*, by extending the monthly observations to 5-7 years, and excluding the event period so that the coefficient estimates are not biased.

2.3. Prior Literature on Stock Returns and Aircraft Crashes

As event studies gained traction as a valid source of getting data for financial models, the airline industry was no exception to research. Chance & Ferris, were the first to research how airline security returns were affected by the occurrence of airline accidents. The research used methodology extremely similar to Fama et al.'s event study literature from 1969, all though it incorporated the Capital Asset Pricing System to predict the expected returns after having used the market model to calculate the market beta *(Chance & Ferris, 1987).* The research was focused solely on airline accidents involving United States enterprises concerning a minimum of 10 fatalities, which was chosen arbitrarily *(Chance & Ferris, 1987)*. Having analyzed 20 trading days, both after and before the day of the event, the average abnormal return across incidents, was only significant on the day of the event with an AAR of -1.2% *(Chance & Ferris, 1987).* Further conclusions stated that there was no significant effect at all for the manufacturers of the involved aircraft, and similarly, other airline operators experienced no abnormal returns either, signifying that the market's attention was focused specifically to the airline operator *(Chance & Ferris, 1987).*

After sparking interest for this field of research, one year later Borenstein & Zimmerman released a publication with similar conclusions in 1988. In terms of methodology, their method was different by the use of the market model to calculate daily abnormal returns, not opting to use the CAPM (*Borenstein & Zimmerman, 1988).* Their results demonstrated on average that an equity loss of 1% occurred on the day of the event averaging a monetary loss of $4.5 million. Only the abnormal return on the day of the event was individually significantly different from zero, while the CAR for the first two days (including the day of the incident) was significant as well (*Borenstein & Zimmerman, 1988).* The conclusion extends to discuss how the average firm loss is less than the societal cost of the incident, explaining that firms carry insurance to protect them from the full cost of the incident. As a final note on their research, customers showed no significant adverse reaction to the crashes (*Borenstein & Zimmerman, 1988).*

More recent research, conducted by Kaplinski & Levy in 2010, go into more detail and dive into aspects of the crash that could make the market react differently to the nature of the incidents. Different from prior mentioned literature, Kaplinksi and Levy analyze the difference in reactions for European and US firms. Their results demonstrate a clear negative significant return for the first 2 days of trading, and also bring forth evidence of a reversal effect in the consecutive period *(Kaplinski & Levy, 2010).* More interestingly, their research shows that on the day, and day after the event, the operator experiences a monetary loss, which is 60 times larger than the direct economic cost of the incident. This disparity is explained by an overreaction by traders, caused by anxiety and fear, resulting in a reduction in demand for the risk bearing *(Kaplinski & Levy, 2010)*. Subsequently, once the behavioral tendencies subside, the reversal effect occurs.

More recently, Ho, Qui & Tang studied how airlines suffer from crashes and study if the number of underlying fatalities plays a significant role in the abnormal returns experienced. Using event study techniques and grouping the incidents depending on the number of fatalities, provides insights on the factors that could distinguish between abnormal returns among separate crashes. Their main findings inform that crashes with single digit fatalities take a negative AR but recover a week later, while crashes with a higher degree of fatalities cause longer lasting persevering effects, resulting in a longer recovery *(Ho et. Al, 2013).* Ho et al. argue that the quantity of fatalities present a larger reduction in customer demand, and takes longer for asset & reputation reparation (*Ho et. Al, 2013).*

2.4. Hypotheses

All prior research, have a primary goal of testing whether negative cumulative abnormal returns exist. Some but not all of this literature, builds and tries to justify according to its own logic, with argumentation to back up the results, but present little statistical evidence on the independent variables that could play a role in distinguishing how the abnormal returns differ from one another. Data collected for this thesis demonstrates that the abnormal returns for one firm exceeds -10% on the day of the event, while others boast a positive abnormal return. This thesis first tackles up to which time horizon abnormal returns exist, and proceeds to dive into the parameters that could influence the returns. Thus, this thesis evaluates the following hypotheses:

$\mathbf{H_1}$: Airline crashes have a significantly negative effect on the stock returns of the respective airline operator.

$\mathbf{H_2}$: The larger the gravity of the crash (amount of fatalities ≥50), the larger the abnormal return that is experienced by the airline operator.

$\mathbf{H_3}$: When the blame for the incident is attributed to the operator there is a stronger abnormal stock return for the respective airline operator.

$\mathbf{H_4}$: When an airline operator experiences multiple aircraft crashes within the period of a year, the negative return effects for the consecutive crash are significantly stronger.

After using event study methodology to statistically answer each hypothesis, a model is created to unify the collected data so that stock traders can predict the abnormal returns that could occur after comparable events.

3. Methodology

3.1 Data:

To receive results regarding the effect of unforeseen crashes on the respective airline operator's stock price, certain data must be collected. The data will belong to two categories, namely: parameters derived from details of the crash and the respective airline operator's stock return data around the period of the event.

To rationally answer the research question of this thesis, the question will be tackled by individually analyzing the different hypotheses. Regardless of the hypothesis, the time series stock return data of the involved companies is a necessity for making the regressions. Stock Returns are taken from the respective stock exchanges to get all of the necessary trading data. With "T" defined as the date of the incident, data from the previous 120 trading days (T-120) are taken to calculate the Expected return in the time of the incident and matched versus the market return. By examining crashes on global scale, not all consecutive days between the stock and market index are available due to non-trading days. In this event, the successive trading day data is used. To analyze post event data, the consecutive 60 trading days (T+60) are retrieved. This allows for multiple time intervals to be used for examination of the abnormal returns. Namely, the intervals that will be used are: 'T,T+1', 'T,T+5', 'T,T+10', 'T,T+15', 'T,T+30' and 'T,T+60'. In each case, the selected time sections are defined as (T, T_k). Prior research on event studies demonstrated statistically significant price reactions up to 10 days after the event *(Busse & Green, 2002),* and thus will be of primary focus for this thesis. Event windows of longer length (T+15, T+30 & T+60) serve to further back up this assumption and validate the selection of CARs for the model. For both pre and post event data, the returns are compared with the market returns on the same day of trading to calculate expected returns.

To see how the incident and how the nature of the incidents influence the abnormal stock returns, data is collected to group the events into clusters. For instance, to answer hypothesis 2 (which focuses on how the quantity of fatalities plays a role), the quantity of fatalities is collected to separate the data pool in two groups, one with above and including 50 and one with fewer than 50 fatalities. Following this logic, the additional data to be collected to act as independent variables includes the party responsible for the crash, whether multiple crashes occurred during the previous year of operations, and the number of fatalities.

3.2 Method:

To isolate the effect of the incident on the respective stock return, this thesis will follow the approach of calculating and evaluating the causal relationships of the underlying factors on the dependent variable "abnormal returns" and its underlying factors. The abnormal return is calculated relative to what would have been expected if the incident had not occurred "$E\ (R_j)$". The following procedure is used to conduct the analysis:

Step 1: Calculating the actual returns "R_{it}"

The actual returns "R" are calculated from data attributing to the period of the incident. Period "t" is defined as the day of the event, and returns are calculated from "T-120" to "T+60" for each incident "i". The actual return is calculated by subtracting the previous price of the security at Pt-1 from Pt, divided by the price at time t-1. This provides a sample of 181 returns per event.

Step 2: Calculating the Estimated returns "$E(R)_{it}$" using the Market model:

$$E(R)_{it} = \beta 0 + \beta 1(E(Rm)$$

Equation 2: Market Model

Data from the previous 120 days of stock trading data are used to regress and achieve coefficients for $\beta 0$ & $\beta 1. R(M)$ is defined as the market return and is calculated using data from the **AXGAL** index. As this thesis researches the effect of incidents on returns on a global scale, an index that represents the performance of airliners, small and large from across the globe is necessary. The AXGAL index is well suited for this purpose as it is a weighted portfolio, based on the liquidity, size and domicile (whether it is a domestic or international airliner) of global airliners (NYSE ARCA, 2014). These figures will be used to predict the expected return in the period of the incident. The Market Model is used due to its simplicity in application, and due to the amount of returns that need to be predicted. As the purpose of this thesis is to evaluate abnormal returns and to create a model to accurately predict expected returns for airline stocks, the market model serves this purpose well. As a final note on the market model, prior research has shown that more complicated multi factor models do not decrease the forecast bias (*K.R. Ahern, 2009)*. Therefore, these would provide little to no advantage for the purpose of this thesis. To test whether using a single global market index was the best approach, this thesis additionally tested how comparing 5 separate indexes from each continent to be compared with the respective companies performed for the prediction accuracy, yet significantly lower R-squared values were produced.

Step 3: Calculating the Abnormal Return of each incident "AR_{i,T_jT_k}"

$$AR_{it} = R_{it} - (\beta 0 + \beta 1(E(R_{Mi}))$$

Equation 3: Abnormal Return

The Abnormal return is defined as the difference between the expected return in absence of the event ($E\ (R)_{it}$), and the realized return (R_{it}). By subtracting the realized return by the expected return, we get the difference between the two, representing the abnormal return. This is done for every trading day, after and including the day of the incident, from T to T+60 providing 61 abnormal returns per examined incident.

To further analyze each incident, the abnormal returns are cumulated into the seven time horizons discussed in subsection 3.1, and are represented as "$CAR\ t: t + k$". This allows examining how the abnormal returns behave collectively.

$$CAR_{i,T:T+k} = \frac{1}{k+1}\sum_{t=0}^{k} AR_{it}$$

Equation 4: Cumulative Abnormal Return

Step 4: Grouping & Testing

To come to a conclusion on how a specific set of events impacts the stock returns of the involved companies, observing the abnormal return of individual events is not sufficient. Therefore, averages for each time period of the multiple observed crashes are calculated with respect to the separate hypotheses. For instance, for hypothesis 2, which examines how the number of fatalities affects the stock price, the cumulative abnormal returns of crashes with fewer than 50 fatalities versus crashes with above and including 50 fatalities are grouped together and tested.

Testing the significance of the average Cumulative Abnormal Returns for each time period is done through the use of the t-statistic. For this we divide the calculated Cumulative Abnormal Returns by the Standard Error of the Cumulative Abnormal Returns. We find the standard error by dividing the standard deviation of the sampling distribution by the root of the number of observations. To begin with, hypothesis 1 has the goal of testing whether abnormal returns exist: If the CAR is significantly different from zero there is a significant abnormal return. This will be the approach to answer the first hypothesis as it is of primary interest to first confirm if abnormal returns exist. Accordingly, we have the following t-statistic:

$$t_{TjTk} = \frac{CAR_{TjTk}}{SE_{AR}}$$

Equation 5: T-test

Consecutively, a similar approach is taken although instead of testing if the CAR is significantly different to zero, the purpose here is to evaluate which factors affect the abnormal returns such stocks experience. For hypothesis 2, 3 and 4, two groups, one with the factor present, and one control group without the factor, are compared. The two groups, defined as $x1$ & $x2$, are tested using two-sampled t-test. As the aim of the later hypotheses (2,3 and 4) is to evaluate if the attributed blame, number of fatalities and repetition of events produce a stronger effect on the respective company, this allows us to evaluate whether one group's abnormal returns are significantly different from the others. The following two-sampled t-test is used:

$$t_{x_1,x_2,TjTk} = \frac{CAR_{x1,TjTk} - CAR_{x2,TjTk}}{SE_{\overline{x_1}-\overline{x_2}}}$$

Equation 6: Two-Sampled T-test

All these tests are conducted to obtain statistical evidence of the causal effect such factors have and whether they should be included in the model explaining how the independent variables affect the dependent variable, which is cumulative abnormal returns. This is the true purpose of this thesis.

3.3 Models

$$CAR = \beta_0 + \beta_1 MarketCap + \beta_2 FatalitiesDummy + \beta_3 RepeatedCrash + \varepsilon$$

Model: Explaining Cumulative Abnormal Returns

The Model developed in this thesis serves the purpose of providing investors with a powerful instrument for predicting how the stock price of an operator will react, in the days following an airline incident. The Model focuses on predicting cumulative abnormal returns and will be applied to three time periods, namely days 0-1, 0-2 & 0-5. The Model uses OLS regression to calculate the optimum level of fit for the regressors.

Each regressor is introduced into the model based on whether the T-tests and Two sampled T-tests demonstrate a statistically significant difference from zero, or if there is a significant difference in means of the two groups. This provides a double-layered test to assure that there is correlation and that the regressors are not being added arbitrarily. Subsequently, once added into the model, the regressors' effects are analyzed in unison to test each individual's effect in the presence of other factors, as well as providing a F-statistic to measure the relevance of the model as a whole.

The Model constitutes of 3 independent variables and 1 control variable:
The constant for each time period is calculated to inform the investor on how much the stock return tends to decrease on average over each consecutive period. "FatalitiesDummy", is a dummy variable that is triggered in the event that a crash experienced above 49 fatalities. "RepeatedCrash", is a dummy variable that accounts for crashes where the same airline operator was involved in another crash involving fatalities within the previous year. A control variable, "MarketCap", is added to take into account the size differences among the firms experiencing crashes. It is not a direct parameter of the crash, but does affect the abnormal returns experienced.

Being a financial analytical thesis, there is a smaller focus on causation but rather on correlation, as to an investor it is not of grave importance to have causal relationships. As long as the predictions are accurate, the model provides value.

4. Data

4.1 Selection of the data

To obtain credible data to be used in the experimentation stages of this thesis, the data needs to qualify based on a number of characteristics. Considering that this thesis will be addressing the question of incidents on a global level, the information must be selected from all incidents worldwide so that there is no discrimination based on geographical preference. For this purpose all incidents globally need to be examined and evaluated to see if they provide useful information for experimentation.

In the year of 2016, a total of 102 aviation crashes occurred *(BAAA, 2017)*. These incidents include all events from different service provisions. Transporting goods, Repositioning flights, Training Crashes are all examples of incidents, which are included in the data made available by the Bureau of Aircraft Accidents Archive, which is used as the primary source of event information in this thesis. This thesis is primarily concerned with Commercial Passenger flights, as these events raise the most awareness in the media and are more prominent in news. To be categorized as a commercial passenger flight it must fulfill the condition of it being a Scheduled Revenue Flight".

A "Scheduled Revenue Flight" is defined as a commercial flight where transporting passengers (who purchased the service) from one location to another is the purpose of the flight (*BAAA, 2017)*. Previous literature on this topic analyzed on average 15 incidents to draw conclusions, while focusing exclusively on a specific geographical area over the period of 30 years. It is also important to note that the terrorist attacks that occurred on the 11th of September in 2001 on the US had a strong effect on the airline industry, and thus this thesis will not be examining any incidents prior to these events. To remain consistent with prior research and use a similar sized pool of events, data has been taken from the BAAA to examine all Scheduled Revenue Flights (SRF) in the period of 2004 – 2017. From the 2000+ flights examined, 400 scheduled revenue flights were identified, with 20 flight incidents qualifying for the experimentation. This number of events is consistent with the quantity used in prior literature, allowing for the comparison of results.

4.2 Data Parameters

The first characteristic of the selected data was that the crash had recorded fatalities. This was selected as a required parameter to increase the validity of the experiment. Airline incidents recorded by the Bureau of Aircraft Accident Archives (BAAA) classify an aircraft having a burst tire on landing, and the utter destruction of an aircraft on impact, both as aircraft crashes in the same database. The two events are of an entirely different nature and have different associated costs, with the latter being exceedingly expensive in terms of reparation costs, legal fees, compensation and loss in reputation, and may potentially even result in a receded license to conduct flights. This thesis will build on the assumption that the latter group plays a far stronger role in potentially affecting an operators' stock price. This lowers the volatility of the sample of abnormal returns.

Many airliners, more specifically the smaller operators, are privately held. Not being traded on the market raises an unsurpassable issue, as the stock trading data is not publicly accessible. Furthermore, investors cannot freely invest into privately held firms, hence the effect of crashes on privately held firms is of no interest. The primary focus of this paper is to bring forth useful information in understand trading in the presence of such unforeseen events, hence privately held firms are not included. Additionally, certain airliners are partly or wholly (100% owner) earned by larger operators. In such an event, the effect on returns of subsidiary is evaluated through the stock return performance of the owning party. As mentioned in subsection 3.1, the stock trading data from the previous 120 trading days, and the successive 60 trading days are retrieved to predict expected returns, and next to calculate abnormal returns.

Taking these factors in to account narrows the selection down to 20 incidents associated with 15 airliners. Two airliners experienced two incidents within period of a year, namely Malaysia Airlines and Trans Asia Airlines. These events are of great interest, as they will allow examining how repeated incidents in a short period of time can affect returns answering Hypothesis 4. The latter of the two grounded its whole fleet forcing all pilots to be re-evaluated for service, (*Shu-fe & Hsin-Yin, 2015)* eventually ceasing operations indefinitely in 2016.

The independent variables to be used are summarize in the following table:

Airline	Fatalities:	Cause:	Repeated Crash
Turkish Airlines	39	Pilot Error	No
Pakistan International Airlines	47	Pilot Error	No
German Wings	150	Pilot suicide	No
Trans Asia Airways 1	43	Pilot Error	Yes
Air Asia Indonesia	162	Technical Failure	No
Trans-Asia Airways 2	48	Pilot Error	No
Malaysia Airlines 1	298	Land Based Missile	No
Malaysia Airlines 2	239	Unknown (Excluded)	Yes
Bearskin Airlines	5	Technical Failure	No
Asiana Airlines	3	Company Negligence	No
Delta Airlines	1	Pilot Error	No
UT Air	33	Company Negligence	No
Air France	228	Company Negligence	No
Turkish Airlines	9	Pilot Error	No
Colgan Air	50	Pilot Error	No
Aeroflot	88	Company Negligence	No
UT Air	6	Pilot Error	No
GOL	154	Traffic Control Error	No
Pakistan Airlines	45	Company Negligence	No
China Yunnan Airlines	55	Company Negligence	No

Table 1: Data Parameters

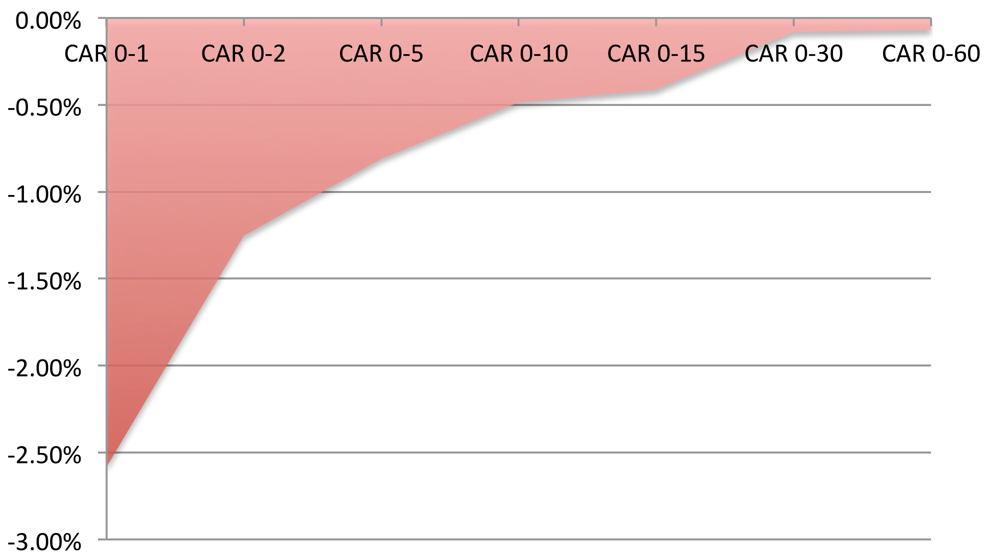
The causes of the incidents were cross-referenced with the Aviation Safety Network (ASN) to assure the accuracy of the data. The causes for each of the events are categorized under 5 groups, namely Technical Failure, Pilor Error/Suicide, Company Negligence, Traffic Control Error and Unknown. Technical Malfunctions and Company Negligence are causes where the blame is attributed to the operator due to improper operations.

4.2 Descriptive Statistics

Once all the stock data has been collected and processed versus the market return, we achieve the following data for the different time periods among all of the incidents Cumulative Abnormal Returns, in order of increasing magnitude. This data is collected from 20 individual incidents, each spanning a maximum of 61 trading days. On the following page, descriptive statistics of the abnormal returns are presented. In addition, a graph of the cumulative returns is presented, illustrating the diminishing cumulative abnormal returns, as the event window lengthens:

	CAR01	CAR02	CAR05	CAR010
Mean	-2,5855%	-1,2522%	-0,8080%	-0,4837%
Median	-2,0000%	-1,5100%	-0,7600%	-0,5400%
Maximum	1,5900%	1,3800%	2,4000%	1,5800%
Minimum	-10,3100%	-4,8300%	-6,5800%	-3,3400%
Std. Dev.	0,025498	0,015932	0,019466	0,011702
Observations	20	20	20	20
	CAR015	**CAR030**	**CAR060**	
Mean	-0,4119%	-0,0819%	-0,0713%	
Median	-0,2850%	-0,1200%	-0,2200%	
Maximum	1,2400%	0,8200%	1,3950%	
Minimum	-4,1800%	-1,2600%	-0,7800%	
Std. Dev.	0,011625	0,004952	0,005426	
Observations	20	20	20	

Table 2 – Cumulative Abnormal Return Statistics



Graph 1 – Cumulative Abnormal Returns for 17 incidents

The data presented a diminishing average abnormal return pattern as the evaluated time period was extended. On the day of the event together with the subsequent trading day, an average cumulative negative return of -2.59% was experienced across the 20 incidents. As time progressed, after 60 days the cumulative effect of the crash across 20 incidents is almost no longer visible, demonstrating that the market is quick in correcting the negative returns into what would have been experienced in absence of the crash. The effects seem to be only very short term, with little to no long term lasting effect.

5. Results

5.1 Hypothesis 1

“$\mathbf{H_1}$: Airline crashes have a significantly negative effect on the stock returns of the respective airline operator.”

The purpose of including Hypothesis 1 is to test which post event CAR windows, are significantly different from zero. This hypothesis may reject the possibility that there is no significant effect at all of crashes on the abnormal returns; in other words, if the CAR is significantly different from zero. To potentially reject the hypothesis, the 20 incidents’ returns were collected and regressed on the market return using the market model. Subsequently, the expected returns were predicted and abnormal returns for each trading day were calculated. Hence, for each time period the Cumulative Abnormal Return is collected *(Table A.1)*. Seven samples are thus created (for each time period), with each consisting of 20 observations. Using a standard t-test, each sample is tested to check if it is significantly different from zero. As this thesis is primarily interested to see if crashes cause abnormal negative returns, the t-test takes form in a one sided t-test. The following results were obtained:

CAR Length	AVERAGE OVER 20 incidents	Standard Deviation	T-test μ=0	2 sided Probability μ<0	1 sided Probability μ<0
CAR 0,1***	-2,59%	0,025498	-4,53424915	0,02%	0,01%
CAR 0,2***	-1,25%	0,015932	-3,514943913	0,23%	0,12%
CAR 0,5***	-0,81%	0,019466	-1,856005003	7,93%	3,97%
CAR 0,10***	-0,48%	0,011702	-1,849261968	8,01%	4,01%
CAR 0,15**	-0,41%	0,011625	-1,587687482	12,96%	6,48%
CAR 0,30	-0,08%	0,004952	-0,737063599	46,88%	23,44%
CAR 0,60	-0,07%	0,005426	-0,586302222	56,40%	28,20%

Table 3 – Hypothesis 1 Results

For periods up until CAR(T:T+10), we can reject the hypothesis with 99% confidence, while for the period of T,T+15, we can reject it with 90% confidence. These results clearly demonstrate that cumulative negative abnormal returns exist due to airline crashes in the very short term, for up to and including 15 days after the crash. The results are inline with the findings of Busse & Green, that abnormal returns are experienced up until 10 days after the event *(Busse & Green, 2012)*, and will be the focus for the subsequent sections of analysis. Additionally, these results are consistent with prior research, although the significance and magnitude of the CAR decrease faster than for prior research (*Homar, 2015)*. This could potentially be attributed to the fact that this research was conducted on a global level, with larger geographical disparities between the expected and realized returns, as opposed to Homar's research that was focused on the US. This research is also based on a period extending to as far back as the 1980's. In such time periods, there was far less immediate media coverage that has been proven to have a significant effect on stock returns. Moreover, strong media coverage has been proven to deliver up to 0.2% of a stock return premium per month to unfeatured companies *(Fang & Peress, 2009)* meaning that high media coverage decreases stock returns. Thus, the reactionary stock traders would be exposed to news slower, resulting in the abnormal return effect being widened over a prolonged period of time.

5.2. Hypothesis 2

"H_2: The larger the gravity of the crash (amount of fatalities ≥50), the larger abnormal returns are experienced for the airline operator.

A factor that is instantly known in the event of a crash is the number of fatalities involved; therefore it is of interest to test if there was a significant difference in the abnormal returns, according to the respective number of fatalities. In the previous hypothesis, it was discovered that the cumulative abnormal returns were significantly different from zero at 1%, up until CAR (t:t+10) with decreasing t-statistics as the CAR was lengthened. Therefore, this hypothesis was evaluated by examining these periods. Group 1 and Group 2 were created, categorized by crashes involving ≥50 and <50 fatalities respectively *(Table A.2)*. Two sampled tests for the equality of means (Equation 6) were conducted to test if there is a significant difference:

	Method	df	Value	Probability
CAR (t:t+1)	t-test	16,00000	-2,29816	3,54%**
>50 casualties	Satterthwaite-Welch t-test*	11,92530	-2,29816	4,05%**
vs	Anova F-test	(1, 16)	5,28156	3,54%**
<50 casualties	Welch F-test*	(1, 11,9253)	5,28156	4,05%**

CAR (t:t+2)	t-test	16,00000	1,65934	11,65%
>50 casualties	Satterthwaite-Welch t-test*	15,54770	1,65934	11,71%
vs	Anova F-test	(1, 16)	2,75340	11,65%
<50 casualties	Welch F-test*	(1, 15,5477)	2,75340	11,71%
CAR (t:t+5)	t-test	16,00000	1,2083170	24,45%
>50 casualties	Satterthwaite-Welch t-test*	10,17382	1,2083170	25,43%
vs	Anova F-test	(1, 16)	1,4600300	24,45%
<50 casualties	Welch F-test*	(1, 10,1738)	1,4600300	25,43%

Table 4 – The effect of fatalities on returns

Of the 20 crashes, 11 had fewer than 50 fatalities; hence the 2 events closest to 50 fatalities were excluded to achieve an equal sample size in each group, constituting of 9 crashes.

For periods T:0-2 and T:0-5, it cannot be claimed that there is a statistically significant difference between the abnormal returns of the two groups. Yet, T:0-2 was close to being statistically significant at 90%. Although, it can be claimed with a confidence level of 95%, that the CARs occurring in time period T,T+1 between incidents above and including 50 deaths versus incidents with under 50 fatalities are statically different from one another. If we compare the averages for the first two days of trading of the two groups, we see that the average of the crashes with more than 50 casualties is more than three times as large (-3.61% vs. -1.11%). The results achieved here are in line with prior research, where the number of fatalities was significant *(Homar, 2015).* For the purpose of model testing, a dummy variable signifying if the event had more than 49 fatalities will be included as an independent causal variable, further tested in section 5.5.

5.3. Hypothesis 3

"**H_3**: When the blame for the incident is attributed to the operator there is a stronger abnormal stock return for the respective airline operator."

Answering this hypothesis sheds light on whether airliner culpability affects the airliner's stock returns. This could be of importance as when the airliner is deemed responsible, it comes with many costs, namely reimbursement to the families of the passengers who lost their lives as well as penalties and tarnishing of company image. Following a similar approach to hypothesis 2 (only for time periods T,T+1), this hypothesis is answered by aggregating crashes into two groups; one where the airline is responsible for the crash, while with the other it is outside of their hands and not their direct responsibility. Table 1 summarizes which flights belong to which group. “Malaysia Airlines flight 2” has been excluded form this test, as the cause is unknown to this day.

	BLAMEDCAR01	NOTBLAMEDCAR01	
Mean	-2,9613%		-2,32880%
Median	-2,0850%		-1,94500%
Maximum	-0,1700%		1,59000%
Minimum	-10,3100%		-5,53000%
Std. Dev.	0,031574		0,022533
Sum	-0,2369		-0,1863
Sum Sq. Dev.	0,006979		0,003554
Observations	8		8
Method	df	Value	Probability
t-test	14,00000	-0,46120	65,17%
Satterthwaite-Welch t-test*	12,66150	-0,46120	65,25%
Anova F-test	(1: 14)	0,21270	65,17%
Welch F-test*	(1: 12,6615)	0,21270	65,25%

*Test allows for unequal cell variances

Table 5 – Effect of culpability on Returns

Based on these results, it is clear that there is not enough evidence to claim that airliner culpability has an effect on the cumulative abnormal returns experienced by airliner operators after a crash. We can make this claim with a 65% confidence level. The time period of T:0-1 had no significant return differences among the groups, therefore this thesis no longer entertains the idea that airline culpability has an effect and excludes it from further model testing in subsection 5.5. The average CARs between groups are also very similar for the two groups leaving little evidence that this plays a role. Prior Research did not evaluate whether airline culpability could have an affect on operator stock returns.

5.4. Hypothesis 4

“**H_4**: When an airline operator experiences multiple aircraft crashes within the period of a year, the negative return effects for the consecutive crash are significantly stronger.”

Hypothesis 4 presents an interesting case, as it is very rare that this happens to an airline. Operators take the upmost caution to assure that crashes do not occur, and even the airlines with the worst track records have not presented opportunities to evaluate such a hypothesis. That is until 2014, since when 2 airliners have experienced consecutive fatal aircraft crashes within the span of one year. More over, the crashes have brought major media attention, bringing forth the question of how this it affected the stock price? For Trans Asia Airlines, both crashes were caused by pilot error while for Malaysia Airlines the same cannot be said, with one crash still being unaccounted for and the other being brought down by a "BUK" surface to air missile *(Bellingcat, 2016).* The statistical test is done though a two-sampled test for mean equality evaluating all 7-time periods as shown below:

1st Crash	**Mar 8, 2014 Malaysia**	**Jul 23, 2014 TransAsia**	**Average**
CAR 0-1	-1,77%	-1,54%	-1,65%
CAR 0-2	-0,40%	-1,15%	-0,77%
CAR 0-5	-1,12%	-0,75%	-0,94%
CAR 0-10	-0,30%	-0,50%	-0,40%
CAR 0-15	-0,83%	-0,43%	-0,63%
CAR 0-30	-0,16%	-0,13%	-0,14%
CAR 0-60	-0,31%	-0,16%	-0,23%
Average	**-0,70%**	**-0,67%**	**-0,68%**
2nd Crash	**Jul 17, 2014 Malaysia**	**Feb 4, 2015 TransAsia**	**Average**
CAR 0-1	-5,53%	-5,26%	-5,39%
CAR 0-2	1,35%	-4,83%	-1,74%
CAR 0-5	2,40%	-2,35%	0,03%
CAR 0-10	1,03%	-1,39%	-0,18%
CAR 0-15	1,24%	-0,98%	0,13%
CAR 0-30	0,53%	-0,54%	0,00%
CAR 0-60	0,39%	-0,51%	-0,06%
Average	**0,20%**	**-2,27%**	**-1,03%**

Table 6 – CAR of 1st and 2nd Crash

Test for Equality of Means between series for Crash 1 & 2 of TransAsia

Included observations: 7			
Method	df	Value	Probability
t-test	12,00000	-2,04696	6,32%
Satterthwaite-Welch t-test*	6,81116	-2,04696	8,10%
Anova F-test	(1: 12)	4,19006	6,32%
Welch F-test*	(1: 6,81116)	4,19006	8,10%

Test for Equality of Means between series for Crash 1 & 2 of Malaysia Airlines

Included observations: 7			
Method	df	Value	Probability
t-test	12,00000	-0,89007	39,09%
Satterthwaite-Welch t-test*	6,59453	-0,89007	40,47%
Anova F-test	(1: 12)	0,79222	39,09%
Welch F-test*	(1: 6,59453)	0,79222	40,47%

Table 7 – Statistical test of difference for 1st and 2nd crashe

From table 7 we can draw the conclusion that for TransAsia there is a significant difference in returns for crash 1 and 2, even though the rest of the parameters of the flights are almost identical. The same cannot be said for Malaysia Airlines, even though the day T:0-1 abnormal returns for the July 17th Crash are ±3x more severe (the stock recovers in the consecutive time periods). Although Malaysia Airlines does not provide enough evidence that there is a difference in cumulative abnormal returns, a dummy variable is added for the model testing in section 5.5.

5.5. Model Testing

In section 3.3 the variables inside the model are discussed with information on how the data was collected. The previous subsections demonstrated the significance of the cumulative abnormal returns, as well as if there were significant differences between groups. Three regressions are shown, for successive CAR lengths. The results of the following OLS regression are presented:

$$CAR = \beta_0 + \beta_1 MarketCap + \beta_2 Fatalities\ dummy + \beta_3 RepeatedCrash + \varepsilon$$

	Coefficient	Std. Error	t-Statistic	Prob.
i) CAR(0-1) **R-Squared: 0.359876**	CAR01= C(1)+C(2)*MARKETCAP + C(3)*FATALITIESDUMMY+ C(4)* REPEATEDCRASH *20 observations*			
C(1)**	-0.019021	0.007478	-2.543768	0.0217
C(2)	2.82E-06	1.92E-06	1.470241	0.1609
C(3)**	-0.023292	0.010599	-2.197587	0.0430
C(4)	-0.026263	0.016795	-1.563735	0.1374
ii) CAR(0:2) **R-Squared 0.060076**	CAR02= C(1)+C(2)*MARKETCAP + C(3)*FATALITIESDUMMY+ C(4)* REPEATEDCRASH *20 observations*			
C(1)*	-0.010627	0.005659	-1.877900	0.0787
C(2)	8.09E-07	1.45E-06	0.558027	0.5846
C(3)	-0.006893	0.008021	-0.859335	0.4028
C(4)	-0.004182	0.012710	-0.329059	0.7464
iii) CAR(0:5) **R-Squared 0.092398**	CAR05= C(1)+C(2)*MARKETCAP + C(3)*FATALITIESDUMMY+ C(4)* REPEATEDCRASH *20 observations*			
C(1)	-0.008668	0.006797	-1.275205	0.2204
C(2)	1.56E-06	1.74E-06	0.893153	0.3850
C(3)	-0.008984	0.009635	-0.932459	0.3650
C(4)	0.011765	0.015268	0.770563	0.4522

Table 8 – Models for different CAR lengths

The results of the OLS regressions are in line with the tests that have been conducted in prior sub-sections. The regression for CAR length (T,T+1), from Table 8, is of primary interest, as the largest abnormal returns occurred in this period with the strongest and most significant coefficients compared to any of the other CAR lengths *(Table A.3)*. Regression i) had the highest R-squared (0.36) of all of the regressions, with the successive periods having comparatively lower prediction accuracies. The regression calculating the dependent variable of CAR (T,T+1) has a F-statistic of 2,99838 giving a probability of 0.06 (to 2 d.p). This means that we can reject the possibility that the independent variables used in this model, are unrelated to the dependent variable of cumulative abnormal returns with a 90% confidence level. The same cannot be said for the extended time periods of CAR (T,T+2) *(Table A.4)* & CAR (T,T+5) *(Table A.5)*, which have low prediction accuracies (R-squared), and insignificant F-statistics. This demonstrates that the market behaves unpredictably after the 2nd trading day with relation to the independent variables analyzed in this thesis, with the corrections in the stock returns depending on other variables.

Although this is the case when longer time periods are fitted through the coefficients of the dependent variables, the constant in each model is of interest. For CAR (T,T+1) the constant was significant at a 95% confidence level, CAR (T,T+2)'s at a 90% confidence level, while for CAR (T,T+5), it was the closest to being statistically significant of all the dependent variables. This shows that even though the parameters of the crashes differ, and do play a role on influencing the cumulative abnormal returns among separate events, the effect of there simply being a fatal crash regardless of the severity in terms of costs or lives lost is most dominant. Although, it is important to note that the coefficients of the constant respective to the other independent variables in the majority of cases do not have the strongest magnitude. For example with dependent variable of CAR (T,T+1), both dummy variables, i.e. if the crash concerned more or equal to 50 fatalities, and if it was a repeated crash, affect the abnormal return more severely. This also applies for CAR (T, T+5), yet is not the case for CAR (T, T+2).

The number of fatalities in the crash is an interesting dependent variable to examine, as it is one of the first pieces of information accessible to the public in the event of a crash and brings forth information to the investors of the nature of the crash. In subsection 5.2, it is demonstrated how there is a statistically significant difference in CAR (T,T+1), for crashes concerning more than 49 versus crashes with under 50 fatalities. The regression model backs this up entirely by providing statistically significant coefficients (95%) exclusively for the CAR (T, T+1) with a magnitude of -2.33% for the dummy variable of if the crash caused more than 49 fatalities. Longer time periods provide much smaller coefficients which are also non-significant, showing that investors act promptly on this information, but that the effect is smoothed out as time progresses.

The "RepeatedCrash" variable from the regressions is a dummy variable introduced due to the significance achieved in subsection 5., that takes the value of "1", if the company had a fatal air crash in the previous year. Two incidents were concerned with this dummy variable, Malaysia Airlines and TransAsia Airways. This independent variable has a strong magnitude for CAR (T, T+1) while having minimum effect over the longer time periods, following a similar behavior to the fatalities dummy. The Repeated Crash coefficient did not manage to break the 90% confidence level for any of the CAR lengths, but was extremely close for CAR (T,T+1). Even though this is the case, this variable is of interest as it had a profound effect on TransAsia Airways, and ultimately is one of the reasons why the company ceased operations in the consecutive year.

The final variable used in the regressions was Market Cap, although this variable served largely as a control variable, since it is not a direct parameter of a crash. Yet, to provide information to investors and provide a more accurate model, it is important to not be omitted. Crashes impose tangible monetary loss for companies in terms of reparation costs, loss in inventories and legal fees (not including the reputation effect), which would be far more damaging to a firm with a fleet of 10 aircraft like BearSkin Airlines, versus Delta Airlines, with a fleet of 400+ aircraft, and much higher revenues. Market Cap serves as an instrumental variable to portray the difference in the size of the firms, taking into account the relative difference in damages that the respective firm would experience. This control variable was near significant in the CAR (T, T+1) model, while experiencing a reduction in significance and effect as the time period is extended. As expected, a higher Market Cap had a positive effect on the CAR for all periods, demonstrating that the smaller a firm, the larger the effects of an airline crash.

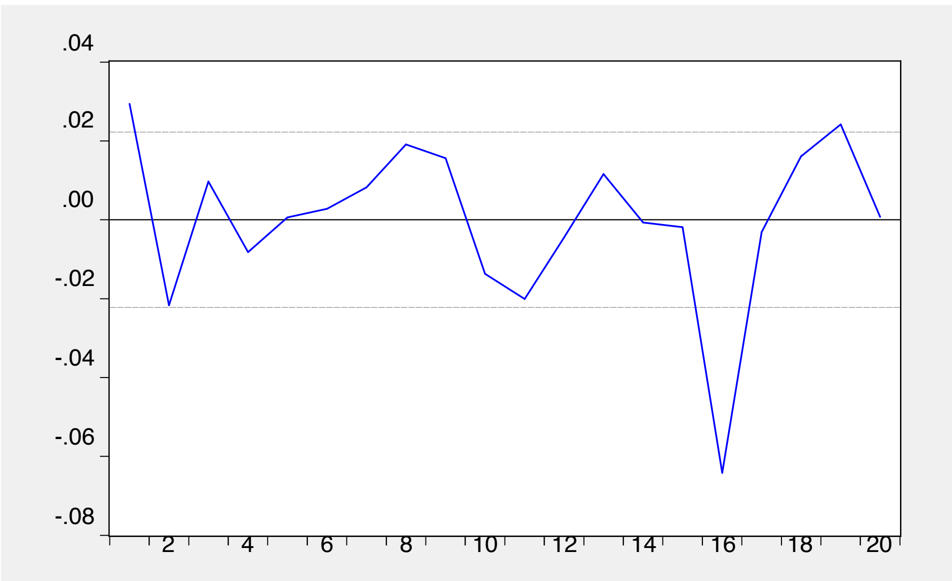
6. Robustness Check

As the regression model was statistically significant solely for the cumulative abnormal returns on the day of the event and the following day, the robustness check is done for this CAR length. The subsequent sections bring forth details on the validity of the results.

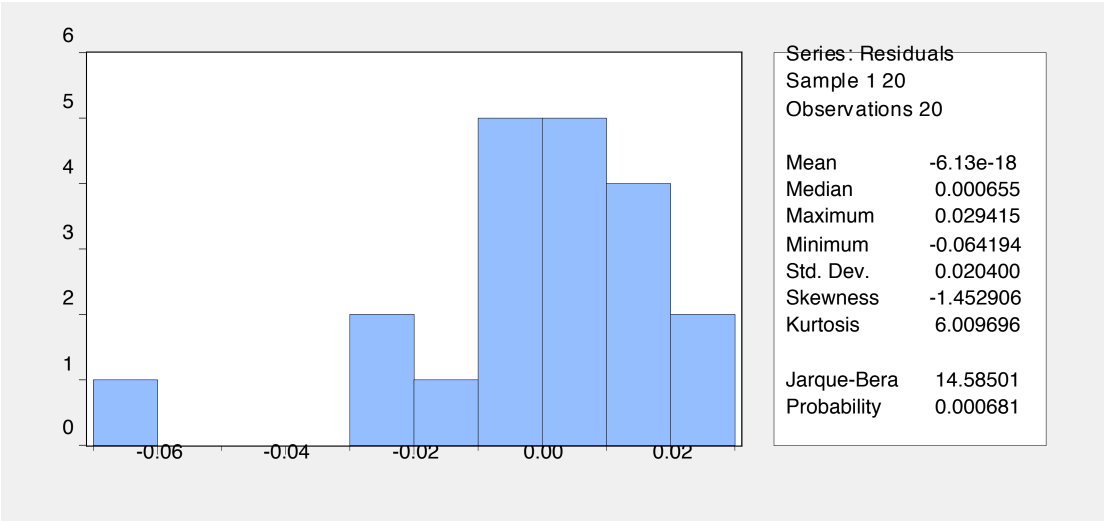
6.1 Stationarity & Autocorrelation

An important assumption made in OLS regressional analysis, is that the residuals are stationary and follow no predictable pattern. If the residuals fluctuate in a predictable trend, dependent on the previous residual, then this would limit the credibility of the model. Autocorrelation of error terms results in an underestimated variance, and in turn an overestimation of the R-squared (*Gujarti & Porter, 2009).* Although this thesis follows the approach of event studies in a cross-sectional form, where stationarity and autocorrelation are not of major importance, all of the events are organized chronologically (although the time intervals differ).

Testing for stationarity and autocorrelation provides evidence of whether each event behaves independently of the last. This is not in conflict with hypothesis 4 (testing if there is a repeated crash for the operator), as it is solely concerned with individual operators while here all events are tested in unison. Graph 2 shows the residuals of each of the 20 events, while Graph 3 presents a histogram of the residuals.



Graph 2: CAR (0, 1) Residuals Graph



Graph 3: CAR (0,1) Residual Histogram

From graph 2, we can see no clearly visible trend in the data, while the histogram (graph 3) shows a normal distribution of the residuals around 0, aside from one outlier at ±6%. At first glance, this can be interpreted that the model is stationary and that the residuals are not correlated in any predictable manner. Although visual representation is a good indicator that the model is stationary, it is not sufficient to statistically claim stationarity. Accordingly, a Breusch-Godfrey Serial Correlation LM Test, examining if the first lagged residual significantly affects the respective residual, is conducted. The results of the test present an F-statistic with the value of 0.025 (to 3 d.p.). Therefore, there is not enough evidence to claim that the residuals suffer from non-stationarity, and that autocorrelation exists and no alterations to the model need to be made.

6.2 Multicollinearity

A second factor that would limit the accuracy of the model is multicollinearity. Multicollinearity occurs when a minimum of two independent variables are highly correlated with one another, resulting in the regressors being dependent on one another. As a consequence, OLS estimators have large variances reducing precision, and making the coefficients and their standard error susceptible to minute changes in data (*Gujarti & Porter, 2009).*

To test the collinearity between regressors of dependent variable CAR (T,T+1), a Variance Inflation Factors test is conducted. The Variance Inflation Factor of a particular independent variable is calculated by dividing its respective variance by the variance of the same coefficient had there been no other regressors included in the OLS regression. Uncentered VIF isolates the independent variable in its entirety, while Centered VIF includes the constant when dividing the two variances. A general rule of thumb for Variance Inflation Factors tests, is that when the Inflation Factor is above 10, multicollinearity between that independent variable and its alternative regressors is high and should be examined further to apply a correction *(Kutner et al, 2004)*. The Centered and Uncentererd VIF's for all 4 independent variables are presented in Table 9.

Sample: 1 20 Included observations: 20			
Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C(1)	5,59E-05	2,2628	NA
C(2)	3,67E-12	1,8833	1,1465
C(3)	0,000112	2,0457	1,1252
C(4)	0,000282	1,1415	1,0274

Table 9: Multicollinearity: Variance Inflation Factors Test

The results for both uncentered and centered VIFs are remarkably low, demonstrating that the independent variables are not even remotely close in collinearity to the point where it would result in a large variance of the estimators. For this event study, where the constant (the fact that a fatal aircraft crash occurred) has the most significant effect, the other regressors' variance barely increases when other variables are removed from the regression. The variance of the coefficient "Market Capitalization" (which is a control variable) suffers the worst when this is done, and increases by a miniscule amount of 14%. Thus, it can be assumed that the model is not affected by multicollinearity.

6.3 Heteroskedasticity & Specification Errors

Heteroskedasticity is defined as when the error terms do not have the same variance *(Gujarati & Porter, 2009).* The famous "funnel" shaped graph of residuals is a prime example of how the variance of residuals can vary based on the event. A consequence of having heteroskedasticity in your model is that any findings made can become misleading as the standard errors of the regressor coefficients become inaccurate (*Gujarati & Porter, 2009).* Heteroskedasticity is of great importance when examining cross-sectional data as it is often encountered in such scenarios *(Hill et al. 2011).*

One of the most recognized tests for heteroskedasticity is the White Test. An advantage of using the White test is that it makes no assumptions on which regressors need to be included in the test, and doesn't require arbitrarily chosen information on the necessary variables *(Hill et al. 2011).* The White Test examines the variables and the squares and gives the option to test the cross terms, which can also show whether specification errors have occurred. The results of both the tests, with and without the cross terms are summarized:

Heteroskedasticity Test: White with Cross			
F-statistic	0,303577	Prob, F(6,13)	0,9240
Obs*R-squared	**2,457872**	**Prob, Chi-Square(6)**	**0,8732**
Scaled explained SS	3,940222	Prob, Chi-Square(6)	0,6848
Heteroskedasticity Test: White without Cross			
F-statistic	0,471237	Prob, F(3,16)	0,7065
Obs*R-squared	**1,623675**	**Prob, Chi-Square(3)**	**0,6540**
Scaled explained SS	2,602918	Prob, Chi-Square(3)	0,4570

Table 10: Heteroskedasticity Test

With cross variables a Chi-squared probability of **0,873** is achieved *(Table A.6)*. From this test, with the null hypothesis being that the model is homoscedastic, there is not enough evidence presented to be able to confidently reject the null hypothesis. With cross terms, if the null hypothesis is rejected, this can mean one of two things; either the model is heteroskedastic, or there is a specification error. Without cross variables, a Chi-squared probability of **0,654** is retrieved from the test *(Table A.7)*. As well as providing proof that the model is homoscedastic, the cross terms test also brings forth no evidence that there is a specification error for calculating dependent variable CAR (T,T+1). Based on these White Tests, we can claim that the coefficients are reliable and that there is no need to use heteroskedasticity-consistent standard errors in our Regressions.

6.4 Wald Test

To test the significance of the individual coefficients, the respective t-statistics were analyzed in the results section of this thesis. Additionally the joint significance of the whole model was estimated through the use of the F-statistic and by examining the R-squared of the model. As the CAR (T,T+1) model includes a control variable, which increases the accuracy of the model, it is still important to test the joint significance of all the independent variables that are of interest, namely, the constant, the dummy for above 49 fatalities, and whether a 2nd crash with fatalities had occurred in the previous year of trading. This brings forth information on whether the parameters of the crash jointly play a significant role in deciding the cumulative abnormal returns experienced in the two days (including the day of the crash). This is the main goal in answering the research question of this thesis, so another test must be completed to validate the results. To analyze this, two Wald Tests are introduced:

Wald Test 1			
Null Hypothesis: C(1)=C(3)=C(4)=0			
Test Statistic	Value	df	Probability
F-statistic	1,0030	(3, 16)	**0,0006 *****
Chi-square	3,0091	3	0,0000
Wald Test 2			
Null Hypothesis: C(3)=C(4)=0			
Test Statistic	Value	df	Probability
F-statistic	3,95500	(2, 16)	**0,04020 ****
Chi-square	7,90999	2	0,01920

Table 11: Wald Test of Coefficients

The first Wald Test demonstrates that the null hypothesis (the constant, fatalities dummy, and repeated crash dummy being equal to zero, can be rejected with a **99%** confidence level, showing that crashes have a constant effect, and that the parameters play a role as well *(Table A.8)*. The second Wald Test focuses only on the parameters of the crash, testing if the Fatalities and Second Crash dummies have are significantly different from zero, and the null hypothesis can be rejected with a **95%** confidence level *(Table A.9)*. This brings substantial evidence that aviation accidents cause a constant abnormal return, but that the parameters of the crash cannot be overlooked when predicting the cumulative abnormal returns in the first two days of the crash.

7. Conclusion

In this thesis, analysis commenced by examining each parameter of the crashes individually. The first step was assuring that abnormal returns exist after an aircraft crash for the operator, and deciding for which post event time windows had significantly abnormal returns. Through the use of the market model, the abnormal returns were calculated for each of the 20 incidents, and cumulated over time windows of T:T+1, T:T+2, T:T+5, T:T+10, T:T+15, T:T+30, T:T+60. The findings revealed that up until 10 days after the incident, the cumulative abnormal returns were significantly different from zero at 99%. The data was then grouped based on the parameters of the crash to get an insight into whether the number of fatalities, the culpability of the operator, and whether it was a 2nd crash, change the returns between the two groups for the time periods where the CAR was significantly (99%) different from zero. The results showed that the number of fatalities and if it was a second crash made a significant difference between the means of the groups, with these factors having a negative coefficient on the return. The cause of the crash, used as an instrumental variable for the airliners culpability, had a very low significance and therefore was excluded from further tests. The results from these initial tests were then used to create a model to predict the cumulative abnormal returns caused by aircraft crashes in the first two days of trading (including the day of the event if possible). 4 independent variables were used: a constant, fatality dummy, 2nd crash dummy and a control variable for the market capitalization of the firm. It was found that the constant and fatality dummy was significant at 95%, while the 2nd crash dummy and market cap were extremely close to being statistically significant at 90%.

It was fully expected that negative cumulative abnormal returns would be found and tested to be statistically significant, approving hypothesis 1. Airline crashes bring large costs to the operator in terms of loss in assets, legal and compensation costs, as well as a loss in customer demand translating to loss in revenues for the future. Stock traders react to this information instantly and start to sell the stocks for a lower price than the previous day, effectively dumping the stock for the first 2 days after the event. Behavioral factors play a large role in this tendency, which is also an explanation why the number of fatalities had a significant negative effect, approving Hypothesis 2. Researching Hypothesis 4 gave evidence that the returns were significantly different between the 1st crash and the following crash, although did not reach the threshold of being counted as statistically significant in the created model, yet it did have a relatively large negative coefficient. The results for both the cumulative abnormal return, and the effect of fatalities are in line with previous literature, while the effect of it being a 2nd crash brings forth new information to the field of research. This being said, once the market calmed down due to the sudden emergence of news, over the successive 60 trading days, the market corrected for the shock, and on average the stock price on day 60 was only 0.07% lower than the stock price on the day preceding the event.

Limitations to this research do exist, one of which is that the market model used to predict the expected returns was not accurate, and the regression for the constant and market coefficient of each incident relative to the AXGAL index had rather high residuals. This was not detrimental to the analysis presented in this thesis, since daily stock returns tend to be quite small and the error terms were randomly distributed, not skewing the returns in any particular direction. Additionally, the shock caused by the incidents was still far larger, which outweighed any random noise that the market model was not able to account for. Nonetheless, a more accurate means to predict the expected return, such as the CAPM model, could potentially improve the accuracy of the expected returns had a crash not occurred. The use of a global AXGAL index, also limited the accuracy, as economical and political factors pertaining specific countries are overlooked by the index.

Based on the results of this thesis, an investing strategy can be made for investors who follow the airline industry closely. If possible, taking a short position on the operator's stock in the first day of trading will allow for a return of 2% on the investment within the first two days including the day of the event, although this thesis acknowledges the idea that the option for shorting an operator's stock who just experienced a crash will be very limited. Using the model created in this thesis, investors will be able to predict the drop in stock price that will occur, and adapt their strategy accordingly. Due to behavioral aspects, investors tend to stay away from a stock that experienced an unforeseen event such as a crash, due to the unpredictability of the upcoming returns. Conflicting with this behavior, buying the stock 2 days after the event allows for significantly positive returns over the successive 60 days. In all 20 of the examined incidents, the abnormal return averaged out over 60 days became basically zero. Buying 2 days after the crash once the shock has occurred and the price is relatively low is a valid strategy backed up by the results of this thesis. This thesis provides evidence of such patterns in security return data, although it cannot be stressed enough that this thesis has limitations and any investments made still bear the risk of behaving differently and not following the pre-discussed trend.

An addition this thesis attempted to make on prior research was to evaluate if the cause of the crash had any effect on the stock return. The results clearly showed that the cause had a highly insignificant effect with a small coefficient. Upon further research and thought, logically speaking this is understandable. Crash reports bringing information on the nature of the crash and what caused are released on average a year after the crash with some being released more than 2 years after the event. This is when the cause of the crash becomes public information. Investors do not know the cause of the crash in the first 60 days that were examined in this thesis, therefore it would be counterintuitive for it to have any effect, significant or not. In accordance to the EMH, any result produced would be randomly generated and therefore was not included in the model regression. The only possible explanation for the cause having an effect aside from being noise, would be insider information or wild speculation by investors. Although this was the case for the analysis, these results do bring forth a direction for future research. The publication of the crash report could be evaluated, as its own separate event. A similar study to this thesis could be made examining parameters of the report, and studying how cumulative abnormal returns could occur after the publication for the respective operators.

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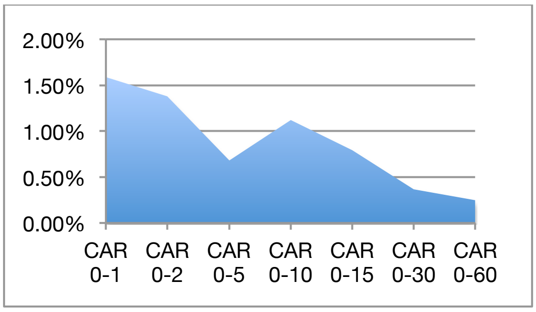
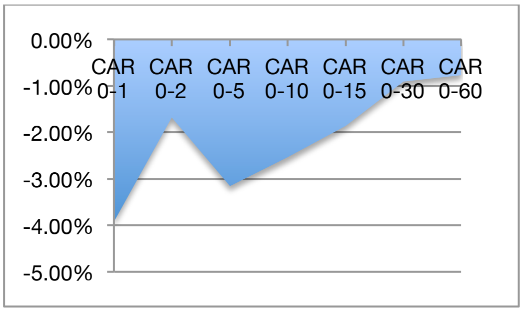
Hill, R. C., Griffiths, W. E., & Lim, G. C. (2011). *Principles of econometrics (Vol. 5).* Hoboken, NJ: Wiley. 306

Appendix:

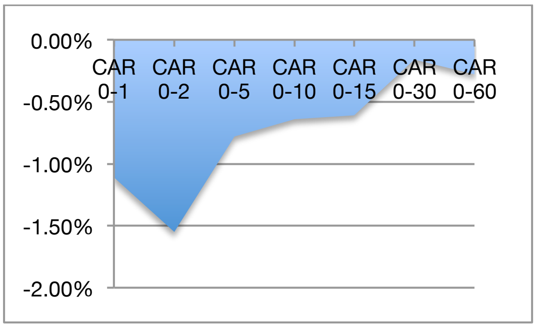
1. Graphs:



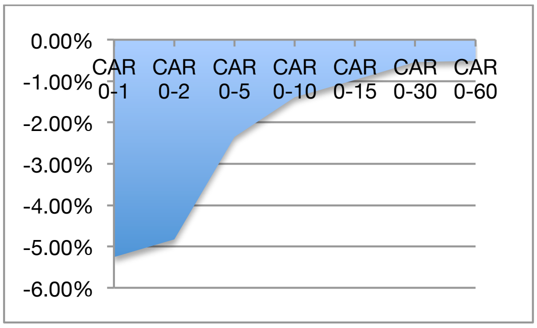
Graph A.1: CAR Turkish Airlines



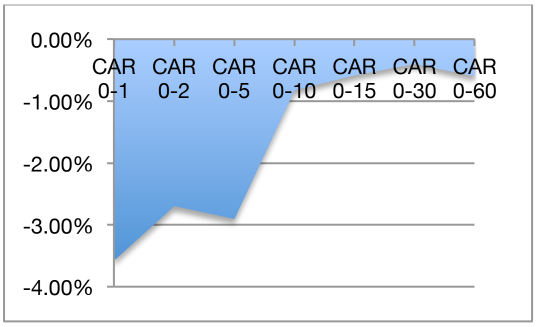
Graph A.2: CAR Pakistan Airlines 2016



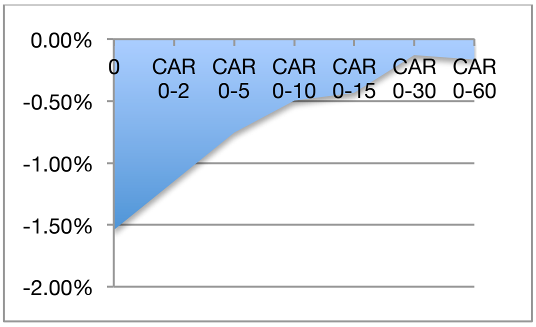
Graph A.3: CAR German Wings (Lufthansa)



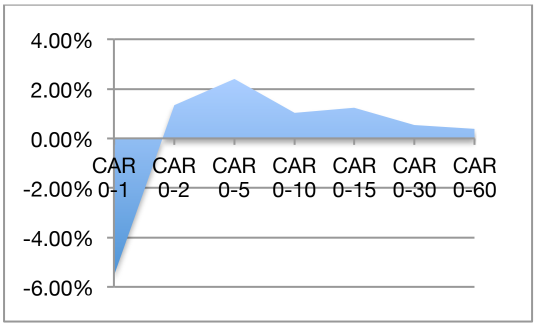
Graph A.4: CAR TransAsia Airways 2015



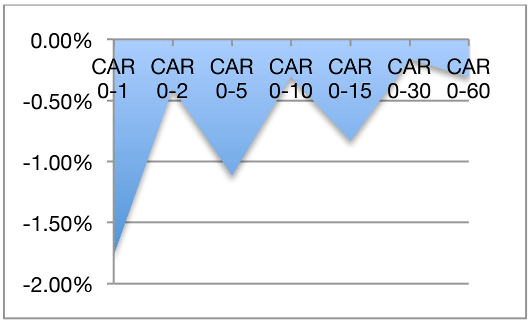
Graph A.5: CAR Air Indonesia



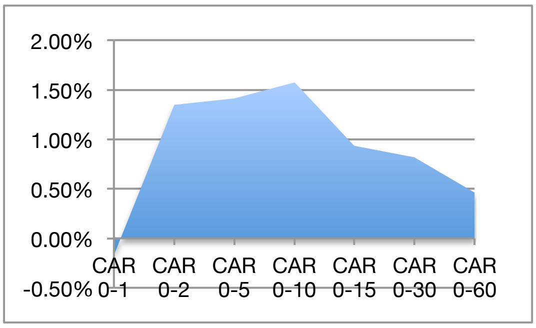
Graph A.6: CAR TransAsia Airways 2014



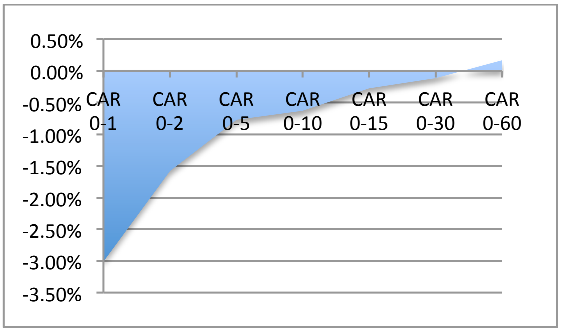
Graph A.7: Malaysia Airlines June 2014



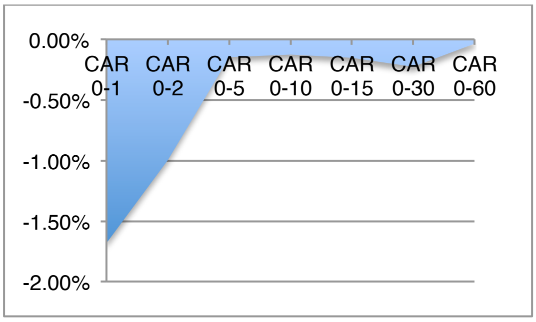
Graph A.8: Malaysia Airlines March 2014



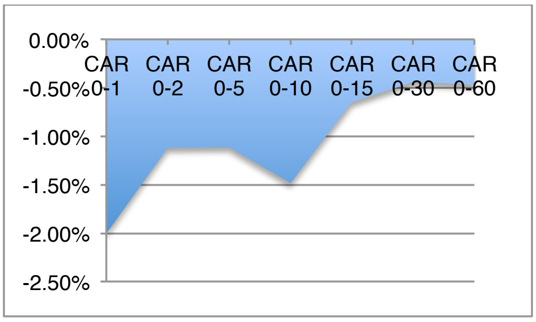
Graph A.9: Bearskin Airlines



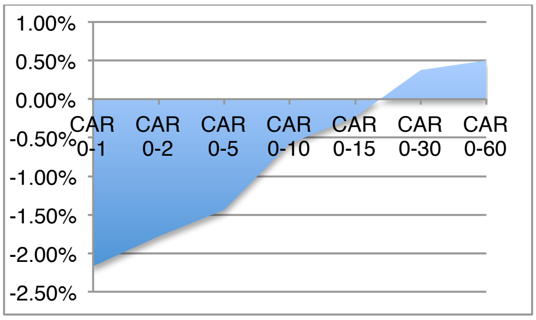
Graph A.10: Asiana Airlines



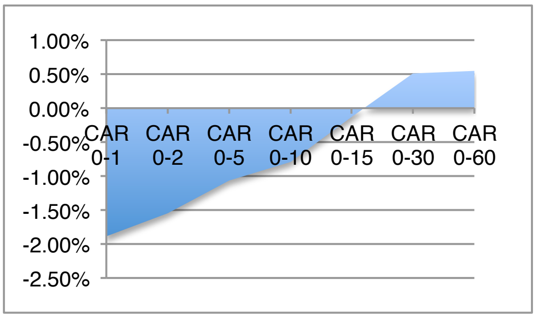
Graph A.11: Delta Airlines



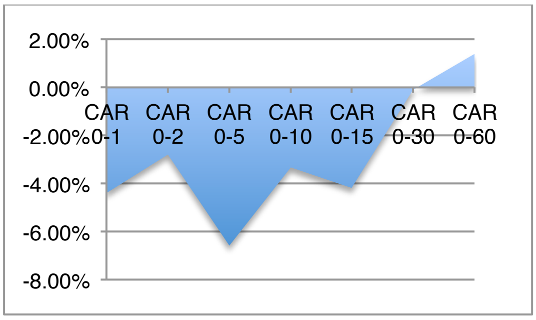
Graph A.12: UT Air 2012

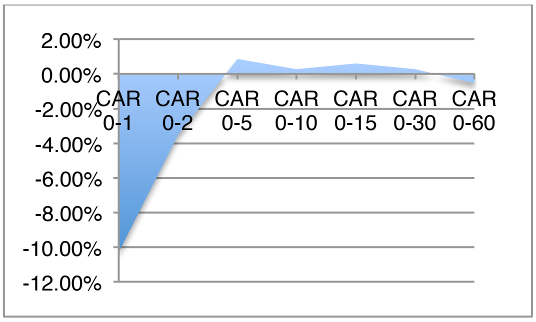


Graph A.13: Air France



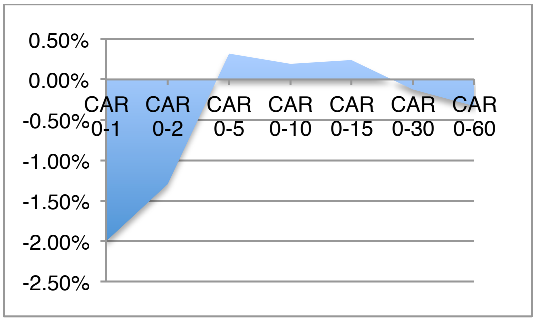
Graph A.14: Turkish Airlines



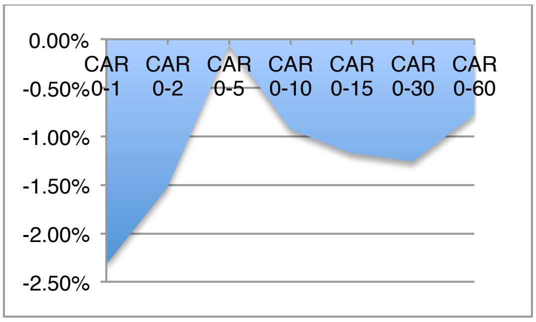


Graph A.15: Colgan

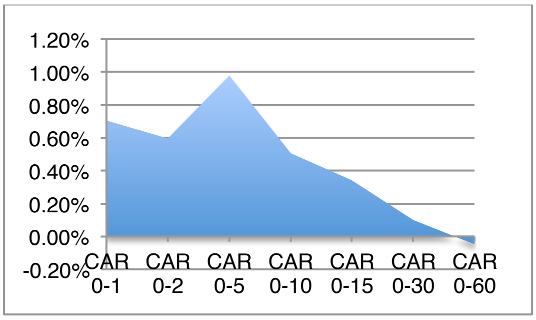
Graph A.16: Aeroflot



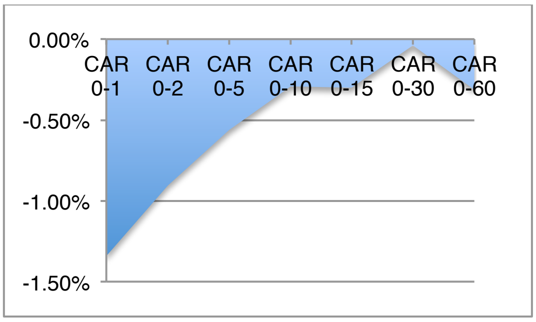
Graph A.17: UT Air 2007



Graph A.18: GOL



Graph A.19: Pakistan Airlines 2006



Graph A.20: China Eastern Airlines

2. Tables:

	CAR01	CAR02	CAR05	CAR010	CAR015	CAR030	CAR060
Mean	-2,5855%	-1,2522%	-0,8080%	-0,4837%	-0,4119%	-0,0819%	-0,0713%
Median	-2,0000%	-1,5100%	-0,7600%	-0,5400%	-0,2850%	-0,1200%	-0,2200%
Maximum	1,5900%	1,3800%	2,4000%	1,5800%	1,2400%	0,8200%	1,3950%
Minimum	-10,3100%	-4,8300%	-6,5800%	-3,3400%	-4,1800%	-1,2600%	-0,7800%
Std. Dev.	0,025498	0,015932	0,019466	0,011702	0,011625	0,004952	0,005426
Skewness	-1,251715	-0,058524	-1,162861	-0,531862	-1,609668	-0,434773	0,920482
Kurtosis	5,460832	3,039347	5,098533	3,478347	6,696303	3,217716	3,648032
Jarque-Bera	10,26905	0,01271	8,17735	1,13361	20,02231	0,66959	3,17424
Probability	0,00589	0,993667	0,016761	0,567336	0,000045	0,715484	0,204513
Sum	-0,517100	-0,250430	-0,161400	-0,096740	-0,082370	-0,016370	-0,014250
Sum Sq. Dev.	0,012353	0,004823	0,0072	0,002602	0,002568	0,000466	0,000559
Observations	20	20	20	20	20	20	20

Table A.1 Hypothesis 1: Descriptive Statistics, Cumulative Abnormal Return

	ABOVE49CAR01	UNDER50CAR01	ABOVE49CAR02	UNDER50CAR02	ABOVE49CAR05	UNDER50CAR05
Mean	-3,6156%	-1,11110%	-1,5378%	-0,48220%	-1,1333%	-0,04890%
Median	-2,3200%	-1,68000%	-1,5500%	-1,12000%	-0,7800%	-0,15000%
Maximum	-1,1100%	1,59000%	1,3500%	1,38000%	2,4000%	1,42000%
Minimum	-10,3100%	-3,01000%	-3,5400%	-1,58000%	-6,5800%	-1,11000%
Std, Dev,	0,0291	0,014901	0,0146	0,01229	0,025234	0,00939
Skewness	-1,444877	0,701097	0,604638	0,725293	-0,939303	0,279737
Kurtosis	4,132687	2,268805	2,841912	1,740071	3,686230	1,610252
Jarque-Bera	3,612620	0,937797	0,557753	1,384357	1,500028	0,841654
Probability	0,164259	0,625691	0,756633	0,500485	0,47236	0,656504
Sum	-0,3254	-0,1	-0,1384	-0,0434	-0,102	-0,0044
Sum Sq, Dev,	0,006774	0,001776	0,001705	0,001208	0,005094	0,000705
Observations	9	9	9	9	9	9

Table A.2 Hypothesis 2 (fatalities): Descriptive statistics Groups

CAR 01
Included observations: 20

CAR01=C(1)+C(2)*MARKETCAP+C(3)*FATALITIESDUMMY+C(4)*REPEATEDCRASH

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.019021	0.007478	-2.543768	0.0217
C(2)	2.82E-06	1.92E-06	1.470241	0.1609
C(3)	-0.023292	0.010599	-2.197587	0.0430
C(4)	-0.026263	0.016795	-1.563735	0.1374

R-squared	0.359876	Mean dependent var	-0.025855
Adjusted R-squared	0.239852	S.D. dependent var	0.025498
S.E. of regression	0.022231	Akaike info criterion	-4.597836
Sum squared resid	0.007907	Schwarz criterion	-4.398689
Log likelihood	4.997836	Hannan-Quinn criter.	-4.558960
F-statistic	2.998380	Durbin-Watson stat	1.809995
Prob(F-statistic)	0.061632		

Table A.3 CAR (0,1) Regression

CAR 02

Included observations: 20

CAR02=C(1)+C(2)*MARKETCAP+C(3)*FATALITIESDUMMY+C(4)
*REPEATEDCRASH

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.010627	0.005659	-1.877.900	0.0787
C(2)	8.09E-07	1.45E-06	0.558027	0.5846
C(3)	-0.006893	0.008021	-0.859335	0.4028
C(4)	-0.004182	0.012710	-0.329059	0.7464

R-squared	0.060076	Mean dependent var	-0.012345
Adjusted R-squared	-0.116159	S.D. dependent var	0.015925
S.E. of regression	0.016824	Akaike info criterion	-5.155.148
Sum squared resid	0.004529	Schwarz criterion	-4.956.002
Log likelihood	5.555.148	Hannan-Quinn criter.	-5.116.273
F-statistic	0.340887	Durbin-Watson stat	1.307.520
Prob(F-statistic)	0.796088		

Table A.4: CAR (0,2) Regression

CAR 010

Included observations: 20

CAR10=C(1)+C(2)*MARKETCAP+C(3)*FATALITIESDUMMY+C(4)
*REPEATEDCRASH

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.005354	0.004159	-1.287436	0.2163
C(2)	8.72E-07	1.07E-06	0.818245	0.4252
C(3)	-0.004215	0.005895	-0.715039	0.4849
C(4)	0.004739	0.009341	0.507366	0.6188

R-squared	0.060170	Mean dependent var	-0.004835
Adjusted R-squared	-0.116048	S.D. dependent var	0.011703
S.E. of regression	0.012364	Akaike info criterion	-5.771231
Sum squared resid	0.002446	Schwarz criterion	-5.572084
Log likelihood	6.171231	Hannan-Quinn criter.	-5.732355
F-statistic	0.341454	Durbin-Watson stat	2.058616
Prob(F-statistic)	0.795689		

Table A.5 CAR (0,5) Regression

Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 1 20				
Included observations: 20				
Collinear test regressors dropped from specification				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000215	0.000470	0.458109	0.6544
(MARKETCAP)^2	-2.06E-12	4.43E-11	-0.046547	0.9636
(MARKETCAP)*(FATALITIESDUMMY)	-1.43E-07	2.02E-07	-0.708677	0.4910
(MARKETCAP)*(REPEATEDCRASH)	-5.03E-07	3.38E-06	-0.148984	0.8839
MARKETCAP	5.16E-08	4.00E-07	0.129037	0.8993
(FATALITIESDUMMY)^2	0.000765	0.000718	1.065527	0.3060
(FATALITIESDUMMY)*(REPEATEDCRASH)	0.000158	0.006159	0.025730	0.9799
R-squared	0.122894	Mean dependent var		0.000395
Adjusted R-squared	-0.281925	S.D. dependent var		0.000908
S.E. of regression	0.001028	Akaike info criterion		-1.065330
Sum squared resid	1.37E-05	Schwarz criterion		-1.030479
Log likelihood	1.135330	Hannan-Quinn criter.		-1.058527
F-statistic	0.303577	Durbin-Watson stat		2.438206
Prob(F-statistic)	0.924031			

Table A.6: White Test with Cross terms Regression

Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Sample: 1 20				
Included observations: 20				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000345	0.000300	1.149.842	0.2671
(MARKETCAP)^2	-6.57E-12	8.31E-12	-0.791018	0.4405
(FATALITIESDUMMY)^2	0.000401	0.000442	0.906911	0.3779
(REPEATEDCRASH)^2	-0.000467	0.000715	-0.652232	0.5235
R-squared	0.081184	Mean dependent var		0.000395
Adjusted R-squared	-0.091094	S.D. dependent var		0.000908
S.E. of regression	0.000948	Akaike info criterion		-1.090.684
Sum squared resid	1.44E-05	Schwarz criterion		-1.070.770
Log likelihood	1.130.684	Hannan-Quinn criter.		-1.086.797
F-statistic	0.471237	Durbin-Watson stat		2.388.429
Prob(F-statistic)	0.706549			

Table A.7: White Test without Cross terms Regression

Null Hypothesis: C(1)=C(3)=C(4)=0			
Test Statistic	Value	df	Probability
F-statistic	1,0030	(3, 16)	0,0006
Chi-square	3,0091	3	0,0000
Null Hypothesis: C(1)=C(3)=C(4)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std, Err,
C(1)		-0,019021	0,007478
C(3)		-0,023292	0,010599
C(4)		-0,026263	0,016795

Table A.8: Wald Test 1

Null Hypothesis: C(3)=C(4)=0			
Test Statistic	Value	df	Probability
F-statistic	3,95500	(2, 16)	0,04020
Chi-square	7,90999	2	0,01920
Null Hypothesis: C(3)=C(4)=0			
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std, Err,
C(3)		-0,023292	0,010599
C(4)		-0,026263	0,016795

Table A.9 Wald Test 2