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FROM AIRPLANE CRASH TO STOCK PRICE CRASH

The effect of airplane crashes on the stock market

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PREFACE AND ACKNOWLEDGEMENTS

I would like to thank my supervisor for his help and suggestions and a dear friend of mine who helped me through good and bad times and who was always there to support me.

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ABSTRACT

This paper examines the effect of aviation disasters on the stock prices of airlines and airplane manufacturers. The airlines experience a significant stock price drop of 2.17% on the event date and the price decline remains significant till at least two days after the disaster. The price decline is driven by the number of fatalities, nationality of the airline and cause of the disaster. The effect on the non-crash airlines is depending on the number of fatalities of the disaster. There are no significant results found for the airplane manufacturers, however, the size of the manufacturer is influencing the stock price.

Keywords:
Stock prices, returns, event study, air transportation, aviation disasters

JEL Classification:
G12, G14, L92

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CHAPTER 1 Introduction

According to the Efficient Market Hypothesis (EMH), stock prices fully reflect all available information. Once new information reaches the market, the stock price will adjust quickly to reflect the value of that information on the firm. Overreaction to certain kinds of information may occur, since some event can often be anticipated by the market. For example, stock splits and dividend increases leak out before the actual announcement occurs[1]. As a result, the reaction of stock prices is often distributed over the pre- and post-announcement periods.

This paper re-examines the reaction of stock prices to new information by focusing on completely unanticipated events, namely, fatal aviation disasters. Here, the EMH suggests that all price adjustments should follow the event immediately. Prior research shows contradictory results in this. Mostly research from the eighties shows results consistent with EMH (Davidson et al. (1987), Barret et al. (1987), Chance and Ferris (1987)), whereas more recent research shows results inconsistent with EMH (Walker et al. (2005), Kaplanski and Levy (2010), Ho et al. (2012)).

Because of this contradiction, in this paper the whole period from 1962 till 2016 is taken into account, with separate regressions of two sub-periods: from 1962 to 1990 and 1990 to 2016, to test if this contradiction is also found in this paper. In most of the cases, prior research only used data of companies based in the United States and with data available in the Center for Research in Security Prices (CRSP). However, all companies registered in CRSP are listed on the New York Stock Exchange and American Stock Exchange. These companies are normally large in size[2]. In this paper the dataset is extended with companies smaller in size and also listed on other exchanges.

The research question of this paper is: What is the effect of aviation disasters on the stock market? I will focus on the effect on two groups of companies: the airlines and the airplane manufacturers. The results in this paper for airlines are in line with more recent papers in which significant price drops are observable for at least two days after the event. The results for airplane manufacturers are not significant and therefore in line with Chance and Ferris (1987).

The paper begins with the theoretical background of earlier research on this topic in chapter 2. Chapter 3 presents the data used and explains the methodology used to test several hypotheses concerning the stock performance of airlines and airplane manufacturers following aviation disasters. The empirical results are presented in chapter 4 and the conclusion and discussion are provided in chapter 5.

[1] Fama et al. (1969)
[2] Davidson et al. (1987)

CHAPTER 2 Theoretical background

Several research has been conducted on the effect of aviation disasters on stock prices over the last decades. Surprisingly, the results were in contrast with each other. Research of Davidson et al. (1987) and Chance and Ferris (1987) only find a significant, negative abnormal return on the event date for airlines involved in the crash. Barret et al. (1987) find a significant, negative abnormal return only one full trading day after the event occurs. We can conclude from this that the market appears to assimilate the new information rapidly and the negative reaction on crashes reverse immediately in the days following the crash. This is consistent with the EMH. However, Walker et al. (2005) and Ho et al. (2013) find significant results for airlines for more than one trading day. Walker et al. (2005) find that airlines experience a significant price decline following the announcement of an aviation disaster of 2.8% during the first trading day after the event, followed by an additional stock price drop of 1.08% during the following week. The cumulative abnormal returns remain negative and highly significant until six months after the crash. The stock price reactions are persistent over time. Kaplanski and Levy (2010) find a highly significant effect on the aviation disaster for airlines. There is a sharp decline in average rates of return on the event date, followed by a reversal effect, which takes about ten days after the decline. Ho et al. (2013) find significant, negative abnormal returns of crash airlines at the event date, with a cumulative abnormal return that remains negative over the next 25 days. In these three cases, the market obviously needs more time to revert back to its "normal" value. This is inconsistent with the EMH. The different results in prior research lead to these first three hypotheses:

> *H1: The average abnormal return (AAR) of crash airlines during the event windows is equal to zero.*
> *H2: The cumulative average abnormal return (CAAR) of crash airlines during the event windows is equal to zero.*
> *H3: According to the EMH the stock prices are recovering immediately after the crash, i.e. on day 0 and 1.*

These first two hypotheses will not only be regressed over the whole time period, but also over two different sub-periods: from 1962 to 1990 and 1990 to 2016. In this way it is possible to test whether the differences in prior research are related to the time periods in which the research is done. Table 1 summarizes the results on these hypotheses of prior research.

Table 1
Summary of prior research on aviation disasters (AAR and CAAR of airlines)

Author(s) (publication year)	**Sample and time period**	**Event and estimation window**	**Market index**	**Result(s) AAR and CAAR**
Davidson et al. (1987)	57 crashes Companies in CRSP database	[-15, 30] [-135, -16]	CRSP value-weighted market index	CAAR [0] -0.78% significant at 5%
Barret et al. (1987)	78 crashed Companies in CRSP database	[1, 20] [-250, -6]	CRSP value-weighted market index	CAAR [-1.1] -0.04% significant at 5%
Chance and Ferris (1987)	46 crashes for airlines 35 crashes for airplane manufacturers Companies in CRSP database	[-20, 20] [-20, -1]	Equally-weighted index of non-crash companies	AAR [0] -1.2% significant at 5% No significant results for CAAR
Bosch et al. (1998)	22 crashes Companies listed on the NYSE	[0, 2] Estimation window not in paper	NYSE market index	AAR [0] -1.17% significant at 10% CAAR [0,2] -2.67% significant at 5%
Walker et al. (2005)	138 crashes Only U.S. companies	[0, 24 months] [-750, -1]	CRSP value-weighted market index	AAR [1] -2.8% AAR [7] -1.08% CAAR [-1,1] to [-1,6 months] between -2.8% and -3.88% significant at 0,1% to 10%
Kaplanski and Levy (2010)	288 crashes Companies in CRSP database	[1, 3] Estimation window not in paper	NYSE value-weighted market index	AAR [1] -0.16% significant at 1%
Ho et al. (2013)	113 crashes Only U.S. companies	[0, 25] [-255, -46]	S&P500 market index	AAR [0] -1.58% significant at 0.1% CAAR [0,25] -2.94% significant at 1%

Additionally, Walker et al. (2005) and Kaplanski and Levy (2010) include different characteristic variables in the regressions to look at the effect of these variables on the abnormal returns of airlines. Walker et al. (2005) find significant results for size, number of fatalities, disaster occurred on U.S. territory versus non-U.S. territory and criminal or terrorist activity as disaster cause. Kaplanski and Levy (2010) find significant results for size and the nationality of the airline company (American-oriented, European-oriented or all other disasters). The effect of the nationality of the airline company on the abnormal returns is based on the reaction of U.S. investors only. In this paper I will also look at the effects in other areas: Europe, Africa and Asia. Therefore, I will collect data not only from U.S. stock markets, but worldwide. This will bring us to the fourth hypothesis:

H4: There is no significant event effect in the characteristic variables.

The characteristic variables I will use are size, number of fatalities, location of disaster, nationality of the airline company and the disaster cause. The results of this research are summarized in table 2.

Ho et al. (2013) not only examine the impact of aviation disasters on the stock prices of the crash airlines, but also studies the effect of the aforementioned crashes on stock prices pertaining to their rival airlines. They find that the stock prices of the crash airline's rivals depend on the interaction of the "contagion" effect and the "switch" effect. On the one hand, the "contagion" effect arises when the news of the airplane disaster also influences the business of the non-crash airlines, for example, if it provokes the general public's concern for air-travel safety. On the other hand, the "switch" effect occurs when air travellers fly with the competitors of the crash airlines and the non-crash airlines benefit from the disaster. They conclude that the non-crash airlines have a delayed reaction of one day and do not experience a value loss in their shares on the event date. Although the non-crash airlines experience a negative effect as well, this effect is much less than that of the crash airlines. Moreover, the "contagion" or "switch" effect depends on the number of fatalities. In case of a disaster with less than ten fatalities, the non-crash airlines experience a "switch" effect and in case of a disaster with more than ten fatalities there will be a "contagion" effect. The effect of an aviation disaster on the non-crash airlines will also be tested using the fourth hypothesis. Table 3 summarizes the results of the paper of Ho et al (2013).

Table 2
Summary of prior research on aviation disasters (characteristic variables of airlines)

Author(s) (publication year)	Characteristic variables	Result(s) AAR and CAAR
Walker et al. (2005)	Number of fatalities (<100 fatalities vs. >100 fatalities)	CAAR [0,7] for <100 –3.283% and for >100 -7.028% with a significant difference at a 5% level With OLS regressions (controlling for other factors) CAAR [0,7] for >100 is still significant at 10%
	Location of disaster (U.S. territory vs. non-U.S. territory)	CAAR [0,7] for U.S. territory -4.596% and for non-U.S. territory -0.105% with a significant difference at a 5% level With OLS regressions (controlling for other factors) CAAR [0,7] for U.S. territory is still significant at 10%
	Conventional cost vs. low-cost airlines	CAAR [0,7] for conventional cost -3.749% and for low-cost -9.775% with a significant difference at a 10% level With OLS regressions (controlling for other factors) the CAAR of low-cost airlines is not significant anymore
	Size (market capitalization >$200 Million vs. <$200)	No significant difference found With OLS regressions (controlling for other factors) CAAR [0,1] for >$200 Million is -1.36% and significant at 5%
	Disaster cause (criminal act/terrorist attack vs. other causes)	CAAR [0,7] for criminal act/terrorist attack -10.654% and for other causes -3.351% with a significant difference at a 5% level With OLS regressions (controlling for other factors) CAAR [0,7] for criminal act/terrorist attack is still significant at 10%
	National/international vs. regional airlines	No significant difference found With OLS regressions (controlling for other factors) CAAR remains insignificant
Kaplanski and Levy (2010)	Nationality of airline (American vs. European vs. rest of the world)	AAR [1] for all regions -0.18%, for America -0.27% and for Europe -0.26% all significant at 1% The rest of the world has a coefficient close to zero and not significant
	Size	AAR [1] for the largest firms (decile 1) -0.24% and for the smallest firms (decile 10) -0.35% significant at 1%

Table 3
Summary of prior research on aviation disasters (contagion and switch effect on non-crash airlines)

Author(s) (publication year)	Number of fatalities	Result(s) contagion and switch effect
Ho et al. (2013)	Crash group	AAR [0] -1.58% significant at 0.1% CAAR [0,25] -2.94% significant at 1%
	Non-crash group	AAR [0] +0.01% but not significant AAR [1] -0.14% and AR [2] -0.11 significant at 10% CAAR [0,1] +0.01% but not significant CAAR [0,2] -0.24% significant at 5%
	Non-crash group: Low fatalities (<10)	CAAR [0,10] +1.27% CAAR [0,15] +1.56% CAAR [0,20] +1.53% CAAR [0,25] +1.25% All significant at 5%, positive CAARs in line with switch effect
	Non- crash group: Medium fatalities (10–99)	CAARs [0,2] to [0,25] vary from -0.52% to -1.38%, all significant at 1% Negative CAARs in line with contagion effect
	Non-crash group: High fatalities (>100)	CAAR [0,1] -1.01% significant at 1% CAAR [0,3] -0.84% significant at 10% CAAR [0,4] -0.77% significant at 5% Negative CAARs in line with contagion effect

The next hypotheses test the effect of aviation disasters on the second group, namely, airplane manufacturers. Chance and Ferris (1987) do not find any empirical evidence that an aviation disaster has an impact on the stock of airplane manufacturers. However, Walker et al. (2005) and Krieger and Chen (2015) find significant results. Walker et al. (2005) find that airplane manufacturers experience a significant price decline during the first seven trading days following the announcement of an aviation disaster. Size, disaster occurred on U.S. territory versus non-U.S. territory and mechanical failure as disaster cause have a significant effect on the abnormal returns. There is a significant difference between mechanical failure as cause and the other causes, which means that mechanical failure has more impact on the stock prices of the airplane manufacturers than all other causes in the sample (e.g. nature, crime and terror). However, on the long-term there appears to be a significant price increase again, after 6 to 24 months. The explanation given is that investors can realize that a lawsuit against the manufacturer is unlikely and a mechanical failure can possibly be ruled out. Research of Krieger and Chen (2015) show strongly negative, significant abnormal returns immediately following an aviation disaster, and the market reverts back to near normal after a couple of weeks. When separated a sample based on whether the manufacturer is judged to have potential link to the incident, results were extremely different from each other. Manufacturer's stocks experience significantly negative abnormal returns in the trading days following the crash when the manufacturer is judged to have potential link to the incident. The reactions to accidents with no potential manufacturer fault are smaller in magnitude, particularly after the initial trading day. The stock prices even experience positive, significant abnormal returns weeks after an accident. Table 4 summarizes the results on the stock prices of the airplane manufacturers.

H5: The average abnormal return (AAR) of crash airplane manufacturers during the event windows is equal to zero.
H6: The cumulative average abnormal return (CAAR) of crash airplane manufacturers during the event windows is equal to zero.

Within this group of airplane manufacturers, the third hypothesis will be tested again and the effect of various characteristic variables will be tested using the fourth hypothesis, as well as the effects on the non-crash manufacturers. Although there already exists prior research on the effect of aviation disasters on non-crash airlines, to my knowledge, there is no prior research yet on the effect of aviation disasters on non-crash airplane manufacturers.

Table 4
Summary of prior research on aviation disasters (AAR and CAAR of airplane manufacturers)

Author(s) (publication year)	**Sample**	**Result(s) AAR and CAAR**
Walker et al. (2005)	Complete dataset	CAARs [0,1] to [0,3] vary between -0.81 and -1.02% at least all significant at 10% CAARs [0,6 months], [0,12 months] and [0,24 months] are +4.95%, +6.06% and +11.08% respectively and at least all significant at 5%
	Location of disaster (U.S. territory vs. non-U.S. territory)	CAAR [0,7] for U.S. territory -1.359% and for non-U.S. territory +0.191% with a significant difference at a 5% level With OLS regressions (controlling for other factors) CAAR [0,7] for U.S. territory is still significant at 10%
	Number of fatalities (<100 fatalities vs. >100 fatalities)	No significant difference found With OLS regressions (controlling for other factors) the CAARs for >100 are not significant either
	Size (market capitalization >$200 Million vs. <$200)	No significant difference found With OLS regressions (controlling for other factors) CAAR [0,7] for >$200 Million is -1.24% and significant at 5%
	Disaster cause (mechanical failure vs. other causes)	CAAR [0,7] for mechanical failure -1.645% and for other causes -0.909% with a significant difference at a 10% level With OLS regressions (controlling for other factors) CAAR [0,7] for mechanical failure is still significant at 10%
Chance and Ferris (1987)	Complete dataset	No significant results found
Krieger and Chen (2015)	Complete dataset	AAR [0] -0.52% significant at 1% CAAR [0,1] -0.49% significant at 5% CAAR [0,2] -0.47% significant at 10%
	Mechanical failure	AAR [0] -0.79% significant at 5% CAARs [0,1] to [0,29] vary between 0.77% and -2.2% significant at 5%
	No mechanical failure	AAR [0] -0.44% significant at 5% CAAR [0,29] +1.79% significant at 10%

CHAPTER 3 Data and methodology

3.1 Data

Data on aviation disasters is collected from the National Transportation Safety Board (NTSB) and Aviation Safety Network (ASN). The NTSB provides the data on aviation disasters from January 1962 through July 2016 and the ASN provides the data from January 1919 through July 2016. The daily stock price information of the airlines and airplane manufacturers is collected from the Center for Research in Security Prices (CRSP) and Datastream. Data is selected from January 1962 till February 2016. Only firms for which data on security returns were available on CRSP or Datastream were selected. Only commercial aviation events will be included in the sample. Crashes for the same airline which occurred within six months of an earlier crash and crashes for the same airplane manufacturer which occurred within one month of an earlier crash will be eliminated. This difference between the airlines and airplane manufacturers is because the airplane manufacturers, especially the large companies, generally experience more crashes per company than airlines do. Additionally, the "switch" effect seems to be more important in case of airlines than airplane manufacturers, because it is easier for people to switch to another airline than to avoid a particular airplane manufacturer, since the group of manufacturers is not that extensive. Also eliminated from the sample are crashes which had less than ten fatalities, to ensure that the sample will only contain events of significant economic impact. In case of any inconsistencies between the NTSB and ASN, information of the NTSB is used in the sample.

3.1.1 Sample size

Two different datasets are used in this research. One dataset consists of aviation disasters based on the airline companies of which stock price information is available. The second dataset consists of aviation disasters based on the manufacturer companies of which stock price information is available. The first dataset includes information on 87 aviation disasters and the second dataset includes information on 138 aviation disasters. Some aviation disasters are included in both datasets, but other disasters are only in one of the two datasets. For example, when a crash of a publicly traded airline involved an airplane manufacturer which is not publicly traded or when a crash of a publicly traded manufacturer involved an airline which is not publicly traded. Over 16,000 people lost their lives in these accidents. Table 5 summarizes the sample size.

Table 5
Sample size

Number of crashes	**Airlines**	**Airplane manufacturers**
Number of crashes total	277	599
Number of crashes after deleting crashes within 6 resp. 1 month(s)	31- 246	117- 482
Number of crashes after merging with dataset daily returns	146- 100	3- 479
Number of crashes after deleting crashes which don't have enough data	13- **87**	341- **138**

3.1.2 Definition of variables

For each aviation disaster the following information is collected: the date of the accident, the name and nationality of the airline and airplane manufacturer, the location of the crash, and the number of fatalities in the air and on the ground. Furthermore, if determined in the first 24 hours after the accident, the cause of the disaster is added to the dataset. This is based on news messages in the database LexisNexis, which consists of news from all over the world from newspapers and Internet. In this way it is possible to hypothesize if the market reacts differently to different causes of the disaster. If the cause of the disaster is a bird strike, for example, the expectation for the airlines group will be that the market does not react, but in case of a crew error a significant stock price reaction is expected. For the manufacturers group, for example, a mechanical failure is expected to give significant stock price reactions. If the cause was not determined within those 24 hours, the cause will be classified as "cause unknown". The following causes are determined: nature, maintenance and training by airline, mechanical failure, air traffic control, crew error, crime and terror, and other cause or cause unknown. Table 6 provides an overview of the classification of the disaster causes.

Table 6
Classification of disaster causes

Variable	**Description**
Nature	Weather (e.g. wind shear, fog) and animal related (e.g. bird strike)
Maintenance/training	Poor maintenance by airline, insufficient crew training by airline
Mechanical failure	Mechanical failure (e.g. engine failure, instrument failure)
Air Traffic Control	Air Traffic Control error (e.g. incorrect commands issued to pilot, landing clearance when runway occupied)
Crew error	Pilot or crew error and fatigue (e.g. runway overrun, overloaded airplane, errors made during flight)
Crime/terror	Criminal activity (e.g. hijack, explosion, 9/11 related)
Other/unknown	Other causes or undetermined/unknown cause

3.2 Methodology

To measure the abnormal stock price performance of airlines and airplane manufacturers following aviation disasters I will use event study methodology, following MacKinlay (1997) and Walker et al. (2005). Event study methodology measures the abnormal return of a stock as the difference between the actual return and the expected (normal) return, around the time of an event. There are different models which could be used to measure the normal performance. In Section 3.2.1 these models will be discussed.

To determine the day of the event, Eastern Standard Time (EST) is used to decide on which trading day the event will be taken. If the disaster occurred within one hour before the close of trading, the next trading day is taken as the event day. If the disaster occurred on a holiday or in the weekend, the next trading day is taken as the event day as well. The date of the event is denoted as t = 0. To estimate the expected return, data for the estimation window will be used from t = [-250, -1]. This is the period used the most in prior research on this topic, which is summarized in table 1. The event window will be t = [0, 21], equal to 1 month, also based on prior research.

3.2.1 Models for measuring normal performance[3]

To examine the reaction of the stock market to an event, it is necessary to estimate what the price of the stock would have been in case the event did not occur. There are several models to estimate the normal performance, and these models can be grouped into two categories: statistical and economic models. Statistical models follow from statistical assumptions concerning the behaviour of asset returns and do not depend on any economic arguments. Economic models, in contrast, rely on assumptions concerning investors' behaviour and are not solely based on statistical assumptions. However, to use economic models in practice it is necessary to add statistical assumptions. According to MacKinlay (1997), the use of economic models (e.g. the Capital Asset Pricing Model and Arbitrage Pricing Theory) in event studies has relatively small gains compared to statistical models. Therefore, statistical models dominate in event studies.

There are three different statistical models to distinguish: the constant mean return model, the market model and the factor model. The constant mean return model is the simplest model, however, according to Brown and Warner (1980, 1985) in most cases it yields results similar to the results of more sophisticated models. In this model the actual return is compared with the mean return of an asset and it is assumed that returns are constant over time. The market model relates the return of a security to the return of the market portfolio. By adding a market portfolio in the model, the portion of the return that is related to variation in the market's return is removed, which reduces the variance of the abnormal return. This can lead to a better ability to detect event effects. Therefore, the market model is an improvement over the constant mean return model. The third statistical model is the factor model. Factor models are motivated by the benefits of reducing the variance of the abnormal return by explaining more of the variation in the normal return. There are different kinds of factor models. An example of a one

[3] MacKinlay (1997)

factor model is the market model. With multifactor models more factors are incorporated into the model. However, in general the gains from using multifactor models for event studies are limited. This is because the marginal explanatory power of these additional factors is small and therefore the reduction in variation of the abnormal return is limited. Another variant of a factor model is a model in which the abnormal returns are calculated by taking the difference between the actual returns and the normal returns of a portfolio of companies with common characteristics, such as size or members of the same industry. When the sample group has common characteristics the reduction in variance will be the most. Based on these theories, for this event study the market model will be used. In the following section there will be some further explanation on this model. In Section 4 the same research will be done with the factor model based on a sample group with common characteristics to check the robustness of the results.

3.2.2 Market model

With the market model the price of the stock is regressed against a market index to control for the overall market effect. The CRSP value-weighted market index will be used as a proxy for the market. This index is used the most in prior research on this topic, conducted from table 1. Although this index only captures companies based in the U.S. and listed on the New York Stock Exchange and American Stock Exchange, it captures the whole time period used in this research, in contrast with for example the Datastream World Airlines index which only starts in 1973. Besides, by using the same market index it is easier to compare the results of this research with prior research. Lastly, more than 50% of the crashes in the sample are of companies listed on those exchanges. The market model for any security *i* is:

$$(1) \qquad R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

$$E(\varepsilon_{it} = 0) \qquad var(\varepsilon_{it}) = \sigma_\varepsilon^2$$

where R_{it} and R_{mt} are the period-t returns on security i and the market portfolio, respectively, and ε_{it} is the zero mean disturbance term. α_i, β_i and σ_ε^2 are the parameters of the market model.

3.2.3 Measuring abnormal returns

Using the market model to measure the normal return, the sample abnormal return (AR) is:

$$(2) \qquad AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt}$$

The abnormal return is the disturbance term of the market model. Under the null-hypothesis, that the aviation disasters have no effect on the stock returns, the abnormal returns will be jointly normally distributed with a zero mean and the variance to be equal to σ_ε^2.

To draw any conclusions for the effect of the disasters on the stock returns, the abnormal returns need to be aggregated. This will lead to the cumulative abnormal return (CAR). The CAR of the event windows is the sum of the included abnormal returns:

(3) $$CAR_{it} = \sum_{t=1}^{t} AR_{it}$$

The following event windows will be used for calculating the CARs (in trading days): 1-day, 2-day, 5-day, 10-day and 21-day CARs.

However, for this research the AR and CAR per event are not needed, but the overall AR and CAR for all companies and events together. Therefore, we need the average abnormal return (AAR) and cumulative average abnormal return (CAAR) for the different event windows and for the two datasets. These returns are calculated as follows:

(4) $$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}$$

(5) $$CAAR_t = \sum_{i=1}^{N} AAR_t$$

where N is the number of events.

3.2.4 Tests for significance

There are three different tests performed to test the significance of the AAR and CAAR in the event windows. In this way it is possible to see how reliable the results are and if unknown external factors possibly could influence the results of this research.

The first method to test the significance is done by regressing the individual AARs and CAARs to come to an overall t-value per event window. These regressions are corrected for heteroscedasticity and have robust standard errors.

The second method is the traditional T-test of Brown and Warner (1980). With this method the AARs and CAARs in the event windows are controlled by the standard deviation of the AARs and CAARs of the estimation window. The t-values are calculated according to the following T-test:

(6) $$T - test\ AAR = \frac{AAR_t}{\hat{S}(AAR_t)}$$

(7) $$T - test\ CAAR = \frac{CAAR_t}{\hat{S}(CAAR_t)}$$

where

(8) $$\hat{S}(AAR_t) = \sqrt{(\sum_{t=-250}^{t=-1}(AAR_t - \overline{AAR})^2)/\text{T-1}}$$

(9) $$\overline{AAR} = \frac{1}{T}\sum_{t=-250}^{t=-1} AAR_t$$

(10) $$\hat{S}(CAAR_t) = (\sum_{t=0}^{+21} \hat{S}(AAR_t)^2)^{0.5}$$

and where $\hat{S}(AAR_t)$ and $\hat{S}(CAAR_t)$ are the estimated standard deviations of AAR and CAAR over the estimation window, N is the number of events and T the number of days in the estimation window.

However, using the estimation window's standard deviation could underestimate the event-induced variance[4], which could lead to unreliable t-values. Therefore, the estimation window's standard deviation can be replaced by the cross-sectional variance in the event window. Boehmer et al. (1991) used a T-test in their research, which is a combination of the Patell's standardized-residual test[5] and the cross-sectional test. This combination allows event-induced variance changes and it also corporates information from the estimation window, which may enhances its efficiency and power. The t-value is calculated as follows:

(11) $$T - test\ AAR = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{i,t}}{\sqrt{\frac{1}{N-(N-1)}\sum_{i=1}^{N}(SAR_{i,t} - \sum_{i=1}^{N}\frac{SAR_{i,t}}{N})^2}}$$

(12) $$T - test\ CAAR = \frac{\frac{1}{N}\sum_{i=1}^{N} CSAR_i}{\sqrt{\frac{1}{N-(N-1)}\sum_{i=1}^{N}(CSAR_i - \sum_{i=1}^{N}\frac{CSAR_i}{N})^2}}$$

where

(13) $$SAR_{i,t} = \frac{AR_{i,t}}{\hat{S}_i\sqrt{1 + \frac{1}{T} + \frac{(AR_{i,t})^2}{\sum_{t=1}^{T}(AR_{i,t})^2}}}$$

(14) $$CSAR_i = \sum_{t=T_1+1}^{T_2} SAR_{i,t}$$

and where $SAR_{i,t}$ and $CSAR_i$ are the standardized abnormal and cumulative standardized abnormal returns, N is the number of events and T is the number of days in the estimation window.

[4] Boehmer et al. (1991)
[5] Patell (1976)

CHAPTER 4 Results

4.1 All crashes of airlines

The first hypotheses are done on the full sample of 87 crashes to examine the effect of the crashes on the stock price returns of the airlines. These results are visible in Panel A of table 7. Because the crashes related to 9/11 had a huge impact on the stock market worldwide, a separate regression is done to make sure the results are not only biased by the crashes on September 11th that year[6]. These results are visible in Panel B of table 7. As observable in Panel A, two of the three tests give a significant stock price decline in the days following the airplane crash. On the event day there is a price decline of 2.17%, significant at a 1% level. The following 2 trading days, the CAAR still shows a significant decline for both T-tests. The first method even gives significant results till 10 days after the crash with price declines that vary between 2.48% and 2.78%. The negative trend over the following days after the crash is in line with results of more recent papers and in contrast with the results of papers from the eighties and the EMH which had as a result that the stock market recovered after 1 or maximum 2 days after the crash. Even if the crashes related to 9/11 are excluded from the sample, the results in Panel B show the same negative trend. The decline is 0.5% to 1% less than the sample including 9/11 crashes, but still varies between 1.34% and 2.22% and remains significant till 10 days after the event. The second method, the Brown and Warner T-test, does not give any significant result at all. A possible explanation for this could be that this T-test uses the standard deviation of the estimation window of one year. However, in this estimation period other external events could have led to an abnormal return as well, events which are not taken into account in this research but can bias the test results, in this case in a way of not giving any significant results because of really low t-values. The first method uses only the event window of 21 days and the third method is using cross-sectional standard deviations.

[6] Arin et al. (2008) did research on the effect of terrorism on the stock market and find that it has a significant effect on the stock market. The impact was bigger in emerging markets, while investors in more developed markets are more resilient to these events. Brounen and Derwall (2010) did research on the 9/11 terrorist attacks. They find that the 9/11 attacks are the only event that caused long-term effects on financial markets.

Table 7
Results airlines full sample
Results of an event study following the market model approach, which shows the effect of airplane crashes on the stock returns of airlines involved in the crashes. In Panel A are the average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) calculated over the event windows, with their corresponding T-values. Panel B consists of the full sample without two 9/11 related crashes. The betas and market risk premiums are calculated based on the value-weighted CRSP market index. There are three different T-tests performed. Method (1) is a regression on AAR and CAAR, method (2) the Brown and Warner (1980) T-test and method (3) the Boehmer, Musumeci and Poulsen (1991) T-test. Note that the days are in trading days.

		(1)	(2)	(3)			(1)	(2)	(3)
Date	AAR	T-value	T-value	T-value	Window	CAAR	T-value	T-value	T-value
Panel A: full sample									
0	-0.0217	-3.230***	-0.762	-3.741***	(0, 0)	-0.0217	-3.230***	-0.762	-3.741***
+1	-0.00306	-0.810	-0.107	-0.734	(0, 1)	-0.0248	-3.820***	-0.615	-2.908***
+2	-0.00298	-0.690	-0.104	-0.181	(0, 2)	-0.0278	-3.310***	-0.562	-2.219**
+5	0.000107	0.030	0.004	0.056	(0, 5)	-0.0262	-2.490**	-0.375	-0.925
+10	-0.00402	-1.260	-0.141	-1.390	(0, 10)	-0.0273	-2.180**	-0.289	-0.711
+21	0.00310	0.920	0.109	0.782	(0, 21)	-0.00775	-0.390	-0.058	-0.196
Observations	87					87			
Panel B: excluding 9/11 related crashes									
0	-0.0134	-3.970***	-0.469	-4.519***	(0, 0)	-0.0134	-3.970***	-0.469	-4.519***
+1	-0.00558	-1.63	-0.195	-1.498	(0, 1)	-0.0190	-3.710***	-0.469	-2.703***
+2	-0.00319	0.720	-0.112	-0.221	(0, 2)	-0.0222	-2.940***	-0.448	-2.024**
+5	-0.000143	-0.040	-0.005	-0.017	(0, 5)	-0.0194	-2.030**	-0.276	-0.743
+10	-0.00479	-1.490	-0.167	-1.677*	(0, 10)	-0.0212	-1.760*	-0.224	-0.610
+21	0.00337	0,980	0.118	0.846	(0, 21)	-0.000660	-0.030	-0.005	-0.142
Observations	85					85			

*** p<0.01, ** p<0.05, * p<0.10

4.1.1 Crashes divided in time periods

Because the results in this paper are in contrast with the results of earlier research from the eighties, it is interesting to determine whether this difference is due to the different time period. Therefore, the crashes were divided into two groups: one group with crashes which occurred before 1990, and the other group with crashes which occurred from 1990 onwards. The results of these regressions based on two different time periods can be seen in table 8. The first time period, Panel A till 1990, shows some changes compared to the full time period. There is still a price decline visible, however, the decline is only 1% to 1.5% compared to the 2% to 2.8% of the full sample. Additionally, only the first 2 days after the crash show significant results according to method 1 and only the first day after the crash according to method 3. This result is more in line with the prior research in that time period. The second time period, Panel B from 1990 onwards, shows a significant negative trend again till 2 days after the event according to method 3 and till 10 days according to method 1. The stock price decline is even stronger in this more recent period. The decrease varies between 3.46% to 4.42%, which is even much higher than the results found in earlier research on this topic. An explanation for this result could be that in the period after 1990 Internet came up, and news can flow faster and reach all over the world.

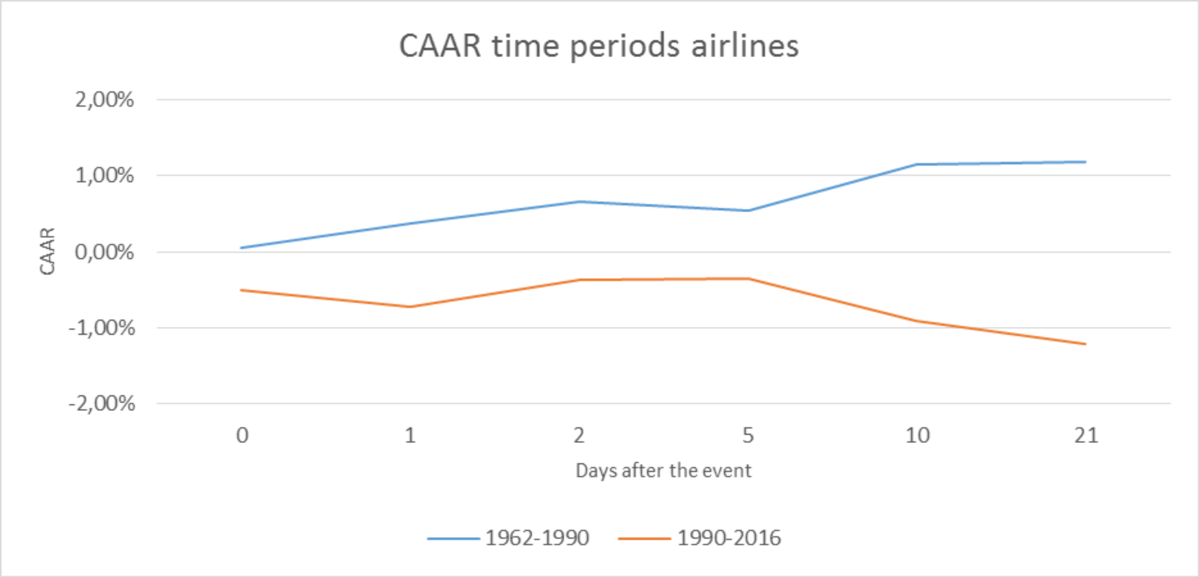
Therefore, investors are informed faster and better on airplane crashes and can react more intensively. Even without the crashes related to 9/11 and dividing the time period, the results remain significant and therefore the first two hypotheses are being rejected. There is an AAR and CAAR significantly different from zero observable. Figure 1 shows the CAAR till 21 trading days after the crash of both time periods.

Table 8
Results airlines divided into two time periods
Results of an event study following the market model approach, which shows the effect of airplane crashes on the stock returns of airlines involved in the crashes. In Panel A and B are the average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) calculated over the event windows, with their corresponding T-values. Panel A consists of the crashes which occurred before 1990. Panel B consists of the crashes which occurred from 1990 onwards. The betas and market risk premiums are calculated based on the value-weighted CRSP market index. There are three different T-tests performed. Method (1) is a regression on AAR and CAAR, method (2) the Brown and Warner (1980) T-test and method (3) the Boehmer, Musumeci and Poulsen (1991) T-test. Note that the days are in trading days.

Date	AAR	(1) T-value	(2) T-value	(3) T-value	Window	CAAR	(1) T-value	(2) T-value	(3) T-value
Panel A: crashes till 1990									
0	-0.0108	-3.220***	-0.433	-3.411***	(0, 0)	-0.0108	-3.220***	-0.433	-3.411***
+1	-0.00502	-1.370	-0.202	-1.268	(0, 1)	-0.0158	-3.110***	-0.449	-2.176**
+2	0.00201	0.520	0.809	0.756	(0, 2)	-0.0138	-2.020**	-0.320	-0.996
+5	-0.000973	-0.240	-0.039	-0.193	(0, 5)	-0.0151	-1.380	-0.247	-0.379
+10	-0.000241	-0.070	-0.010	-0.686	(0, 10)	-0.0156	-1.180	-0.190	-0.412
+21	-0.00142	-0.610	-0.057	-0.039	(0, 21)	-0.0107	-0.480	-0.092	-0.101
Observations	47					47			
Panel B: crashes from 1990 onwards									
0	-0.0346	-2.480**	-1.049	-2.835***	(0, 0)	-0.0346	-2.480**	-1.049	-2.835***
+1	-0.000761	-0.110	-0.231	-0.174	(0, 1)	-0.0354	-2.790***	-0.758	-2.145**
+2	-0.00884	-1.070	-0.268	-0.955	(0, 2)	-0.0442	-2.740***	-0.773	-2.087**
+5	0.00135	0.200	0.041	0.207	(0, 5)	-0.0393	-2.080**	-0.486	-0.898
+10	-0.00846	-1.470	-0.256	-1.237	(0, 10)	-0.0411	-1.830*	-0.375	-0.589
+21	0.00841	1.250	0.255	0.907	(0, 21)	-0.00432	-0.130	-0.279	-0.183
Observations	40					40			
Panel C: crashes from 1990 onwards excluding 9/11 related crashes									
0	-0.0166	-2.630***	-0.498	-3.114***	(0, 0)	-0.0166	-2.630***	-0.498	-3.114***
+1	-0.00627	-1.010	-0.186	-0.982	(0, 1)	-0.0229	-2.380**	-0.485	-1.806*
+2	-0.00963	-1.110	-0.288	-1.013	(0, 2)	-0.0325	-2.230**	-0.562	-1.843*
+5	0.000863	0.120	0.258	0.119	(0, 5)	-0.0247	-1.470	-0.301	-0.666
+10	-0.0104	-1.770*	-0.311	-1.638	(0, 10)	-0.0282	-1.300	-0.254	-0.447
+21	0.00928	1.310	0.278	0.981	(0, 21)	0.0117	0.340	0.748	-0.099
Observations	38					38			

*** p<0.01, ** p<0.05, * p<0.10

Figure 1
CAAR time periods for airlines
Cumulative average abnormal returns (CAAR) for the group of airlines from the event date till 21 trading days after an airplane crash, divided into two sub periods, from 1962 to 1990 and from 1990 to 2016. The first period consists of 47 airplane crashes and the second period consist of 40 crashes.



According to the third hypothesis, the stock prices should recover immediately after the crash, on day 0 and 1. Figure 1 shows the AAR from [-21,+21] for the airlines. Figure 2 shows the same period for the CAAR. From figure 2 the big significant price drop is observable on the event date. In figure 3 it is visible that the CAAR is significantly lower than the CAAR before the airplane crash for at least 10 trading days, where after the CAAR is moving slowly to the old level. However, this takes more than 21 trading days and therefore we can reject the third hypothesis.

Figure 2
AAR for airlines
Average abnormal returns (AAR) for the group of airlines during the 21 trading days prior to and after an airplane crash. The sample consists of 138 airplane crashes between 1962 and 2016.

Figure 3
CAAR for airlines
Cumulative average abnormal returns (CAAR) for the group of airlines during the 21 trading days prior to and after an airplane crash. The sample consists of 138 airplane crashes between 1962 and 2016.

4.1.2 Results of characteristic variables airlines

To gather results on the different subsamples of the characteristic variables, a T-test which compares the means of both subsamples is performed. The T-test used is the Welch's T-test. This test is correcting for unequal variances by using the Welch's degrees of freedom. Table 9 shows the results of these T-tests. The comparison of the location of the crash and the nationality of the airline is done with a different market index, namely, the World Airlines Index of Datastream. This index consist of several airlines over the whole world and is, therefore, better to use for these two tests (the market index used for the rest of the research only consist of U.S. based companies). Because this index only has data available from 1973 onwards, earlier crashes are dismissed from that sample. The T-tests are performed over the CAAR with event window [0, 2]. Within this event window, the prior results were still significant for method 1 and 3. The following variables were distinguished: small and large airlines (based on the average market capitalization of the airline), the amount of fatalities, the location of the disaster and the nationality of the airline company (divided per continent), the cause of the disaster (fault of airline and crime/terror) and the crash vs. the non-crash group.

Table 9
Mean comparison test airlines
The difference in means of the subsamples of airlines are tested for significance according to the Welch's T-test. The results are based on the CAAR [0, 2]. N is the number of observations, Mean is the average coefficient given as a percentage of the subsample. The T-value indicates whether there is a significant difference in the means of the two subsamples or not.

Subsample 1	N Mean	Subsample 2	N Mean	Tests of differences Means (T-value)
Mean comparison test				
Large Airlines (Market Capitalization > $200 Million)	87 -3.302%	Small Airlines (Market Capitalization <$200 Million)	174 -2.516%	0.7450
Less than 100 Fatalities	174 -1.590%	More than 100 Fatalities	87 -5.155%	3.2425***
Airplane crashed in Europe	42 -1.867%	Airplane crashed outside Europe	156 -3.720%	-2.0096**
Airplane crashed in North America	78 -4.978%	Airplane crashed outside North America	120 -2.254%	1.9553*
Airplane crashed in Latin America	21 -0.353%	Airplane crashed outside Latin America	177 -3.680%	-3.6252***
Airplane crashed in Asia	45 -4.193%	Airplane crashed outside Asia	153 -3.072%	0.7540
Airplane crashed in Africa	12 0.338%	Airplane crashed outside Africa	186 -3.564%	-2.5626**
European airline	45 -1.289%	Airline from outside Europe	153 -3.927%	-2.7386***
North American airline	93 -4.336%	Airline from outside North America	105 -2.434%	1.5111
Latin American airline	9 -0.551%	Airline from outside Latin America	189 -3.512%	-5.3619***
Asian airline	42 -4.413%	Airline from outside Asia	156 -3.035%	0.8833
African airline	9 -1.908%	Airline from outside Africa	189 -3.395%	-1.2664
Crew error/Poor maintenance	33 -2.422%	Other causes	228 -2.289%	0.3437
Crime/Terror	15 -11.39%	Other causes	246 -2.253%	2.6211***
Crash group	261 -2.792%	Non-crash group	3059 -0.486%	4.6245***
Crash group > 100 fatalities	203 -3.134%	Non-crash group > 100 fatalities	2462 -0.666%	4.2366***
Crash group < 100 fatalities	58 -1.595%	Non-crash group < 100 fatalities	660 0.361%	2.0897**

*** p<0.01, ** p<0.05, * p<0.10

There is no significant difference found for the size of the airline company. Even though the group of large airlines has a more negative coefficient, this difference with the smaller airlines is not significantly different from zero. This is also in line with prior research. For the subsamples of fatalities there is a significant difference in the means. The group with more than 100 fatalities has a much higher negative coefficient than the group with fatalities below 100. The coefficient of the first group is -5.155%, while the other group is only -1.590%. This is not a surprising result, it makes sense that crashes with a lot of fatalities have a bigger impact on the people and stock market than less fatal airplane crashes. These results are in line with the results of Walker et al. (2005). Regarding the location of the crash, there are significant results for Europe, North America, Latin America and Africa. However, for three of them the location of the subsample's coefficient is less negative than the group with the rest of the locations. This means that the impact on the stock market is less extreme than for crashes in the other parts of the world. North America is the only subsample which has a higher negative coefficient which is significantly different from the other group. This result is also not surprising, since the largest group of the crashes collided in North America. Walker et al. (2005) find a significant difference for crashes in the U.S. as well. For the nationality of the airline there are two groups significant, the European airlines and the airlines from Latin America. However, the coefficients of these subsamples are again less negative than the rest of the sample. When looking at the cause of the crash, there is a significant difference found in the subsample crime/terror. In case of this cause, there is an average drop of more than 11% in the stock price, compared to a 2% drop in stock price for the other causes. Since 9/11 was a terrorist attack and therefore also included in this sample, this can explain the huge drop in stock prices. Walker et al. (2005) also found a significant difference in this group and in their research the crime and terror group had a similar high coefficient (10.65%). Surprisingly when the cause is due to a fault by the airline company, there is not a significant difference found compared to the other causes. The difference in average price drops is also small compared to the other subsample. An explanation for this could be that it is quite difficult to say within 48 hours after the accident that it is a fault by the airline company and only in that case it would be in this subsample.

When comparing the crash group with the non-crash group, the existence of the contagion and switch effect can be tested. There is a significant difference between the crash and the non-crash group at a 1% significance level. The crash group has an average stock price decline of 2.79%, compared to the non-crash group which has an average price decline of only 0.49%. However, they are both negative, which means that the non-crash group is also influenced by the consequences of an airplane crash on the stock market. Ho et al. (2013) find a relation between the contagion and switch effect and the number of fatalities. Regarding the group with crashes with high fatalities, there was significant evidence of the contagion effect and regarding the group with low fatalities, there was evidence for the switch effect. In this research the same results are observable. In case of more than 100 fatalities, the crash group and the non-crash group have a negative coefficient, thus an average stock price decline over the event window [0, 2]. Both groups suffer from the airplane crash, which indicates the contagion effect. However, in case of less than 100 fatalities, the crash group experiences a price decline of 1.60%, but the non-crash group experiences a small price increase of 0.36%. The difference between these two groups is significant at a 5% level, therefore, this result indicates the existence of the switch effect.

The above results are in contrast with the fourth hypothesis, which states that there is not a significant event effect in the characteristic variables.

4.2 All crashes of airplane manufacturers

The dataset with airplane manufacturers consists of 138 crashes in total. The results of the effect of airplane crashes on the stock price of the manufacturers are visible in table 10. For this dataset the sample is also divided into two subsamples, one before 1990 and the other one from 1990 onwards. Panel A consists of all crashes and the two subsamples are visible in Panel B and C. For the full sample, there is a stock price decline of 0.21% on the event day, however, the next two days there is a price increase again. Only on the second day after the crash the AAR is significant according to the first method, at a 10% level, with a positive AAR of 0.32%. The CAAR is negative on day 0 and 1, but there are no significant results for the whole event window. It is obvious that the crashes have less impact on the stock prices of the airplane manufacturers than on the airlines. This is in line with the research of Chance and Ferris (1987). They did not find any significant results in their paper for the airplane manufacturers. However, Walker et al. (2005) and Krieger and Chen (2015) did find significant price declines the first days after the crash.

When the sample is divided into the two subsamples the results over the second subsample in Panel C, from 1990 onwards, show more negative and some significant AAR and CAAR when using method 1. On the event day there is a significant price decline of 0.50% at a 10% level. However, the effect on the airplane manufacturers is still smaller than on airlines, namely, 0.50% compared to 3.46% at a 5% significance level for the same subsample for airlines. There is a significant negative CAAR on day 0 and 1 of respectively 0.50% and 0.72% at a 10% and 5% level. The results of this more recent period are more in line with the other two papers. The research of Krieger and Chen (2015) is also done on a more recent sample, from 1980 to 2013, which can explain the difference in the full sample. However, method 1 is the only test which gives significant results. Therefore, it is difficult to fully rely on these results.

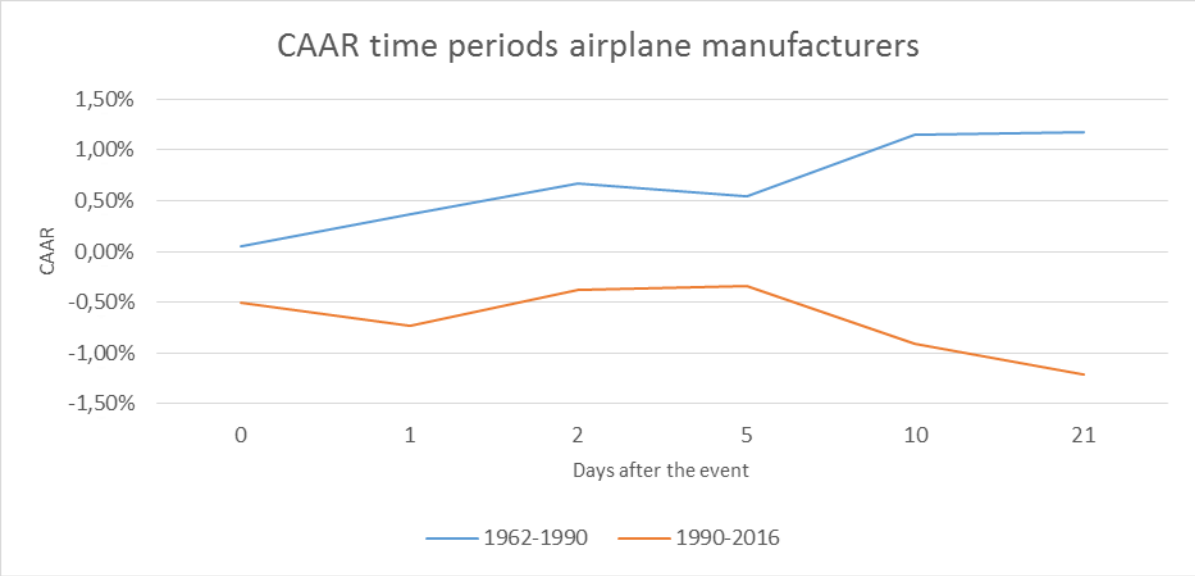
Hence the fifth and sixth hypotheses cannot be rejected for the airplane manufacturers. Figure 4 shows the CAAR till 21 trading days after the crash of both time periods.

Table 10
Results airplane manufacturers
Results of an event study following the market model approach, which shows the effect of airplane crashes on the stock returns of airplane manufacturers involved in the crashes. In Panel A, B and C are the average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) calculated over the event windows, with their corresponding T-values. Panel A consists of the full sample of crashes. Panel B consists of the crashes which occurred before 1990. Panel C consists of the crashes which occurred from 1990 onwards. The betas and market risk premiums are calculated based on the value-weighted CRSP market index. There are three different T-tests performed. Method (1) is a regression on AAR and CAAR, method (2) the Brown and Warner (1980) T-test and method (3) the Boehmer, Musumeci and Poulsen (1991) T-test. Note that the days are in trading days.

		(1)	(2)	(3)			(1)	(2)	(3)
Date	AAR	T-value	T-value	T-value	Window	CAAR	T-value	T-value	T-value
Panel A: full sample									
0	-0.00213	-1.08	-0.079	-1.120	(0, 0)	-0.00213	-1.08	-0.079	-1.120
+1	0.000578	0.32	0.022	0.180	(0, 1)	-0.00155	-0.58	-0.041	-0.534
+2	0.00324	1.78*	0.120	1.101	(0, 2)	0.00169	0.51	0.036	0.003
+5	-0.00106	-0.55	-0.039	-0.200	(0, 5)	0.00117	0.26	0.018	0.064
+10	-0.00103	-0.54	-0.038	-1.002	(0, 10)	0.00170	0.30	0.019	-0.019
+21	-0.00434	-0.98	-0.161	-0.741	(0, 21)	0.000398	0.05	0.003	-0.004
Observations	138					138			
Panel B: crashes till 1990									
0	0.000491	0.17	0.018	-0.124	(0, 0)	0.000491	0.17	0.018	-0.124
+1	0.00323	1.26	0.120	1.411	(0, 1)	0.00372	0.88	0.098	0.548
+2	0.00294	1.18	0.110	0.786	(0, 2)	0.00666	1.37	0.143	0.654
+5	-0.000613	-0.21	-0.023	-0.230	(0, 5)	0.00541	0.78	0.083	0.190
+10	-0.000869	-0.33	-0.032	-0.839	(0, 10)	0.0115	1.40	0.130	0.306
+21	0.000597	0.23	0.022	-0.073	(0, 21)	0.0118	1.15	0.095	0.061
Observations	72					72			
Panel C: crashes from 1990 onwards									
0	-0.00498	-1.83*	-0.203	-1.500	(0, 0)	-0.00498	-1.83*	-0.203	-1.500
+1	-0.00231	-0.94	-0.094	-1.097	(0, 1)	-0.00729	-2.38**	-0.210	-1.460
+2	0.00356	1.32	0.145	0.758	(0, 2)	-0.00373	-0.85	-0.088	-0.683
+5	-0.00154	-0.61	-0.063	-0.039	(0, 5)	-0.00345	-0.58	-0.057	-0.110
+10	-0.00120	-0.43	-0.049	-0.586	(0, 10)	-0.00902	-1.18	-0.111	-0.328
+21	-0.00972	-1.10	-0.397	-0.947	(0, 21)	-0.0121	-1.00	-0.105	-0.056
Observations	66					66			

*** p<0.01, ** p<0.05, * p<0.10

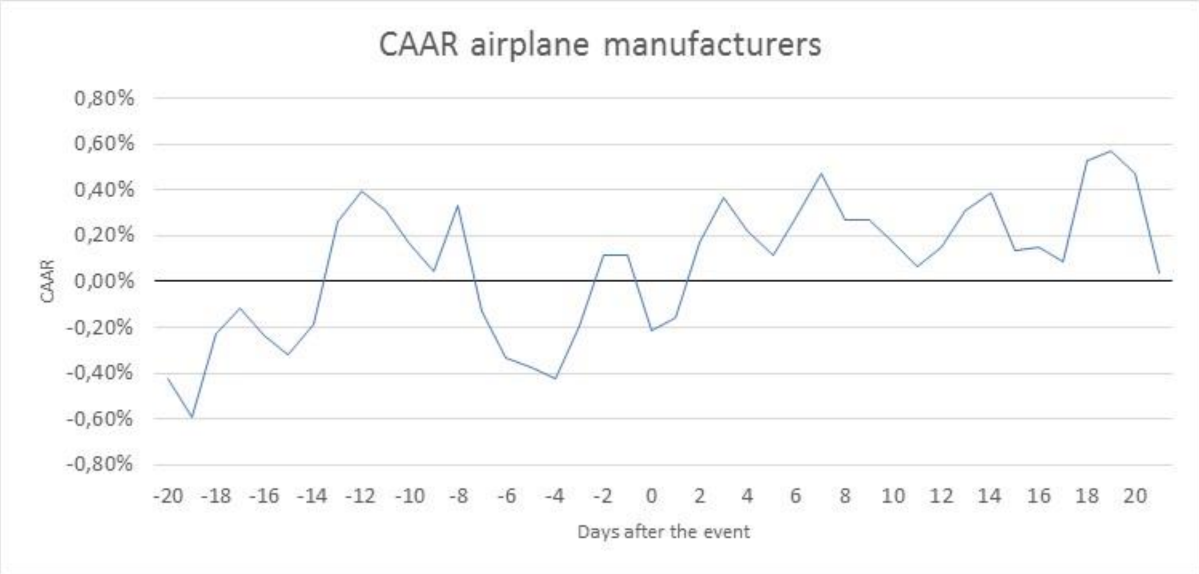
Figure 4
CAAR time periods for airplane manufacturers
Cumulative average abnormal returns (CAAR) for the group of airplane manufacturers from the event date till 21 trading days after an airplane crash, divided into two sub periods, from 1962 to 1990 and from 1990 to 2016. The first period consists of 72 airplane crashes and the second period consist of 66 crashes.



Furthermore, the significant, negative returns found by method 1 are only on the event day and the first day after the event. This means that the market already recovers after two days. According to the EMH, the market should recover immediately since all information should be reflected in the value of the stock price. Figure 5 shows the AAR from [-21,+21] for the airplane manufacturers. Figure 6 shows the same period for the CAAR. In figure 3 and 4 it is observable that the AAR and CAAR do not have considerable differences before and after the event date. Therefore, the third hypothesis cannot be rejected for the group of airplane manufacturers.

Figure 5
AAR for airplane manufacturers
Average abnormal returns (AAR) for the group of airplane manufacturers during the 21 trading days prior to and after an airplane crash. The sample consists of 87 airplane crashes between 1962 and 2016.

Figure 6
CAAR for airplane manufacturers
Cumulative average abnormal returns (CAAR) for the group of airplane manufacturers during the 21 trading days prior to and after an airplane crash. The sample consists of 87 airplane crashes between 1962 and 2016.



4.2.1 Results of characteristic variables manufacturers

In contrast with the results of the airlines, there are few significant results for the characteristic variables of airplane manufacturers, which are observable in table 11. There is a significant difference in the size of the airplane manufacturers, but only at a 10% significance level. The group with large manufacturers has a negative coefficient of -1.02%, while the group with smaller manufacturers have a positive coefficient of 0.27%. Because the overall coefficient for the whole group for the event window [0, 2] is positive as well, it can be concluded that the larger manufacturers suffer more from the airplane crashes than the smaller manufacturers. The number of fatalities and the location of the crash did not show any significant results. When looking at the cause of the airplane crashes, two different causes are distinguished, an error of the airplane manufacturer (i.e. mechanical failure) and crime and terror. Crime and terror has a negative coefficient of 0.45%, while mechanical failure has a positive coefficient of 1.14%. Even though both groups do not have a significance difference with the other causes, the positive coefficient for mechanical failure is unexpected. Another unexpected result is the difference in the crash and non-crash group, which has a significant difference at a 10% level. The crash group has a slightly positive coefficient of 0.16% , while the non-crash group has a slightly negative coefficient of -0.18%. Apparently the investors do not punish the airplane manufacturers after a crash, but slightly reward them. Although some of the characteristic variables give surprising results, the real impact on the stock market is questionable, because earlier results in the tables were not significant and the coefficients are very small. However, there is evidence of significant differences between the subsamples of some of the variables and the fourth hypothesis can be rejected.

Table 11
Mean comparison test airplane manufacturers
The difference in means of the subsamples of airplane manufacturers are tested for significance according to the Welch's T-test. The results are based on the CAAR [0, 2]. N is the number of observations, Mean is the average coefficient given as a percentage of the subsample. The T-value indicates whether there is a significant difference in the means of the two subsamples or not.

Subsample 1	N Mean	Subsample 2	N Mean	Tests of differences Means (T-value)
Mean comparison test				
Large Manufacturers (Market Capitalization > $200 Million)	11 -1.024%	Small Manufacturers (Market Capitalization <$200 Million)	127 0.272%	1.8004*
Less than 100 Fatalities	372 0.151%	More than 100 Fatalities	42 0.328%	-0.5720
Airplane crashed in Europe	45 0.187%	Airplane crashed outside Europe	369 0.167%	-0.0250
Airplane crashed in North America	141 -0.031%	Airplane crashed outside North America	273 0.272%	0.7840
Airplane crashed in Latin America	96 0.407%	Airplane crashed outside Latin America	318 0.097%	-0.6991
Airplane crashed in Asia	90 -0.002%	Airplane crashed outside Asia	324 0.216%	0.4954
Airplane crashed in Africa	42 0.643%	Airplane crashed outside Africa	372 0.115%	-0.8034
Mechanical failure	27 1.141%	Other causes	387 0.101%	-0.9514
Crime/Terror	9 -0.447%	Other causes	405 0.183%	0.9920
Crash group	414 0.186%	Non-crash group	1661 -0.182%	-1.7139*
Crash group >100 fatalities	290 0.209%	Non-crash group > 100 fatalities	1156 -0.223%	-1.7166*
Crash group low fatalities	124 0.132%	Non-crash group < 100 fatalities	1443 -0.138%	-0.7093

*** p<0.01, ** p<0.05, * p<0.10

CHAPTER 5 Conclusion and discussion

5.1 Conclusion

Regarding the first group, the airlines, there is a price decline of 2.17% significant at a 1% level, on the event day. The following 2 trading days, the CAAR still shows a significant decline. Even if the crashes related to 9/11 are excluded from the sample, the results show the same negative trend. The decline is 0.5% to 1% less than the sample including 9/11 crashes, but still varies between 1.34% and 2.22% and remains significant till at least 2 days after the crash.

When dividing the sample into two time periods, from 1962 to 1990 and from 1990 to 2016, the first time period shows some changes compared to the full time period. There is still a price decline visible, however, the decline is only 1% to 1.5% compared to the 2% to 2.8% of the full sample and it is only significant till 1 day after the crash. The second time period shows a significant negative trend again till at least 2 days after the event. The stock price decline is even stronger in this more recent period. The decrease varies between 3.46% to 4.42%

When testing for the characteristic variables, the number of fatalities has a significant effect on the returns. The group with more than 100 fatalities has a much higher negative coefficient than the group with fatalities below 100. The coefficient of the first group is -5.16%, while the other group is only -1.59%. When the crash occurred in North America, the negative impact is also bigger on the stock price than somewhere else. Remarkably, when the cause of the crash is an error by the airline, there is no significant difference found then in the case of another cause. However, when the cause is crime and terror there is an average drop of more than 11% in the stock price, compared to a 2% drop in stock price for the other causes.

When comparing the crash and non-crash airlines, there is evidence of the existence of the contagion and switch effect. In case of less than 100 fatalities, the non-crash group has a slightly positive coefficient, while the coefficient is negative for both groups in case of more than 100 fatalities.

When looking at the second group, the airplane manufacturers, the AAR shows a stock price decline of 0.21% on the event day, however, the next two days there is a price increase again. The CAAR is negative for two days, but is positive as well after those two days. Furthermore, the results are not significant. Even divided in the two time periods, there is not enough evidence for significant results.

Regarding the characteristic variables, there is a significant difference in the size of the manufacturers. The larger airplane manufacturers suffer more from airplane crashes than the smaller manufacturers. Crime and terror has a negative coefficient again of 0.45%, while mechanical failure has a positive coefficient of 1.14%. Even though both groups do not have a significance difference with the other causes, the positive coefficient for mechanical failure is unexpected. Another unexpected result is the difference in the crash and non-crash group, which has a significant difference at a 10% level. The crash group has a slightly positive coefficient of 0.16%, while the non-crash group has a slightly negative coefficient of -0.18%. Apparently the investors do not punish the airplane manufacturers after a crash, but slightly reward them.

5.2 Discussion

It would be interesting to do further research on this topic on the long-term, especially for the airlines, because of the significant and big price drops. In this way it is possible to examine how long it exactly takes before the stock market recovers. Furthermore, it would also be interesting regarding the causes. In some of the cases it will take a couple of months before the exact cause of the airplane crash is known, and it is possible that the new information leads to a change in the stock price again.

Another interesting topic would be regarding the relation of an airplane crash and distress of the airline. Airline companies nowadays are in general not profitable, consumer prices have fallen significantly and airlines go bankrupt more often[7]. It could be interesting to study the possibility of an airplane crash leading to bankruptcy, or less extreme, if the recovery time of the stock price of an airline in distress takes longer than the recovery time of an airline which is not in distress.

[7] Dempsey (2008)

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Databases:

Aviation Safety Network database (www.aviation-safety.net)

Center for Research in Security Prices (CRSP)

Datastream

LexisNexis

National Transportation Safety Board (NTSB) database (www.ntsb.gov)