UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS

MASTER’S THESIS

THE EFFECTS OF AIRPLANE CRASHES ON STOCK PERFORMANCE OF U.S. AIRLINES AND AIRPLANE MANUFACTURERS BETWEEN 1983 AND 2013

Ljubljana, September 2015 AMBROŽ HOMAR

AUTHORSHIP STATEMENT

The undersigned **AMBROŽ HOMAR**, a student at the University of Ljubljana, Faculty of Economics, (hereafter: FELU), declare that I am the author of the master's thesis entitled **The effects of airplane crashes on stock performance of U.S. airlines and airplane manufacturers between 1983 and 2013**, written under supervision of **doc. dr. Mitja Kovač.**

In accordance with the Copyright and Related Rights Act (Official Gazette of the Republic of Slovenia, Nr. 21/1995 with changes and amendments) I allow the text of my master's thesis to be published on the FELU website.

I further declare

- the text of my master's thesis to be based on the results of my own research;
- the text of my master's thesis to be language-edited and technically in adherence with the FELU's Technical Guidelines for Written Works which means that I
    - cited and / or quoted works and opinions of other authors in my master's thesis in accordance with the FELU's Technical Guidelines for Written Works and
    - obtained (and referred to in my master's thesis) all the necessary permits to use the works of other authors which are entirely (in written or graphical form) used in my text;
- to be aware of the fact that plagiarism (in written or graphical form) is a criminal offence and can be prosecuted in accordance with the Criminal Code (Official Gazette of the Republic of Slovenia, Nr. 55/2008 with changes and amendments);
- to be aware of the consequences a proven plagiarism charge based on the submitted master's thesis could have for my status at the FELU in accordance with the relevant FELU Rules on Master's Thesis.

Ljubljana, ________________________ Author's signature:

CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

INTRODUCTION

In the last two years, the general public directed as much attention to airplane crashes as it did following the terrorist attacks on September 11, 2001. Two planes of Malaysia Airlines, a well-known and respected carrier, crashed in a period shorter than six months. The plane on Flight 370 from Kuala Lumpur to Beijing is believed to have been hijacked and landed in the Indian Ocean, but the wreckage has still not been found to this day. The second plane on Flight 17 en route from Amsterdam to Kuala Lumpur was hit by (not yet identified) high-energy objects over eastern Ukraine. In March 2015, a copilot of a Germanwings airplane crashed 150 passengers and crewmembers into a mountain in the middle of the French Alps.

Airplane crashes are subject to massive attention by global media: Barnett (1990) analyzed New York Times front-page stories and found that the attention given to airplane crashes dwarfs the attention given to stories covering any other kind of loss of life. He compared the number of stories covering air crashes to those covering AIDS, homicide, automobile accidents and cancer on per capita death basis - multipliers ranged from sixty to several thousand times. Singer and Endreny (1987) explain the discrepancy: “a rare hazard is more newsworthy than a common one, other things being equal; a new hazard is more newsworthy than an old one; and a dramatic hazard - one that kills many people at once, suddenly or mysteriously - is more newsworthy than a long-familiar illness”. These characteristics make empirical studies of airplane crashes a very attractive opportunity to evaluate the efficiency of financial markets’ information processing and to provide insight on whether the changes in stock prices are a consequence of rational decision making or induced by short-term fear and anxiety.

The U.S. Department of Transportation estimates air travel to be 29 times safer than driving a car, but many passengers perceive flying as a high-risk and traumatic experience. According to Greist and Greist (1981), approximately 20% of them suffer from severe flight anxiety. Do similar fears also manifest in ex post investors’ reactions when these low probability risks materialize, i.e. when they are subjected to information on airplane crashes? Research shows that they do. Kaplanski and Levy (2010) looked at the effect reports on aviation disasters have on investors. They established that they increase investors’ fear and anxiety which negatively affects stock prices.

In this paper, we look at the effects airplane crashes have on stock prices in the aviation industry. We establish five key hypotheses and subject them to statistical testing:

- **Hypothesis 1:** Airplane crashes negatively affect stock performance of airlines.
- **Hypothesis 2:** Airplane crashes negatively affect stock performance of aircraft manufacturers.
- **Hypothesis 3:** Crashes with 50 or more casualties result in higher average absolute abnormal returns of airlines’ stocks.

- **Hypothesis 4:** Competitors of the manufacturer, whose airplane crashed due to mechanical failure, exhibit positive abnormal stock returns.
- **Hypothesis 5:** Crashes with 50 or more casualties result in similar average absolute abnormal returns of airplane manufacturers' stocks as those crashes with less than 50 casualties.

The chosen observation period covers U.S. based airplane crashes in a period of 30 years (1983-2013), which involved U.S. carriers and U.S. airplane manufacturers. Hypothesis testing is based on the event study methodology – a popular research method that is used in diverse fields such as corporate communications, security fraud litigation, mergers and acquisitions (M&A) research and investment analysis and political economy research. Based on the semi-strong version of the efficient market hypothesis, the methodology allows us to extract the effect of the observed event from the price movements that are deemed expected for a security under a chosen market model. The effect of the event is assessed based on how much the price of the chosen security deviated from the known linear relation to the movement of the market index. The obtained abnormal returns are then tested for statistical significance.

Our key results are the following:

- **Hypothesis 1:** We confirm the negative influence of the crashes on stock performance up to 13 days after the accident with statistical significance of 99% using one-tailed test. Average first-day abnormal return is -4.3% and the negative effect seems to continue to influence the stock performance up to Day 6 after the accident when the cumulative average abnormal return (CAAR) reaches -12.5%. The results are robust with regards to changes in the estimation window; they are consistent with those obtained by other researchers (Walker et al., 2005, Chance & Ferris, 1987), but the magnitude of the observed effect is much stronger.
- **Hypothesis 2:** We find market reaction in case of airplane manufacturers' stock price to be much less pronounced. The cumulative average abnormal returns do not fall below -1.3% in the first 15 days of trading. The t-statistic is not statistically significant except on Days 1 and 2. Cumulative average abnormal returns beyond Day 2 are not robust to changes in the estimation window. Results are in line with those of Walker et al. (2005) who observed statistically significant declines in intervals 1, 2 and 7 trading days after the crash.
- **Hypothesis 3:** We confirm that crashes, which resulted in more than 50 casualties, are associated with higher absolute abnormal returns in comparison to those that caused between 20 and 50 casualties (3.4% versus 2.3%). Results are statistically significant and robust to changes in the estimation window.

- **Hypothesis 4:** Our results show negative cumulative average abnormal returns in the first days following the crash, but they are not statistically significant. Longer-term positive cumulative average abnormal returns (also reported in Walker et al. (2005)) are not robust to changes in the length of the estimation window and are not statistically significant.
- **Hypothesis 5:** We confirm that crashes, which resulted in more than 50 casualties, do not result in higher average absolute abnormal returns in comparison to crashes that caused between 20 and 50 casualties (0.93% versus 0.98%). The observed difference is not statistically significant in any observed estimation window scenario.

We acknowledge the limitations of the obtained results. First, the event sample is very specifically defined: it involves only U.S. based airplane crashes in which publicly-traded U.S. airlines or airplane manufacturers were involved. Reactions to airplane crashes in other countries or to other companies may be different. Secondly, the extent of the market reaction to airplane crashes may be dependent on the cause of the crash; disasters caused by terrorists or technical errors may spur stronger reactions by airplane passengers and investors than those caused by bad weather. We are unable to claim that the events in our sample are representative for the general population of airplane crashes in terms of the underlying causes. Our strict definition of the event samples results in them being rather small (data from twelve airplane crashes was used in testing the effects on airlines' stock performance and fourteen crashes in the case of airplane manufacturers), thus putting a constraint on the generalizability of our conclusions.

The remainder of the paper is organized as follows:

- The first chapter provides an overview of research work performed in the area of financial markets' efficiency and describes the relevant results in the case of airplane crashes.
- The second chapter provides a description of the event study methodology, its characteristics, limitations and applications.
- The third chapter presents the approach used in the empirical analysis of this paper.
- Chapter four introduces the reader to the industries of airlines and airplane manufacturers.
- Chapter five presents the data used in the subsequent analysis and its descriptive statistics.
- Chapter six discusses the results of empirical analysis and robustness checks and provides likely explanations as to how financial markets react to aviation disasters.
- The conclusion summarizes the paper's main findings.

1 FINANCIAL MARKETS AS INFORMATION PROCESSORS

In the first chapter we provide an overview of the research work performed in the area of financial markets' efficiency. We state the efficient market hypothesis (EMH), which is a key enabler of the event study methodology, in all its three forms. We provide an overview of research findings related to EMH, describe the challenges to its validity posed by behavioral economists and discuss the implications on event studies. We conclude the chapter with the review of existing findings related to information processing after airplane disasters.

1.1 Efficient market hypothesis

The efficient market hypothesis states, that the price of an instrument traded at financial markets provides an unbiased estimate of the true value of the investment and fully reflects all available information (Damodaran, 2014). Fama (1970) states sufficient conditions for capital market efficiency:

- there are no transactions costs in trading securities,
- all available information is available to all market participants at no cost (meaning perfect information),
- all investors agree on the implications of current information for the current price and distributions of future prices of each security.

Organized stock exchanges have significantly lowered transaction costs in comparison to a direct exchange of goods by allowing to investors forego a personal examination of the credibility of the seller and the goods sold (Demsetz, 1968) and financial information has become widely available. Yet today's real-world markets still deviate in many aspects from the frictionless market in which all information is widely available at no cost and where investors agree on its implications. Grossman and Stiglitz (1980) showed that it is impossible for a real market to be perfectly informational-efficient. Because information is costly, prices cannot perfectly reflect the available information. If they did, investors who spent resources on obtaining and analyzing information would receive no compensation. Thus, a sensible model of market equilibrium must leave some incentive for information-gathering (security analysis). Fama (1970) notes however, that above-stated conditions are sufficient for an efficient market, but their violation does not necessarily make it inefficient.

The efficient market hypothesis does not require all the investors to be rational. It allows that some of them underreact and some overreact to new information. All that is required by the EMH is that those reactions are random and normally distributed. Any, even every, investor can be wrong about the meaning of new information, but the market as a whole is always right (Kallianiotis, 2013). Kahneman (2011, p. 84) provides a relevant, easy-to-understand example from James Surowiecki's book 'The Wisdom of the Crowds'

(Surowiecki, 2005), which illustrates this principle. In the experiment, a large number of observers are given the same task: to estimate a number of pennies in a set of jars (an equivalent to estimating the future performance of a set of stocks in the stock market case). As noted by Kahneman, an individual observer (investor) can perform very poorly in her estimations, but a pool of judgments (in our case, the stock market price) can be remarkably accurate. The accuracy comes from the fact that over- and underestimations average out. However, there are several preconditions for the 'wisdom-of-the-crowds-effect' to lead to a reasonably accurate estimate: the individuals must look at the same jar under the same conditions (available information) and their judgments are done independently – requiring no communication among actors. The magic of error reduction disappears if the observers share any kind of systematic bias; in such case no aggregation of estimates can reduce the underlying error (Kahneman, 2011, p. 84).

1.2 Forms of efficient market hypothesis

EMH comes in three major forms: weak, semi-strong and strong, which differ based on the degree of information that is supposed to be incorporated in the current market prices of securities. Harry Roberts was the first to make a distinction between the forms in an unpublished manuscript in 1967; the taxonomy became widespread after used in Fama (1970).

a) Weak form

The weak form states that future prices cannot be predicted by analyzing prices in the past as the current market price already reflects this information. It implies that technical analysis of stock performance (studying price charts and historical price relationships) would not be able to consistently generate excess returns, though that may still hold for fundamental analysis techniques. Under the weak form of the efficient market hypothesis, investors are still able to earn profits by researching financial statements, for example by uncovering how stock prices are related to certain financial ratios (Event study, 2014).

b) Semi-strong form

Semi-strong EMH claims that stock prices react immediately to newly available information, thus not presenting opportunity to earn excess returns using this information. It implies that using both technical and fundamental analysis would not lead to consistent excess returns. Using the same example as above, an investor that would buy some balance sheet data and software to analyze it in order to uncover potential price/ratio relationships would (on average) only be compensated with higher returns to the degree that covers additional costs. As Jensen (1978) argues, the marginal benefits (profits) of obtaining and analyzing information under semi-strong EMH do not exceed the marginal costs.

c) Strong form

In the strong form of market efficiency, share prices reflect all public and private information allowing no one to consistently generate excess returns. A precondition for the strong version of EMH is that information and trading costs, the costs of getting prices to reflect information, are always zero (Grossman & Stiglitz, 1980). Any investors achieving excess market returns are simply the ones on the lucky side of the (random) normal distribution.

1.3 Research history related to the EMH

Until recently, EMH was widely accepted by financial economists. Market efficiency was mentioned as early as in 1889, in George Gibson’s book ‘The Stock Markets of London, Paris and New York’. Gibson (1889) wrote that when ‘shares become publicly known in an open market, the value which they acquire may be regarded as the judgment of the best intelligence concerning them’. Keynes (1923) stated that investors are rewarded not for knowing better than the market what the future will bring, but rather for risk baring, which is a consequence of the EMH (Sewell, 2011). MacCauley (1925) observed a striking similarity between the fluctuations of the stock market and those of a chance curve which may be obtained by throwing a dice, implying no predictable patterns. Jensen (1968) wrote, ‘I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis.’ Schwert (2003) showed that when anomalies are published, practitioners implement strategies implied by the papers and the anomalies subsequently weaken or disappear, causing the market to become more efficient. The belief in EMH even contributed to the following joke, mentioned by Malkiel (2003):

‘A finance professor and a student come across a $100 bill lying on the ground. As the student stops to pick it up, the professor says, “Don’t bother—if it were really a $100 bill, it wouldn’t be there.”’

Empirical research on market efficiency did not yield unambiguous results, but the strong form of the hypothesis has generally been rejected (Nicholson, 1968), (Basu, 1977), Rosenberg et al., 1985), (Fama & French, 1992), (Chan et al., 2003). According to Klick and Sitkoff (2008), the majority of financial economists agree that the U.S. stock market is semi-strong efficient. In the last few years, however, several doubts have been raised, mainly based on experimental work done by behavioral economists.

1.4 Behavioral critique and implications for event studies

Behavioral economists, inspired by the work of Kahneman and Tversky (1979) and later discoveries in cognitive psychology, claim that investors are subject to various cognitive biases and predictable human errors that lead to systematic deviations from rational pricing in financial markets. The critique questions the premise that humans are rational and behave consistently as economic subjects. Kahneman (2011, p. 105) defines two ways (which he calls ‘System 1’ and ‘System 2’) in which we as human beings perform decision making. Some characteristics of decision making under System 1 are of particular interest to us, namely:

- inference and invention of causes and intentions,
- neglect of ambiguity and suppression of doubt,
- bias to believe and confirm,
- exaggeration of emotional consistency ,
- focus on existing evidence and ignoring absent evidence,
- generation of a limited set of basic assessments,
- over-weighting of low probabilities,
- diminishing sensitivity to quantity.

If System 1 was employed by investors across the market at a given time it could be the reason that the market prices depart from what would be expected under the EMH. Investors could systematically misinterpret information as described above and act upon the same information for longer periods of time.

Such decision making would question the use of event study methodology that is usually employed to study the effects of various kinds of events. However, Bhagat and Romano (2007) concluded that the debate over the validity of the market efficiency hypothesis concerns matters that do “not invalidate the event study methodology”. Still, some studies that focus on effects that major events have on broad market indices have taken into account systematic patterns in index performance, such as serial correlation, “January effect”, day of the week effect, “holiday’s effect” and the unusual returns in the first days of taxation year, which can be explained by behavioral biases (Kaplanski & Levy, 2010).

1.5 Financial markets’ information processing related to airplane crashes

Airplane crashes are rare and unpredictable events that could easily trigger the behavior described using System 1. In the first days after the crash, investors may be exposed mainly to media speculations as very few official pieces of information are disseminated from the authorities. Kahneman (2011, p. 75) uses an example from Nassim Taleb’s book

‘The Black Swan’ (Taleb, 2010) which shows how prone the media are to the uncritical search for causality:

‘He (Nassim Taleb) reports that bond prices initially rose on the day of Saddam Hussein’s capture in his hiding place in Iraq. Investors were apparently seeking safer assets that morning, and the Bloomberg News service flashed this headline: U.S. TREASURIES RISE; HUSSEIN CAPTURE MAY NOT CURB TERRORISM. Half an hour later, bond prices fell back and the revised headline read: U.S. TREASURIES FALL; HUSSEIN CAPTURE BOOSTS ALLURE OF RISKY ASSETS. Obviously, Hussein’s capture was the major event of the day, and because of the way the automatic search for causes shapes our thinking, that event was destined to be the explanation of whatever happened in the market on that day. The two headlines look superficially like explanations of what happened in the market, but a statement that can explain two contradictory outcomes explains nothing at all. In fact, all the headlines do is satisfy our need for coherence: a large event is supposed to have consequences, and consequences need causes to explain them.’

Reacting upon news of an airplane crash without critical examination may thus appear irrational. Kahneman (2011, p. 322) furthermore illustrates how exaggerated the reaction of the general public can be in case of rare events such as bombings:

‘I visited Israel several times during a period in which suicide bombings in buses were relatively common—though of course quite rare in absolute terms. There were altogether 23 bombings between December 2001 and September 2004, which had caused a total of 236 fatalities. The number of daily bus riders in Israel was approximately 1.3 million at that time. For any traveler, the risks were tiny, but that was not how the public felt about it. People avoided buses as much as they could, and many travelers spent their time on the bus anxiously scanning their neighbors for packages or bulky clothes that might hide a bomb.’

So how do investors react upon receiving the news of a deadly airplane crash – a rare event with plenty of room for distorted interpretations by media? Kaplanski and Levy (2010) estimated that a major airplane crash decreases market capitalization of NYSE Composite index by more than $60 billion, even though the direct economic cost does not exceed $1 billion. What additional factors do investors take into account when estimating the correct stock prices?

According to the discounted cash flow valuation method, originally expressed by Fisher (1930), the price of a company’s stock represents investors’ assessment of its future ability to generate profits and cash flows and reflects the willingness of investors to commit capital to the firm. If the stock price reacts negatively to an event it implies that investors expect riskier or lower cash flows in the future. The reaction of airline companies’ stock to airplane crashes has been repeatedly confirmed. Indirect adverse effects that influence stock prices include changed competitive dynamics, impact on regulation and overall effects on consumer demand.

For example, Ito and Lee (2005) have looked at the effects September 11th terrorist attacks had on airline demand around the world. They found a significant downward shift in demand for international air travel, ranging between -15% in -38% with the effect most pronounced in Europe and Japan. Several U.S. carriers declared bankruptcy in the aftermath of the attacks, notably United Airlines and US Airways, two of the country's largest carriers. Globally, the attacks contributed to bankruptcies of Australian Ansett, Belgian national carrier Sabena and Air Canada (Ito & Lee, 2005).

Wong and Yeh (2003) analyzed the impact flight accidents had on passenger traffic volume in Taiwan. After controlling for seasonal and cyclical factors, they estimated that an air accidents leads to a 22.1% percent monthly traffic decline for the involved airline and the effect carries on for about two months and a half. Rivals, on the other hand, benefit from a switching effect, which is still outset by general increase in fear of flying. Cumulatively, air accidents result in average 5.6% drop in passenger volume for uninvolved airlines.

Bosch et al. (1998) examined stock market reactions to air crashes, focusing on the effect of consumers responding to these disasters by switching to rivals and flying less. They have segmented the sample of competitive airlines based on how much their traffic routes overlap with those of the involved airline. They discovered a positive relation between competitor stock price reactions and the degree of overlap, supporting a switching effect. They also found a negative effect on stock prices of airlines with minor overlap, confirming a negative spillover effect.

Walker et al. (2005) widened the analysis of how airplane crashes affect the air transport industry and also studied the effects on airplane manufacturers (besides airlines). They observed an average decline of 2.8% for stocks of carriers and a milder but still significant effect on airplane manufacturers of 0.8%. They find that airlines' stock performance is negatively related to firm size and number of fatalities and that declines are most significant when crashes are a result of criminal activity. Manufacturers' stocks react similarly, but are most affected in case of mechanical failures.

2 EVENT STUDY METHODOLOGY

In the second chapter we introduce the event study methodology that is employed in the empirical part of the paper, its history, characteristics and diverse areas of application.

2.1 Event studies and their underlying assumptions

Event study is an empirical study performed on a security that has experienced a significant catalyst occurrence, and has subsequently changed dramatically in value as a result of that catalyst (Event study, n.d.). These studies are useful because, given rationality of investors; the effects of an event will be immediately priced in. The economic impact of an event can thus be estimated over a relatively short time period whereas direct productivity related measures may require many months or even years of observation (MacKinlay, 1997).

Every event study represents a joint test of the research hypothesis, the particular model of expected returns used and the underlying finance theory assumptions (Schimmer et al., 2014). In order to estimate the effects of an event on a security price we first need to employ techniques to separate event effects to any other dynamics of stock movement that might come from a different source.

To estimate the stock price movement without the event happening, event study methodology usually employs some kind of market model. In order to use such a model, we employ two key assumptions (Klick & Sitkoff, 2008): the (semi-strong) form of efficient capital market hypothesis holds and the relationship between an individual stock and the market is relatively stable in the short term (MacKinlay, 1997). The semi-strong version of EMH implies that the price of a publicly traded security reflects all public information on the present value of the future cash flow associated with the ownership of the security (Malkiel, 2003). Using the second assumption, we can estimate abnormal returns for a security based on how much its price deviated from the known linear relation to the movement of the market index. Together, these two ideas allow us to assess the effect of the observed event on the price of a chosen security.

2.2 History

According to MacKinlay (1997) the first published study was done by James Dolley in 1933. He examined the price effects of stock splits, studying nominal price changes at the time of the split. Using a sample of 95 splits from 1921 to 1931, he found that the price increased in around 60% of the cases. In the period from the early 1930s until the late 1960s the level of sophistication of event studies increased. The improvements included removing general stock market price movements and separating out confounding events (MacKinlay, 1997). At that time, the event study methodology was used as a statistical tool for empirical research in accounting and finance (Ball & Brown 1968; Fama et al. 1969), but has since been popular in other disciplines, including economics, marketing, strategy research, information technology/systems, law, and political science (Schimmer et al. 2014).

2.3 Methodology characteristics and limitations

Schimmer et al. (2014) note that with the choice to employ the event study methodology a researcher faces multiple challenges, such as defining the date of interest, choosing a model of expected return, choosing the model calibration and event observation period and dealing with event clustering. We look at each of these challenges in the following subsections.

2.3.1 Event date definition

In many cases such as corporate acquisitions, defining the relevant event date is not a trivial task. There may be several relevant events (request for proposal, submissions of bids, selection of the bidder, legal merger, operational integration…) to which investors react and adjust their views on probability of the following events occurring. In this respect, studying the effects of unexpected, unpredictable events such as natural disasters or airline crashes does not require much effort in analyzing prior to date developments, but demands careful examination of the post-event period, as new pieces of information may be discovered days, weeks or months after the event took place. This affects the choice of an appropriate observation window.

2.3.2 Models of expected return

Schimmer et al. (2014) list several approaches to obtaining expected market returns which are used to estimate abnormal returns that can be attributed to the event. These models include:

- Simple market model, which defines security's performance relative to market index
$$R_t=\alpha+\beta_i\cdot R_{M_t} \tag{1}$$

- Matched firm model, which defines security's performance relative to a portfolio of similar stocks
$$R_t=\alpha+\beta_i\cdot R_{f_t} \tag{2}$$

- CAPM model, which takes into account the risk free rate of return and security's linear relation to market index
$$R_t=R_{riskfree,\ t}+\beta_i\cdot(R_{M_t}-R_{riskfree,\ t}) \tag{3}$$

- Fama and French 3-factor model, which (besides linear relation to market index) also accounts for size and price-to-book ratio

$$R_t = R_{riskfree,\,t} + \beta_i \cdot (R_{M_t} - R_{riskfree,\,t}) + b_s \cdot SMB + b_v \cdot HML + \alpha \qquad (4)$$

- Multifactor statistical models, based on empirical relations in individual stock performance data

$$R_t = \alpha + b_{1,t} \cdot F_2 + b_{2,t} \cdot F_1 + \ldots + b_{n,t} \cdot F_n + \varepsilon \qquad (5)$$

While there may be some differences in employing these models, it has been repeatedly shown that the use of more complex models to calculate the expected returns to estimate the abnormal returns does not significantly influence the results (Brenner, 1979), (Brown & Warner, 1980), (Campbell et al., 1997), (Walker et al., 2005), (Bhagat & Romano, 2007), (Klick & Sitkoff, 2008). Use of alternative models is usually reserved for robustness tests.

2.3.3 Model calibration and event observation window

There is no definite rule on the length of the time window in which to calibrate the model of expected returns and in which toobserve the abnormal returns due to the event. The researcher needs to find the right balance between improved estimation accuracy and potential parameter shifts. Larger samples of returns in longer calibration periods may lead to greater accuracy, but may include periods of structural breaks in the model factors, which lead to biased estimators. Similarly, longer event observation windows are designed to capture the effects of information leakage and longer information processing but must be carefully balanced with the need for short windows to avoid confounding events to contaminate the results (Schimmer et al., 2014).

2.3.4 Event clustering

The problem of confounding events or event clustering occurs if multiple significant events of any type (earnings release, natural disaster, regulatory change...) affect a firm's stock in close succession. In that case, their estimation and event windows may overlap and lead to biased estimators due to cross-correlation. The potential problem is aggravated in studies of small samples, where potential flaws of the results do not cancel each other out in calculating mean values over large numbers of observations (Schimmer et al., 2014).

2.4 Applications of event study methodology

Schimmer et al. (2014) estimate the research body using event study methodology to consist of several thousand studies. They cover extremely diverse topics; in this section we present some typical areas where the methodology has been extensively used.

2.4.1 Corporate communications

One of the areas of practical application is to observe how the capital markets react to corporate press releases. Corporate communication specialists can use event study methodology to determine the editorial factors that contribute to a favorable reception of news items by the investment community. Furthermore, the method is valuable for surveying investor perspectives on strategic corporate announcements. It provides an indication of how investors perceive competitive moves of the firm and how successful they expect it to be in their implementation (Schimmer et al., 2014).

2.4.2 Security fraud litigation

In securities fraud litigation cases, the event study methodology is frequently used to establish materiality and calculate damages caused by an allegedly fraudulent action. The method has become an increasingly important instrument in private suits and enforcement actions by the U.S. Securities and Exchange Commission (SEC) (Mitchell & Netter, 1994). Klick and Sitkoff (2008) provide an example of investors suing Imperial Credit Industries, Inc. in which the court proclaimed the plaintiffs' expert's report "deficient for failure to provide an 'event study' or similar analysis".

2.4.3 M&A research and advisory

Mergers and acquisitions have been one of the most fruitful areas of event study methodology applications. Studies of abnormal returns have mostly found positive cumulative abnormal returns of target firm stocks and negative cumulative abnormal returns of the acquirers (Kaplan & Weisbach, 1992, Andrade et al. 2000, Mulherin & Boone, 2000, Graham et al. 2002) while Bhagat et al. (2005) found positive affect for firms on both sides of the transaction, although the results were not statistically significant.

The methodology can also be used for commercial purposes to complement the traditional analysis of comparable transactions analysis. Investment bankers use valuations in comparable deals in the past as one of the ways to estimate the value of a potential transaction. Using event study methodology, the investment banking analyst can incorporate market reaction to the deal to determine whether the transaction was perceived to be over- or undervalued (Schimmer et al., 2014).

2.4.4 Investment management

Event study methodology has been combined with natural language processing algorithms to translate news releases and social media sentiment into valuable investment information for quantitative trading (Mitra & Mitra, 2011).

2.4.5 Political economy research

Event studies are also widely used in political research. Researchers employed the methodology to measure the financial impact of regulation (Schwert, 1981), the value of political connections (Fisman, 2001, Acemoglu et al., 2013), the effectiveness of a tobacco control program (Abadie et al., 2010), the influence of grocery bag ban on public health (Klick & Wright, 2012) and many other political topics that require economic scrutiny.

3 THESIS APPROACH

In the third chapter we introduce concrete implementation of the event study methodology that is employed to test the outlined hypotheses.

3.1 Description of the approach

In order to estimate the effects of an event on a security price we firstly use techniques to separate event effects to any other dynamics of stock movement that might come from a different source. To estimate the stock price movement without the event happening, event study methodology usually employs some kind of market model. In order to use such a model, we employ two key assumptions (Klick & Sitkoff, 2008): the (semi-strong) form of efficient capital market hypothesis holds and the relationship between an individual stock and the market is relatively stable in the short term (MacKinlay, 1997). The semi-strong version of EMH implies that the price of a publicly traded security reflects all public information on the present value of the future cash flow associated with the ownership of the security (Malkiel, 2003). Using the second assumption, we can estimate abnormal returns for a security based on how much its price deviated from the known linear relation to the movement of the market index. Together, these two ideas allow us to assess the effect of the observed event on the price of a chosen security.

We employ a standard event study methodology, following Davidson (1987) and Klick and Sitkoff (2008):

1) Identify the event days and define the observation period
2) Define the relevant securities
3) Measure the actual returns of the selected securities on the days of interest
4) Estimate the securities' expected return on the selected dates using a market model
5) Calculate the abnormal returns by subtracting the expected returns from the actual returns
6) Asses the statistical significance of the abnormal returns.

Once these steps are completed, it is possible to evaluate the economic significance of the abnormal return on the days of interest.

1) The event day is the first trading day of New York Stock Exchange (NYSE) after the airplane crash. Abnormal returns are observed in periods 60 days before the crash and 60 days after the crash. Different specifications of time window are included in the robustness tests.

2) Securities used in the analysis are those of publicly traded companies related to the crash (airlines, manufacturers) and in some cases their historical predecessors or acquirers.

3) Actual returns are calculated by subtracting the price of the security at time *t-1* from the price at time *t*, divided by the price at time *t-1*.The price is adjusted by cash value of dividends.

4) The expected value of the stock is obtained using the following regression model:

$$ER_{it}=\lambda_{it}+\phi_i \cdot E_{Mt} \quad (6)$$

ER_{it} = the expected return on security *I* at time *t*;
λ_i = a security specific constant;
ϕ_i = a security specific coefficient;
E_{Mt} = market index return over timeframe *t*.

The parameters of the market model shown above are measured for each of the companies in the sample using regression of security returns against market portfolio as specified by the model. This regression to estimate model parameters λ_i and ϕ_i uses the 120 days from t = - 120 to t = 0. The obtained parameters are then applied to the actual market return E_{Mt} for days t =- 60 to t = + 60, to obtain the expected returns for security *i*.

5) These expected returns are compared to the actual returns for each of the observed securities for days – 60 to + 60. By subtracting expected return of security *I* at time *t* we obtain the desired abnormal return, AR_{it}.

$$AR_{it}=R_{it}-\lambda_{it}-\phi_i \cdot E_{Mt} \quad (7)$$

R_{it} represents the actual return on security *i* at time *t*, from which we subtract the previously defined expected return. The average abnormal return across securities, AR_t, is computed by summing the AR_{it} across all *i* firms for the *n* number of firms in the sample, at each relative event time.

$$\overline{AR_t} = \frac{1}{n} \sum_{i=0}^{n} AR_{it} \tag{8}$$

The $\overline{AR_t}$ shows the market adjusted abnormal return on a particular day relative to the event. If an $\overline{AR_t}$ is significantly different from zero, we interpret it as if the investors reacted to the news of the event. To examine how long the event affected security prices, we compute cumulative abnormal returns (*CARs*) for various time periods over the intervals *Tj* to *Tk*. *Tj* and *Tk* can be any sequential set of dates during the abnormal return estimation period. A *CAR* is defined as follows:

$$CAR_{T_jT_k} = \sum_{t=T_j}^{T_k} \overline{AR_t} \tag{9}$$

In an efficient market, the security price will react immediately to an event that affects the intrinsic value of a security. Under these conditions, the *CAR* should be random except upon receipt of the news of an event. Previous studies have shown that reactions to aviation disasters exhibit price reversal effects, which can be identified by examining cumulative abnormal returns under different specifications.

6) To assess the statistical significance of the obtained results, a time series t-test is conducted to determine if the $CAR_{T_jT_k}$ is significantly different from zero. The t-test is computed using the standard deviation of the $\overline{AR_t}$ as an estimate for the standard error in the traditional t-test formula. The method assumes $\overline{AR_t}$ are independent and identically normally distributed across event time (Intriligator, 1978).

$$t_{T_jT_k} = \frac{CAR_{T_jT_k}}{SD_{AR}} \tag{10}$$

3.2 Illustrative example

We provide a practical application of the described methodology on single event data, related to the US Airways plane crash on March 22, 1992. The Fokker F28 plane with 51 people on board crashed just beyond the end of the runway of LaGuardia Airport in New York City. 27 people died.

1) Identify the event day and define the observation period

The event day is March 23, 1992 - the first trading day of NYSE after the crash took place. Observation period of 120 trading days starts on 2.10.1991.

2) Define the relevant securities

US Airways (then known as USAir) stock, traded at NYSE under the ticker U.

3) Measure the actual returns of the selected securities on the days of interest

The returns are calculated based on data collected by the Center for Research in Security Prices at the University of Chicago (CRSP) and accessed through Wharton Research Data Services (2014).

Table 1. Daily returns of USAir stock returns on days around the crash date.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
USAir daily return (%)	-1,4	0,7	0,7	0,0	-1,4	-0,7	0,7	1,4	-1,4	-2,1

Source: *Wharton Research Data Services*, 2014.

4) Estimate the securities' expected return on the selected dates using a market model

Expected return is calculated using the coefficients obtained by linear regression in Stata.

Table 2. Linear regression output of regressing USAir stock returns on CRSP Value-weighted market index.

USAir	**Coef.**	**Std. Err.**	**t**	**P>t**	**95% Conf.**	
Market index	2.66844	0.4267083	6.25	0.000	1.823442	3.513439
_cons	0.00435	0.0030906	1.41	0.162	-0.001771	0.010469

Table 3. Expected daily returns of USAir stock returns on days around the crash date.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
USAir expected daily return (%)	-0,4	-0,4	-0,1	0,2	-2,2	-0,1	0,7	0,4	-2,2	0,4

5) Calculate the abnormal returns

Abnormal returns are calculated by subtracting the expected returns from the actual returns on a particular day.

Table 4. Abnormal returns of USAir stock returns on days around the crash date.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
USAir daily return (%)	-1.4	0.7	0.7	0.0	-1.4	-0.7	0.7	1.4	-1.4	-2.1
USAir expected daily return (%)	-0.4	-0.4	-0.1	0.2	-2.2	-0.1	0.7	0.4	-2.2	0.4
USAir abnormal daily return (%)	-1.0	1.1	0.8	-0.2	0.8	-0.6	0.0	1.0	0.8	-2.5

6) Asses the statistical significance of the abnormal returns

Table 5. Cumulative abnormal returns for several intervals after the crash, with tests of statistical significance.

Interval of days after the crash	CAR (%)	T-statistic
0-1	-1.0	-0.32
0-5	-0.2	-0.21
0-10	0.2	-0.02
0-15	-21.9	-0.89
0-20	-35.1	-2.07
0-30	-41.5	-2,33
0-60	-55.5	-2,20

Legend: *** denotes statistical significance at 1%, ** statistical significance at 5% and * statistical significance at 10% level.

US Air stock seems to only be affected by the crash beyond Day 10 after the event. None of the obtained cumulative abnormal returns are statistically significant based on the calculated t-statistic, despite sizable declines in later periods.

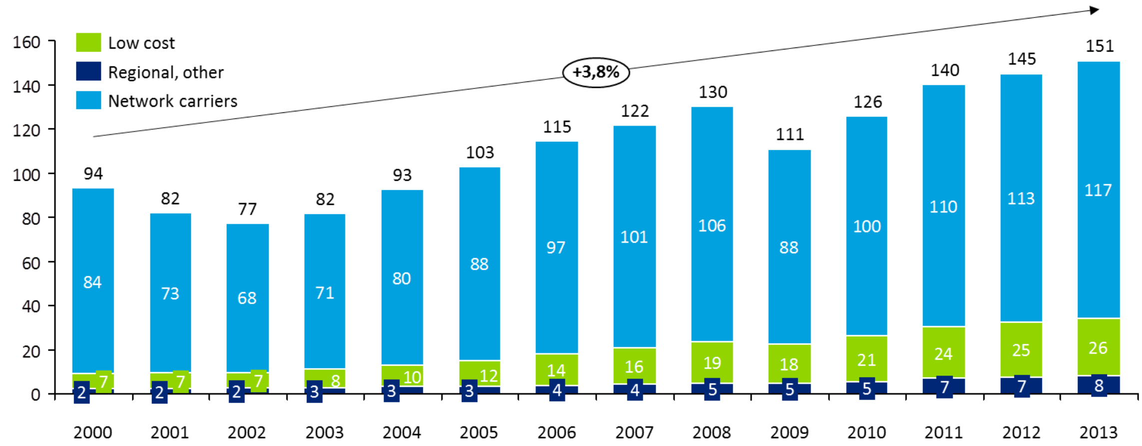
4 AVIATION INDUSTRIES

In order to provide the reader with the industry context, we review the history and the current state of airlines and the airplane manufacturing industry.

4.1 Airlines

The global airline industry consists of around 200 airlines, operating more than 23 thousand aircrafts that connect over 3700 airports (Henckels, 2011). PwC estimates that revenue by passenger transport reached a new high of $596 billion in 2013 (Tailwinds: 2014 airline industry trends, 2014). The air travel growth rate has been about twice as high as the GDP growth rate, averaging around 5 percent over the past 30 years. The number of air passengers exceeds 2 billion annually (Henckels, 2011). US air carriers have transported more than 570,000 passengers and generated revenue of around $200 billion in 2013. Low cost carriers and regional airlines (such as Alaska and Hawaiian) achieved above market growth (Swelbar & Belobaba, 2014).

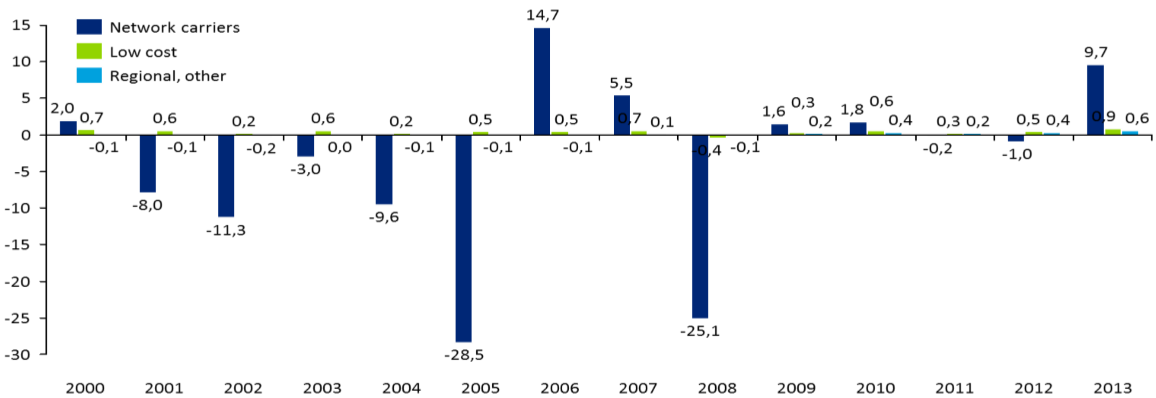
Figure 1. Revenue growth of U.S. air carriers 2000-2013, $ billions



Source: W. S. Swelbar & P. P. Belobaba, *Airline data project: revenue and related*, 2014.

The industry employs around 500,000 employees who enable more than 30,000 flights per day. Commercial aviation contributes to around 8 percent of the U.S. gross domestic product (Henckels, 2011). It has been marked with two crucial events: deregulation and the 9/11 attacks. Since 1937, air travel has been regulated by Civil Aeronautics Board as public utility. In 1978 U.S. Congress passed a law (Airline Deregulation Act of 1978), which intensified competition and contributed to the fact that inflation-adjusted cost per passenger declined by about a third until the 1990s. Terrorist attacks in 2001 severely affected the industry by lowering demand and increasing safety standards. Five major airlines (US Air, United Airlines, Delta Airlines, Northwest Airlines and American Airlines) declared bankruptcy between 2001 and 2011. In an effort to reduce costs and improve profitability following the financial crisis of 2007, the industry consolidated, notably with giant mergers between Delta and Northwest Airlines in 2009 and Continental and United Airlines in 2010 (Henckels, 2011). In 2013, the industry profitability was restored, reaching over 11 billion dollars in net profit (Swelbar & Belobaba, 2014).

Figure 2. U.S. Air carrier profitability by segment (2000-2013), $ billions

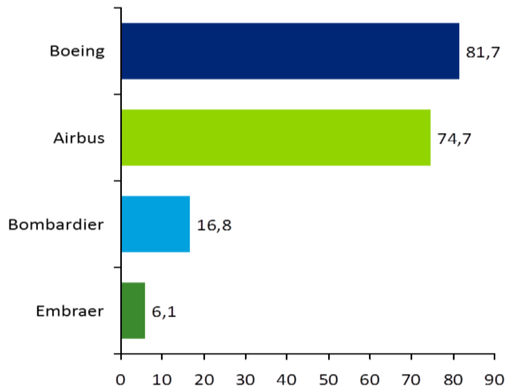


Source: W. S. Swelbar & P. P. Belobaba, *Airline data project: revenue and related*, 2014.

4.2 Airplane manufacturers

The commercial aircraft manufacturing industry (aircrafts, auxiliary equipment and parts) generates around $290 billion in annual revenue (Global Commercial Aircraft Manufacturing report: Market Research Report, 2014). The large commercial aircraft market is a duopoly shared by the U.S. aircraft manufacturer Boeing and the European aircraft maker Airbus, while Canada-based Bombardier and Brazil's Embraer dominate the regional jet market (Platzer, 2009 and Revenue of the worldwide leading aircraft manufacturers and suppliers in 2013, 2014).

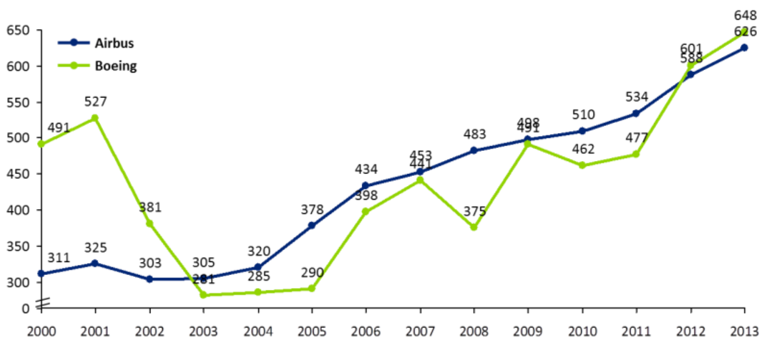
Figure 3. Leading commercial airplane manufacturers by revenue in 2012, $ billions



Source: *Revenue of the worldwide leading aircraft manufacturers and suppliers in 2013*, 2014.

Competition between Airbus and Boeing has been intense since 1990s, when a series of mergers changed the global aircraft manufacturing industry (Anichebe, 2014). Airbus began as a consortium of European plane manufacturers, while Boeing merged with its leading U.S. competitor, McDonnell Douglas, in 1997. Other manufacturers, such as Lockheed Martin, British Aerospace and Fokker, struggled to remain competitive but eventually exited the market of big passenger jets (Anichebe, 2014).

Figure 4. Airplane deliveries by the two biggest manufacturers, Airbus and Boeing (2000-2013)



Source: *Orders and Deliveries, 2014; Orders & Deliveries*, 2014.

Both Boeing and Airbus forecast a strong long-term demand growth for airplanes, based on continued above-GDP growth in number of air passengers (4.2 percent versus 3.2 percent). Twenty-year projections suggest that the current fleet of airplanes worldwide is expected to grow by as much as 60 percent – not counting replacements and retained fleet (Global Market Forecast 2013-2032, 2014, Current Market Outlook, 2014).

4.3 Airplane crashes and their economic consequences

Today, the direct cost of an aviation disaster is transferred from the involved air carrier to its insurers. Insurance companies bear two types of losses: the loss of the airplane itself and the compensation per lost life of airplane passengers. The industry norm for the insurance coverage (a proxy for direct cost) per plane ranges between $2 billion and $2.5 billion (Wallace, 2014). In the case of airplane manufacturers, the highest loss was recorded in the case of 1979 McDonnell Douglas DC-10, when all aircrafts of the type were grounded indefinitely after an accident, but the consequences to the company did not exceed $200 million in today's dollars (Kaplanski & Levy, 2010). Comparing these direct effects to the 60 billion dollar decrease in the NYSE market index capitalization after a major airplane crash, observed by Kaplanski and Levy (2010), we conclude that the majority of the loss in value can be attributed to indirect effects of an airplane crash on the economy or irrational reactions by investors.

5 DATA

In chapter five, we describe the multiple sources we combined in order to conduct the analysis, how it was processed and present its main descriptive statistics.

5.1 Sources and pre-processing

The aviation accident database of National Transportation Safety Board (NTSB) serves as the information source for data on airplane crashes. The database contains information about civil aviation accidents and incidents since 1962 (NTSB website, 2014). Our selected observation period covers 30 years (January 1, 1983-December 31, 2013) and perfectly complements the observation period of Chance and Ferris (1987), whose last analyzed event took place on July 9 1982. The data sample for analysis of airlines' stock reaction was obtained using the following search parameters:

- Country: United States of America
- Injury severity: Fatal
- Aircraft category: Airplane
- Amateur Built: No
- Number of fatalities: More than 20

A record of the plane crash at Sharjah airport (United Arab Emirates) was clearly misclassified and was eliminated from the sample. Four records of September 11, 2001 crashes and a record of the 1987 crash of a Pacific Southwest Airlines were eliminated as they were caused by criminal activity (terrorist attacks and mass murder via passenger suicide). The record of American Airlines plane crash at Belle Harbor was eliminated as the estimation period spans over 9/11 attacks. The records of 12 crashes of airplanes by carriers, whose information on stock price for the period of interest was not available, were not used in the analysis. The entry of Midwest Express airplane crash was eliminated as the carrier's parent company was Kimberly Clark, a large personal care corporation. The final sample thus consists of 12 crashes between February 1, 1991 and December 2, 2009.

The data obtained through the NTSB database was complemented with information from the Aviation Safety Network (ASN) database (ASN website, 2014), which contains descriptions of over 15,000 aviation safety occurrences since 1921 and is weekly updated. The additional pieces of data involved reasons for the crash and its exact timing.

In order to select the relevant event date, we followed the standard approach, described in Kaplanski and Levy (2010). We considered crash times as they happened relative to the Eastern Daylight Time (EDT), corresponding to the NYSE trading hours. In all cases, the crash happened after 2:00 PM EDT (two hours before the closing bell). Similarly as in Chance and Ferris (1987), we used the date of the next trading day as the event date.

Table 6. List of airplane crashes used in the airlines' analysis

Crash Date	**Trading day**	**Location**	**Air Carrier**	**Total Fatal Injuries**
1.2.1991	4.2.1991	Los Angeles, CA	SkyWest Airlines	34
1.2.1991	4.2.1991	Los Angeles, CA	US Airways	34
5.4.1991	8.4.1991	Brunswick, GA	Atlantic Southeast Airlines	23
22.3.1992	23.3.1992	Flushing, NY	US Airways	27
2.7.1994	5.7.1994	Charlotte, NC	US Airways	37
8.9.1994	9.9.1994	Aliquippa, PA	US Airways	132
31.10.1994	1.11.1994	Roselawn, IN	American Eagle Airlines	68
11.5.1996	13.5.1996	Miami, FL	ValuJet	110
17.7.1996	18.7.1996	East Moriches, NY	Trans World Airlines	230
9.1.1997	10.1.1997	Monroe, MI	Comair	29
31.1.2000	1.2.2000	Port Hueneme, CA	Alaska Airlines	88
12.2.2009	12.2.2009	Clarence Center, NY	Colgan Air	50

Source: NTSB Aviation Accident Database and Synopses, 2014; ASN Aviation Safety Database, 2014

The data sample for analysis of aircraft manufacturers' stock reaction was obtained from the NTSB database using the following search parameters:

- Country: United States of America
- Injury severity: Fatal
- Aircraft category: Airplane
- Make: Boeing or McDonnell Douglas or Lockheed
- Number of fatalities: More than 20

The manufacturers sample consists of air crashes in which three largest U.S. airplane manufacturers were involved. Only Boeing, McDonnell Douglass and Lockheed were involved in two or more crashes in the selected time period in the NTSB database and were then publicly traded at NYSE. The sample was complemented by two more records used in airlines' sample for which the manufacturer was determined to be one of the three aforementioned companies.

Table 7. List of airplane crashes used in the aircraft manufacturers' analysis

Crash date	**Trading day**	**Location**	**Manufacturer**	**Fatal Injuries**
21.1.1985	21.1.1985	Reno, NV	Lockheed	70
2.8.1985	5.8.1985	Fort Worth, TX	Lockheed	135
6.9.1985	9.9.1985	Milwaukee, WI	McDonnell Douglas	31
31.8.1986	2.9.1986	Cerritos, CA	McDonnell Douglas	82
16.8.1987	17.8.1987	Romulus, MI	McDonnell Douglas	156
15.11.1987	16.11.1987	Denver, CO	McDonnell Douglas	28
19.7.1989	19.7.1989	Sioux City, IA	McDonnell Douglas	111
25.1.1990	26.1.1990	Cove Neck, NY	Boeing	73
1.2.1991	4.2.1991	Los Angeles, CA	Boeing	34
3.3.1991	4.3.1991	Colorado Springs, CO	Boeing	25
8.9.1994	9.9.1994	Aliquippa, PA	Boeing	132
11.5.1996	13.5.1996	Miami, FL	McDonnell Douglas	110
17.7.1996	18.7.1996	East Moriches, NY	Boeing	230
6.8.1997	5.8.1997	Nimitz Hill, GU	Boeing	228

Source: NTSB Aviation Accident Database and Synopses, 2014; ASN Aviation Safety Database, 2014

Stock price data was obtained from CRSP (Center for Research in Security Prices from the University of Chicago) through WRDS (Wharton Research Data Services, 2014). The CRSP value-weighted market index is used as a market proxy. An adjustment for a stock split, which was not accounted for in CRSP, was done for Alaska Airlines stock. Several entries with negative stock values and misclassified dividends were corrected.

Table 8. List of publicly traded companies included in the analysis

Company	Ticker	Note
SkyWest Airlines Inc.	SKYW	
US Airways	U	* Until 1996 operated as USAir
Atlantic Southeast Airlines Inc.	ASAI	
AMR Corporation Inc.	AMR	* Parent company of American Eagle Airlines
ValuJet Inc.	VJET	
Trans World Airlines Inc.	TWA	
Comair Inc.	COMR	
Alaska Airlines Inc.	ALK	
Pinnacle Airlines Corporation Inc.	PNCL	* Acquired Colgan Air in January 2007
Boeing Inc.	BA	
Lockheed Inc.	LK	
McDonnell Douglas Inc.	MD	

Source: *US Airways chronology,* 2014; *American Airlines Group Overview*, 2014; *History of Colgan Air*, 2014.

5.2 Descriptive statistics

Table 9. Airplane crashes in airlines' sample, by cause and carrier

Air carrier	Air traffic control (ATC) error	Inadequate regulation	Mechanical failure	Pilot error	Weather	Total
ValuJet			1			1
SkyWest Airlines	1					1
US Airways	1	1	1	1		4
Atlantic Southeast Airlines			1			1
American Eagle Airlines					1	1
Trans World Airlines			1			1
Comair		1				1
Alaska Airlines			1			1
Colgan Air				1		1
Grand Total	**2**	**2**	**5**	**2**	**1**	**12**

Source: *NTSB Aviation Accident Database and Synopses,* 2014; *ASN Aviation Safety Database*, 2014.

The most common cause of airplane crashes in the sample was mechanical failure (over 40%). The planes were operated by nine different airlines, with US Airways involved in four of the selected 12 accidents.

Table 10. Airplane crashes in manufacturers' sample, by cause and manufacturer

Manufacturer	ATC error	ATC technology limitations	Inadequate maintenance	Mechanical failure	Pilot error	Grand Total
Boeing	1			3	2	6
Lockheed					2	2
McDonnell Douglas		1	1	2	2	6
Grand Total	**1**	**1**	**1**	**5**	**6**	**14**

Source: *NTSB Aviation Accident Database and Synopses, 2014; ASN Aviation Safety Database*, 2014.

In the manufacturers' crash sample, the vast majority of crashes were attributed to mechanical failures or pilot errors. Two were related to errors or inadequate equipment at air traffic control, while one happened due to inadequate maintenance.

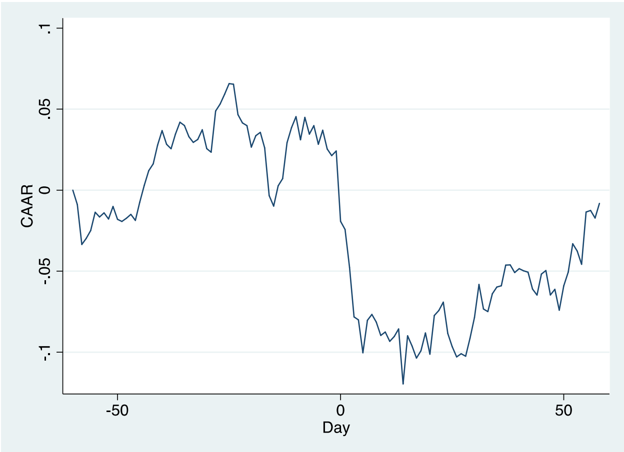
6 RESULTS

In chapter six we provide a description of statistical analyses performed to test our hypotheses, discuss the limitations of obtained results and present additional tests to estimate their robustness.

6.1 Hypothesis testing

6.1.1 Hypothesis 1: Airplane crashes negatively affect stock performance of airlines.

Figure 5. Cumulative average abnormal return across 60 days before and after the crash (based on 12 crash events).



The visual representation of the results shows that the airplane crashes significantly influence the stock price of related airlines. Average first day abnormal return is above 4% and the negative effect seems to continue to influence the stock performance up to Day 6 after the accident when the cumulative average abnormal return (CAAR) reaches -12.5%. All results up to day 15 are significant at 1% level using one-tailed test. The results are consistent with those obtained by other researchers (Walker et al., 2005, Chance & Ferris, 1987), but the magnitude of the observed effect is much stronger. The composition of the crash sample could provide an explanation of this phenomenon. It consists of crashes on US territory in which US-based airlines were involved. If only direct economic loss was taken into account by investors there should be no significant difference in reaction to crashes abroad or at home. But in case that publicity around crashes affects both potential passengers' willingness to travel and investor confidence in future cash flows to be generated by the affected airline. According to Kaplanski and Levy (2010), the crashes where US companies were involved received more (prolonged) publicity, which could also explain the fact that negative abnormal returns persist for several days after the crash. Walker et al. (2005) found significantly larger first week declines for crashes on US territory (-4.6%) than for those that happened elsewhere (-0.2%).

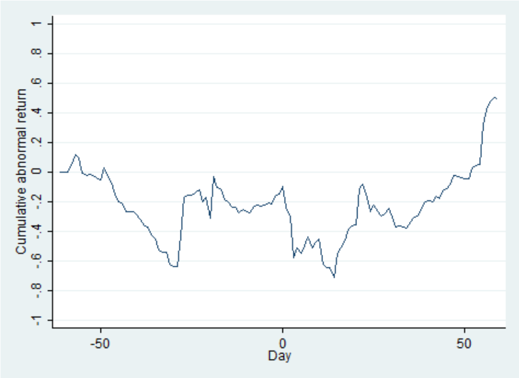
Table 11. Cumulative average abnormal returns for 15 days after the crash, with tests of statistical significance.

Interval of days after the crash	**CAAR (%)**	**T-statistic**
0-1	-4.3	-3.93***
0-2	-4.8	-3.09***
0-3	-7.2	-3.75***
0-4	-10.2	-4.62***
0-5	-10.4	-4.21***
0-6	-12.5	-4.60***
0-7	-10.5	-3.57***
0-8	-10.1	-3.23***
0-9	-10.6	-3.18***
0-10	-11.4	-3.26***
0-11	-11.2	-3.05***
0-12	-11.7	-3.06***
0-13	-11.4	-2.87***
0-14	-11.0	-2.65 **
0-15	-14.4	-3.36***

Legend: *** denotes statistical significance at 1%, ** statistical significance at 5% and * statistical significance at 10% level.

Interestingly, charts on cumulative abnormal returns on individual stocks of involved airlines (Figure 6 to Figure 17) exhibit very little resemblance among each other, but on aggregate still produce a distinct pattern of negative abnormal returns in first days after the crash (Figure 5).

Figure 6 and *Figure 7*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. Colgan Air plane crash on 12.2.2009 (left) and Alaska Airlines plane crash on 31.1.2000 (right).



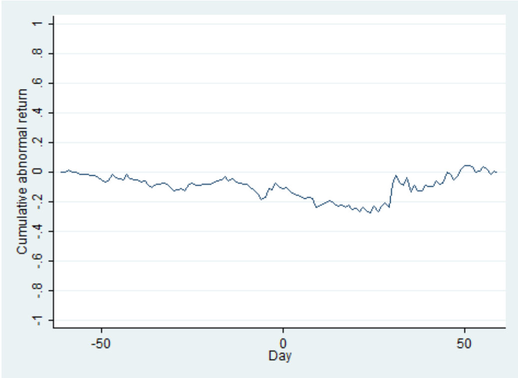
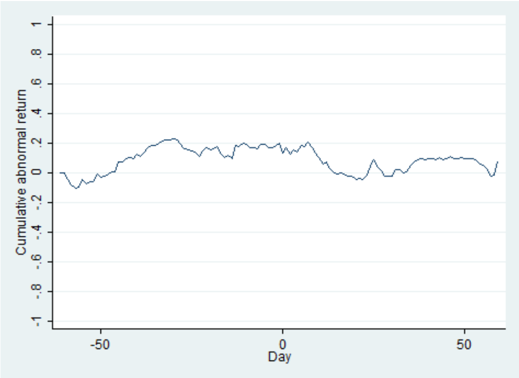


Figure 8 and *Figure 9*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. Comair plane crash on 9.1.1997 (left) and Trans World Airlines plane crash on 17.7.1996 (right).



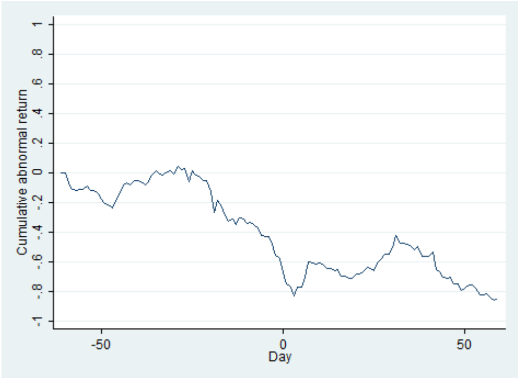
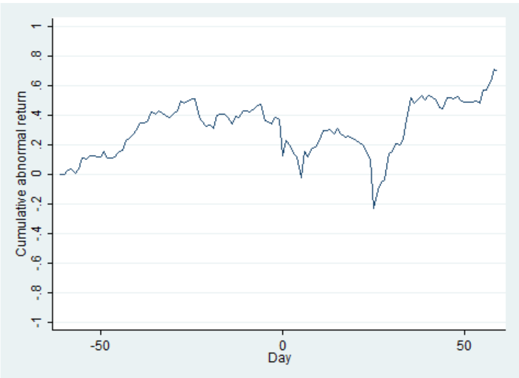


Figure 10 and *Figure 11*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. ValuJet plane crash on 11.5.1996 (left) and American Eagle Airlines plane crash on 31.10.1994 (right).



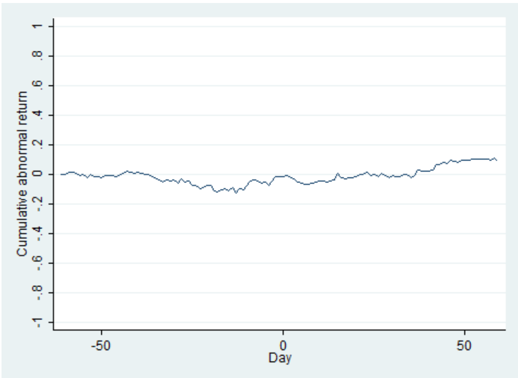
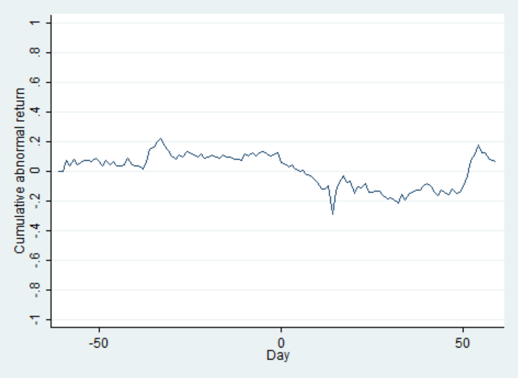


Figure 12 and *Figure 13*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. US Airways plane crash on 8.9.1994 (left) and US Airways plane crash on 8.9.1994 (right).



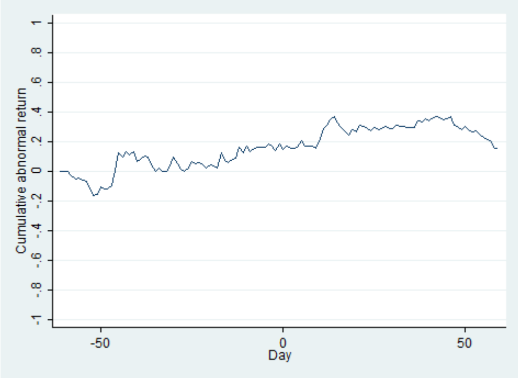
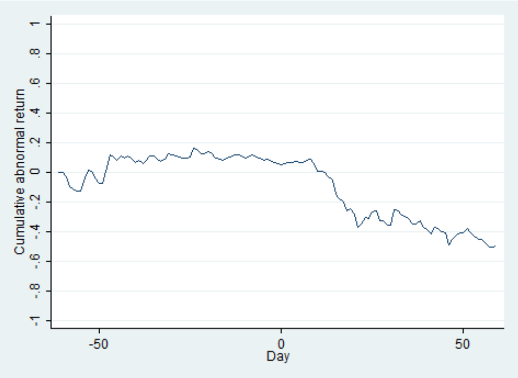


Figure 14 and *Figure 15*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. US Airways plane crash on 22.3.1992 (left) and Atlantic Southwest Airlines plane crash on 5.4.1991 (right).



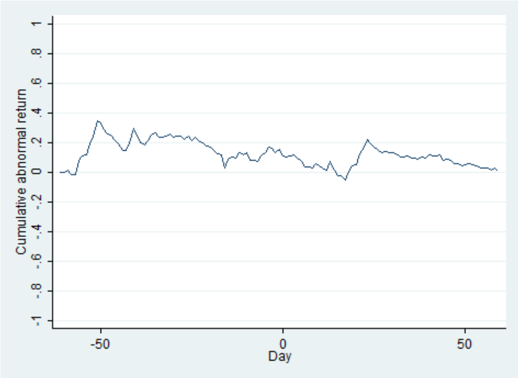
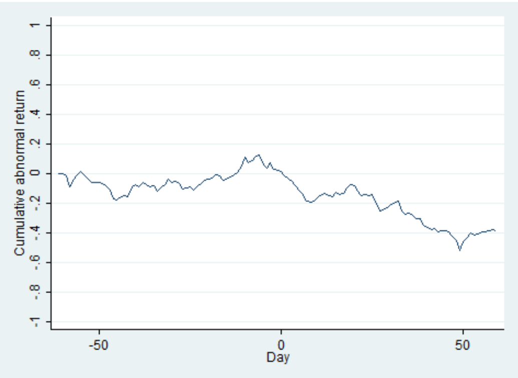
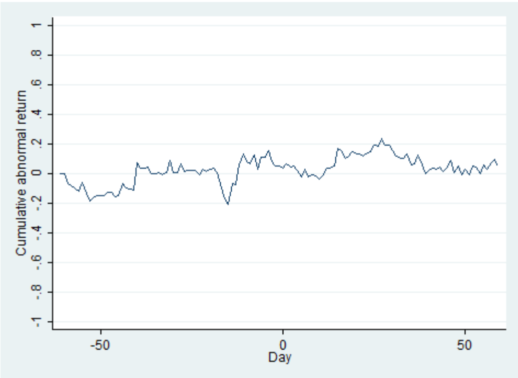


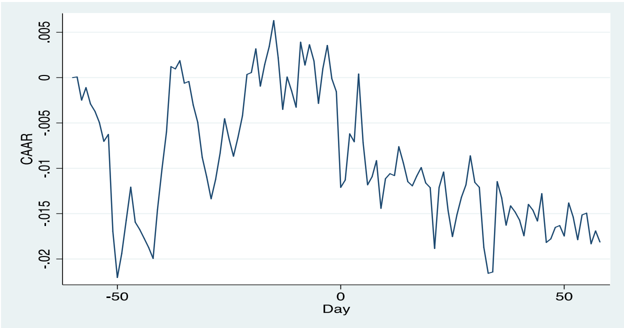
Figure 16 and *Figure 17*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. US Airways plane crash on 1.2.1991 (left) and SkyWest Airlines plane crash on 1.2.1991 (right).





6.1.2 Hypothesis 2: Airplane crashes negatively affect stock performance of aircraft manufacturers.

Figure 18. Cumulative average abnormal return across 60 days before and after the crash (based on 14 crash events).



In case of airplane manufacturers' stock price reaction to airplane crashes we immediately observe that the scale of market response is several times lower than in the case of airlines. Cumulative average abnormal returns do not decline below -1.5% in the first 15 days of trading but seem to persist to Day 30 and beyond. The t-statistic also tells us that the obtained results are not statistically significant except on Days 1 and 2.

These results are in line with Walker et al. (2005) who observed statistically significant declines in intervals 1, 2 and 7 days after the crash. The price reversal effect is present on Day 3 and Day 5 (abnormal returns of 0.5% and 0.8%, respectively).

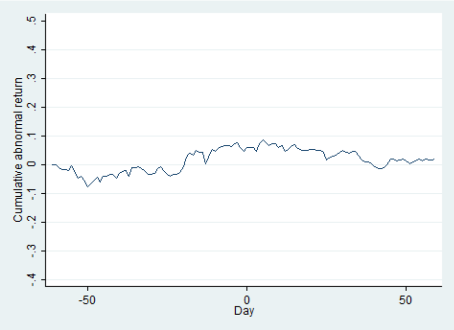
Table 12. Cumulative average abnormal returns for 15 days after the crash, with tests of statistical significance.

Interval of days after the crash	CAAR (%)	T-statistic
0-1	-1.1	***-2,68
0-2	-1.0	*-1,75
0-3	-0.5	-0,68
0-4	-0.6	-0,70
0-5	0.2	0,22
0-6	-0.6	-0,58
0-7	-1.0	-0,99
0-8	-0.9	-0,84
0-9	-0.8	-0,64
0-10	-1.3	-1,03
0-11	-1.0	-0,74
0-12	-0.9	-0,66
0-13	-0.9	-0,65
0-14	-0.6	-0,41
0-15	-0.8	-0,51

Legend: *** denotes statistical significance at 1%, ** statistical significance at 5% and * statistical significance at 10% level.

Similarly to the data used to test Hypothesis 1, charts on cumulative abnormal returns on individual stocks of involved manufacturers (Figure 19 to Figure 32) exhibit very little resemblance among each other, while cumulatively still producing statistically significant negative abnormal returns shortly after the crash (Figure 18).

Figure 19 and *Figure 20.* Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. Boeing plane crash on 6.8.1997 (left) and Boeing plane crash on 17.7.1996 (right).



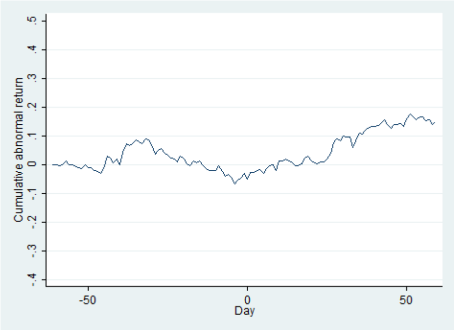
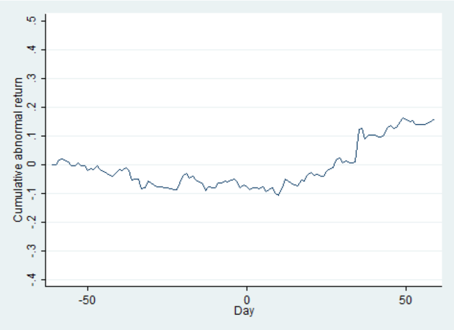


Figure 21 and *Figure 22.* Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. McDonnell Douglas plane crash on 11.5.1996 (left) and Boeing plane crash on 8.9.1994 (right).



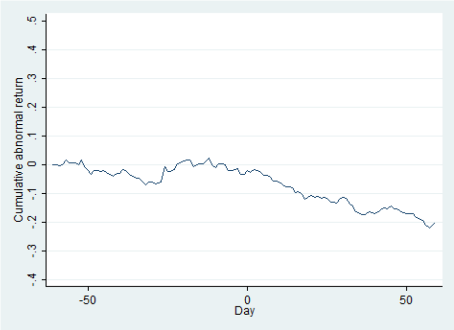
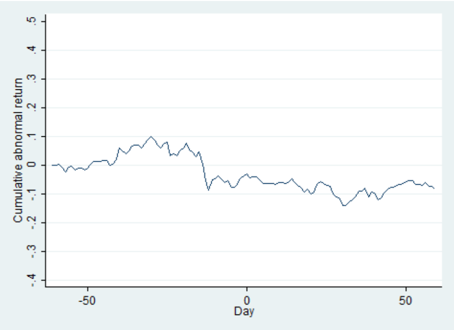


Figure 23 and *Figure 24.* Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. Boeing plane crash on 3.3.1991 (left) and Boeing plane crash on 1.2.1991 (right).



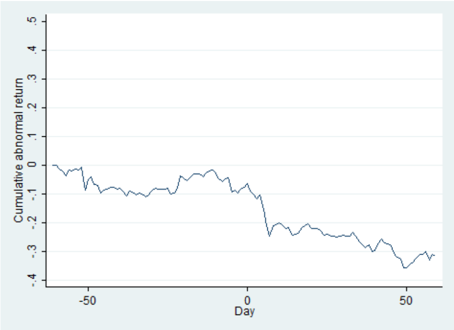
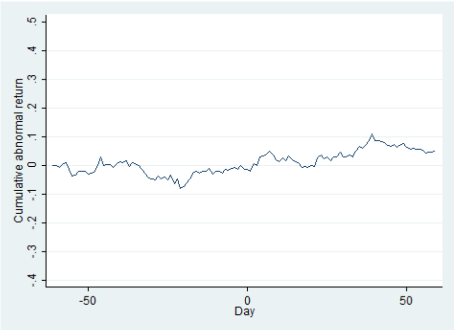


Figure 25 and *Figure 26.* Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. Boeing plane crash on 25.1.1990 (left) and McDonnell Douglas plane crash on 19.7.1989 (right).



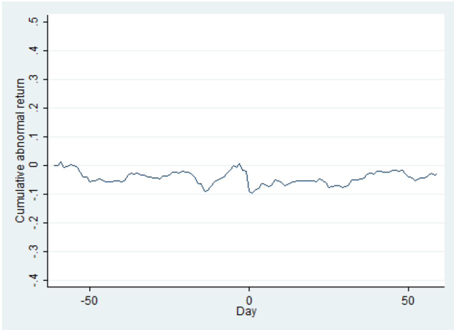
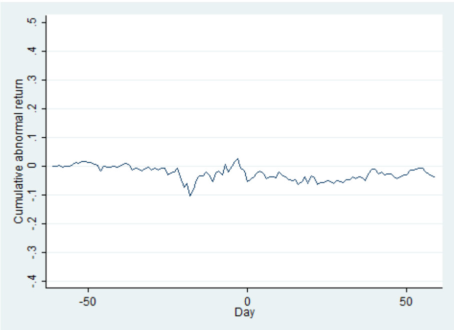


Figure 27 and *Figure 28.* Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. McDonnell Douglas plane crash on 15.11.1987 (left) and McDonnell Douglas plane crash on 16.8.1987 (right).



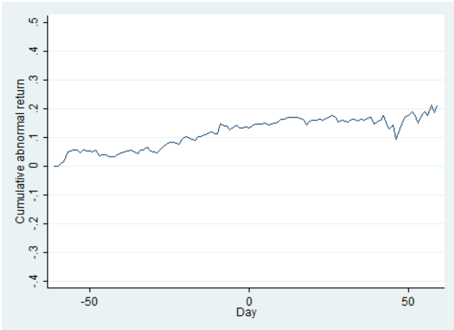
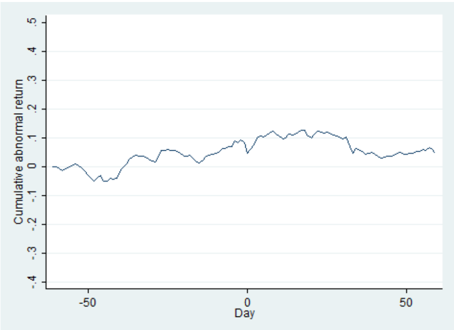


Figure 29 and *Figure 30.* Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. McDonnell Douglas plane crash on 31.8.1986 (left) and McDonnell Douglas plane crash on 6.9.1985 (right).



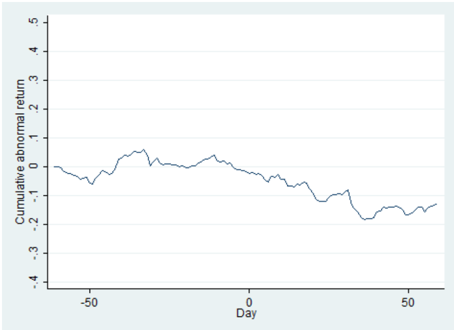
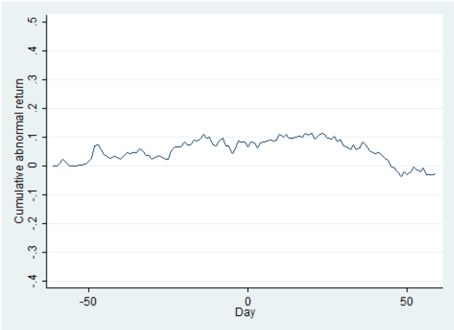
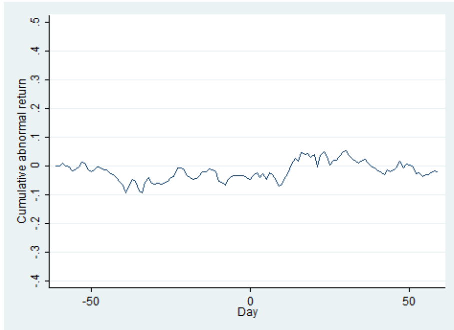


Figure 31 and *Figure 32*. Cumulative average abnormal return on involved airline stock across 60 days before and after the crash. Lockheed plane crash on 2.8.1985 (left) and Lockheed plane crash on 21.1.1985 (right).





6.1.3 Hypothesis 3: Crashes with 50 or more casualties result in higher average absolute abnormal returns of airlines' stocks.

The hypothesis is based on the reasoning that indirect effects of a crash (mainly lower customer demand) are more pronounced in cases where more victims were involved. More concretely, we hypothesize that crashes with more fatalities result in higher absolute abnormal returns in the observation period. We measure the effect in absolute terms as the stock price might exhibit a price reversal phenomenon in the observation period. We test our hypothesis by a two-sample t-test on average absolute abnormal returns of two groups of crash events, shown below.

Table 13. List of crashes with less than 50 casualties.

Crash Date	Trading day	Location	Air Carrier	Total Fatal Injuries
1.2.1991	4.2.1991	Los Angeles, CA	SkyWest Airlines	34
1.2.1991	4.2.1991	Los Angeles, CA	US Airways	34
5.4.1991	8.4.1991	Brunswick, GA	Atlantic Southeast Airlines	23
22.3.1992	23.3.1992	Flushing, NY	US Airways	27
2.7.1994	5.7.1994	Charlotte, NC	US Airways	37
9.1.1997	10.1.1997	Monroe, MI	Comair	29

Source: *NTSB Aviation Accident Database and Synopses,* 2014; *ASN Aviation Safety Database*, 2014.

Table 14. List of crashes with 50 or more casualties.

Crash Date	Trading day	Location	Air Carrier	Total Fatal Injuries
8.9.1994	9.9.1994	Aliquippa, PA	US Airways	132
31.10.1994	1.11.1994	Roselawn, IN	American Eagle Airlines	68
11.5.1996	13.5.1996	Miami, FL	ValuJet	110
17.7.1996	18.7.1996	East Moriches, NY	Trans World Airlines	230
31.1.2000	1.2.2000	Port Hueneme, CA	Alaska Airlines	88
12.2.2009	12.2.2009	Clarence Center, NY	Colgan Air	50

Source: *NTSB Aviation Accident Database and Synopses,* 2014; *ASN Aviation Safety Database*, 2014.

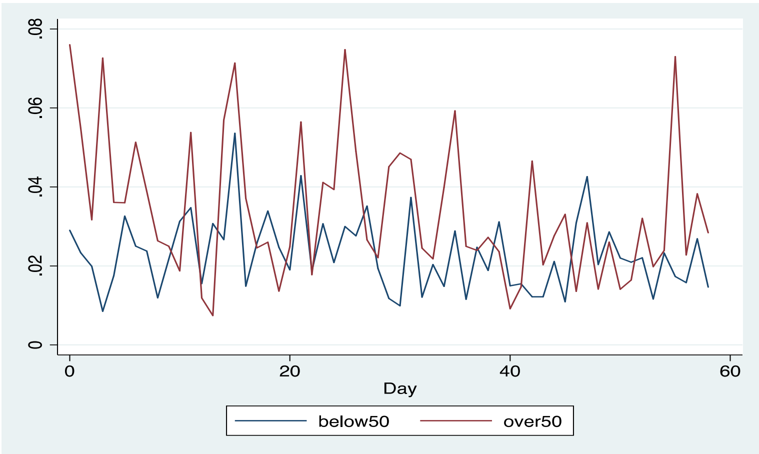
Table 15. Paired t-test results.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0231	0.0012	0.0092	0.0207	0.0254
over50	60	0.0338	0.0023	0.0178	0.0292	0.0384
diff	60	-0.0107	0.0023	0.0180	-0.0154	-0.0061

Paired t-test Degrees of freedom = 59 t = -4.6056 Significant at p < 0.001.

The test reveals statistically significant differences between average absolute abnormal returns of the two selected groups. As expected, the amplitude of abnormal returns is higher for the group of crashes that resulted in more than 50 casualties (3.4% versus 2.3%).

Figure 33. Average absolute abnormal returns of more fatal crashes (over 50 people killed) in 60 days after the event exceed those that resulted in less than 50 casualties.



The result seems intuitive, but is in apparent contradiction to findings related to another type of disaster, the infamous 1989 Exxon Valdes oil spill. Kahneman (2011, p. 93) cites a study conducted by Boyle et al. (1994) which found that participants had very low sensitivity to the number of deaths (in this case, of water birds) in terms of economic consequences. Different groups of participants were asked how much they were willing to pay for protective nets to cover oil ponds in which migratory birds often drown. The number of birds these nets could save varied from 2,000 to 20,000 to 200,000 birds according to the experimental design. The willingness to pay for the nets (and save the threatened birds) however, varied very little (average intended contributions were $80, $78, $88, respectively). The results imply that the number of birds makes almost no difference and that saving a (bird's) life does not behave like an economic good in the eyes of the survey participant.

Kahneman (2011, p. 93) argues that the participants in all cases neglected the number of birds in danger but reacted to a mental image of a helpless bird drowning in thick oil. In the case of airplane crashes, investors could have reacted only to a mental image of a burning plane, scattered debris and mourning relatives of the victims. Interestingly however, the effect of additional deaths on stock price in the case of aviation disasters is significant, implying that investors were affected by the number of victims – either rationally by considering the economic consequences or irrationally by reacting to more dramatic media reports.

6.1.4 Hypothesis 4: Competitors of the manufacturer, whose airplane crashed due to mechanical failure, exhibit positive abnormal stock returns.

The hypothesis is based on the following logic: An airplane crash caused by a mechanical failure negatively affects the trust in the manufacturer of the plane. Due to lower trust in the company, its customers will consider ordering airplanes from its competitors which should result in lower expected cash flows for the manufacturer and higher for the competition. However, there are alternative explanations of how a crash could affect airplane manufacturers:

- a crash of an old airplane could encourage air carriers to replace older planes in their fleets with new ones, increasing demand for new aircrafts
- a crash could stir doubts in air passenger safety, decrease the overall demand for flying and consequently demand for airplanes.

Bosch et al. (1998) examined competitive effects on airlines and found that the stock returns of airlines that competed on overlapping routes with the affected carrier exhibited positive abnormal returns. The competitive effect on airplane manufacturers, which is of interest to this paper, has not yet been studied.

Table 16. Crashes in the sample that were caused by a mechanical failure.

Date	Trading day	Location	Manufacturer	Total Fatal Injuries
6.9.1985	9.9.1985	Milwaukee, WI	McDonnell Douglas	31
3.3.1991	4.3.1991	Colorado Springs, CO	Boeing	25
8.9.1994	9.9.1994	Aliquippa, PA	Boeing	132
11.5.1996	13.5.1996	Miami, FL	McDonnell Douglas	110
17.7.1996	18.7.1996	East Moriches, NY	Boeing	230

Source: *NTSB Aviation Accident Database and Synopses*, 2014; *ASN Aviation Safety Database*, 2014.

The crash sample consists of five crashes. Stocks of three different U.S. firms are studied to determine competitive effects:

- the pair Boeing-Lockheed is used for the Milwaukee crash in 1985,
- the pair McDonnell Douglas-Lockheed is used for the Colorado Springs crash in 1991 and Aliquippa crash in 1994,
- only Boeing stock is used for the Miami crash in 1996,
- only McDonnell Douglas stock is used for East Moriches crash in 1996

The competitive effect of the last two crashes is observed on one company only (either Boeing or McDonnell Douglas), as Lockheed was no longer primarily an airplane manufacturer, but became a highly diversified corporation after the March 1995 merger with Martin Marietta, involved in various businesses such as defense, chemicals and electronics.

Figure 34. Competing manufacturers exhibit negative cumulative abnormal returns, but the negative trend starts before Day 0 and does not stand out in the generally volatile performance in the (-60, +200) period.

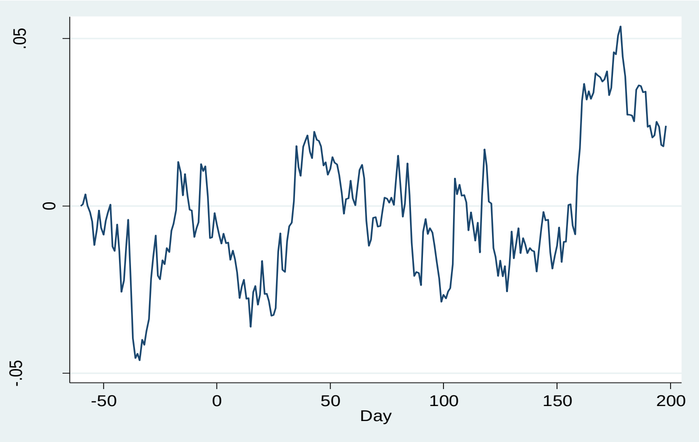


Table 17. Cumulative average abnormal returns for competitors with tests of statistical significance.

Interval of days after the crash	**CAAR (%)**	**T-statistic**
0-1	-0.3	-0.49
0-2	-0.7	-0.70
0-3	-0.9	-0.78
0-4	-0.6	-0.46
0-5	-0.9	-0.60
0-6	-0.9	-0.53
0-7	-1.4	-0.78
0-8	-1.1	-0.59

(continued)

(table continues)

Interval of days after the crash	CAAR (%)	T-statistic
0-9	-1.4	-0.68
0-10	-1.8	-0.83
0-11	-2.5	-1.14
0-12	-2.2	-0.94
0-13	-2.0	-0.82
0-14	-2.6	-1.01
0-15	-2.5	-0.97
0-50	1.1	-0.24
0-100	-2.6	-0.39
0-150	-1.3	-0.15
0-200	2.1	0.22

Legend: *** denotes statistical significance at 1%, ** statistical significance at 5% and * statistical significance at 10% level.

Our results show negative cumulative average abnormal returns in the first days following the crash, but they are not statistically significant. The decline starts before Day 0 and is smaller than changes in abnormal return around Days -40 and +160. Statistically significant longer-term positive cumulative abnormal returns, reported in Walker (2005) are also not present. The absence of a statistically significant effect could have one of the following explanations:

1. A crash of a single airplane has too little of an effect on a stock of such a large company such as Boeing, Lockheed or McDonnell Douglas (Davidson, 1987).
2. The crash happened in a volatile period for the manufacturers and is relatively small comparing to other important events in the observation period.
3. Manufacturer's stock strongly reacts only in case it is proved that mechanical error caused the crash. The evidence of mechanical error is usually not obtained immediately after the crash and may only be a result of long term investigation, thus obfuscating the effect.
4. Lockheed, Boeing and McDonnell Douglas are not the competitors that would benefit in case of plane crashes of one these companies, but other firms might. This option is not investigated as there were no other major publicly traded airplane manufacturers in the U.S. at the time and Airbus is a European corporation, which does not belong to our sample.

Explanation 1 is unlikely - there still are important indirect consequences for a manufacturer after an airplane crash. Additional data in robustness test section (high beta coefficients) present some supporting evidence for Explanation 2. Explanations 3 and 4 cannot be verified using the data scope available to this paper.

6.1.5 Hypothesis 5: Crashes with 50 or more casualties result in similar average absolute abnormal returns of airplane manufacturers' stocks as those crashes with less than 50 casualties.

The hypothesis is based on the reasoning that the number of airplane crash casualties should have no significant effect on manufacturers stock if investors consider only economic reasons. The most important consequence of a crash for a manufacturer should be the influence on future orders which is independent of the number of casualties. If investors reacted emotionally to more dramatic media reports, neglecting economic fundamentals then we could observe more pronounced absolute abnormal returns. We test our hypothesis by a two-sample t-test on average absolute abnormal returns of two groups of crash events, described below.

Table 18. List of crashes with less than 50 casualties.

Crash Date	Trading day	Location	Manufacturer	Total Fatal Injuries
6.9.1985	9.9.1985	Milwaukee, WI	McDonnell Douglas	31
15.11.1987	16.11.1987	Denver, CO	McDonnell Douglas	28
1.2.1991	4.2.1991	Los Angeles, CA	Boeing	34
3.3.1991	4.3.1991	Colorado Springs, CO	Boeing	25

Source: *NTSB Aviation Accident Database and Synopses*, 2014; *ASN Aviation Safety Database*, 2014.

Table 19. List of crashes with 50 or more casualties.

Crash Date	Trading day	Location	Manufacturer	Total Fatal Injuries
21.1.1985	21.1.1985	Reno, NV	Lockheed	70
2.8.1985	5.8.1985	Dallas/FT Worth, TX	Lockheed	135
31.8.1986	2.9.1986	Cerritos, CA	McDonnell Douglas	82
16.8.1987	17.8.1987	Romulus, MI	McDonnell Douglas	156
19.7.1989	19.7.1989	Sioux City, IA	McDonnell Douglas	111
25.1.1990	26.1.1990	Cove Neck, NY	Boeing	73
8.9.1994	5.7.1994	Aliquippa, PA	Boeing	132
11.5.1996	9.9.1994	Miami, FL	McDonnell Douglas	110
17.7.1996	13.5.1996	East Moriches, NY	Boeing	230
6.8.1997	18.7.1996	Nimitz Hill, GU	Boeing	228

Source: *NTSB Aviation Accident Database and Synopses*, 2014; *ASN Aviation Safety Database*, 2014.

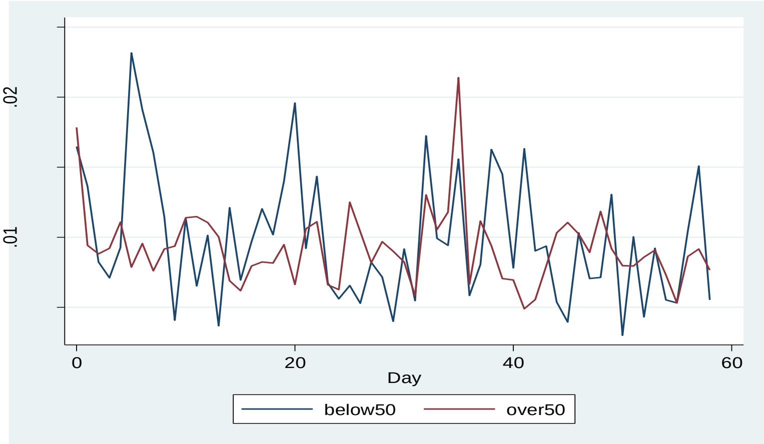
Table 20. Paired t-test results.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0098	0.00058	0.00450	0.0086	0.0110
over50	60	0.0092	0.00035	0.00270	0.0085	0.0099
diff	60	0.0006	0.00062	0.00482	-0.0007	-0.0018

Paired t-test   Degrees of freedom = 59   t = 0.9280   Significant at p < 0.3572.

The test reveals no statistically significant difference between average absolute abnormal returns of the two selected groups. The amplitude of abnormal returns is even slightly higher for the group of crashes that resulted in less than 50 casualties (0.98% versus 0.92%).

Figure 35. Average absolute abnormal returns of more fatal crashes (over 50 people killed) in 60 days after the event are on average not significantly higher than those that resulted in less than 50 casualties.



The results suggest that a higher number of casualties does not significantly affect investors in the stock of the involved airplane manufacturer. This supports the explanation that these investors consider fundamental economic factors and disregard the influence of factors such as the number of victims which is relevant to the involved airline, but not the manufacturer.

6.2 Robustness checks to alternative estimation window specifications

In order to check if the obtained results have been influenced by the specific setting of the chosen methodology, we also run the regressions using alternative specifications of the estimation window to compare the results to the ones obtained using the base case of 120 trading days. The parameters of the market model are measured using regression of security returns against market portfolio 60, 90, 150 and 180 trading days before the crash.

6.2.1 Hypothesis 1: Airplane crashes negatively affect stock performance of airlines.

Figure 36. Alternative specifications of the estimation window produce similarly significant change in cumulative abnormal return for airlines around the days of the crash.

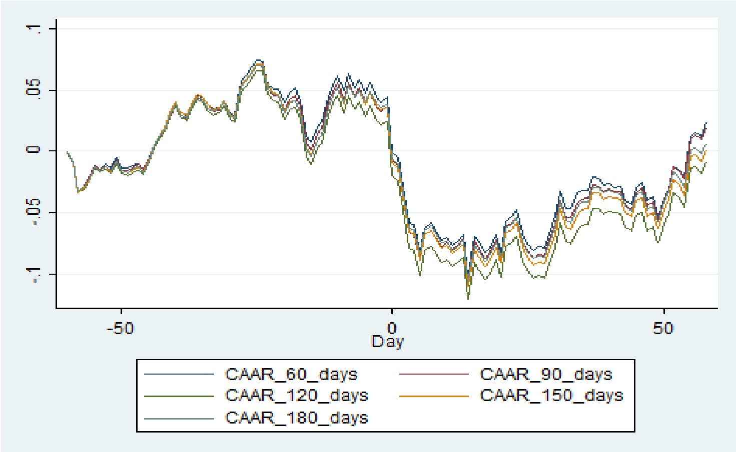


Table 21. Statistical significance of cumulative abnormal return is unchanged under different specifications of estimation window.

Interval of days after the crash	CAAR 60 days (%)	T-statistic 60 days	CAAR 120 days (%)	T-statistic 120 days	CAAR 180 days (%)	T-statistic 180 days
0-1	-4.4	-3.81***	-4.3	-3.93***	-4.5	-4.14***
0-2	-4.8	-2.96***	-4.8	-3.09***	-4.9	-3.23***
0-3	-7.2	-3.63***	-7.2	-3.75***	-7.1	-3.82***
0-4	-10.2	-4.42***	-10.2	-4.62***	-10.0	-4.69***
0-5	-10.3	-4.02***	-10.4	-4.21***	-10.2	-4.25***
0-6	-12.5	-4.45***	-12.5	-4.60***	-12.2	-4.66***
0-7	-10.6	-3.48***	-10.5	-3.57***	-10.3	-3.63***
0-8	-10.2	-3.15***	-10.1	-3.23***	-9.9	-3.26***
0-9	-10.7	-3.11***	-10.6	-3.18***	-10.4	-3.24***
0-10	-11.6	-3.18***	-11.4	-3.26***	-11.2	-3.32***
0-11	-11.3	-2.97***	-11.2	-3.05***	-11.1	-3.12***
0-12	-12.0	-3.01***	-11.7	-3.06***	-11.8	-3.19***
0-13	-11.6	-2.81***	-11.4	-2.87***	-11.5	-2.99***
0-14	-11.1	-2.59 **	-11.0	-2.65 **	-11.0	-2.75 ***
0-15	-14.5	-3.26***	-14.4	-3.36***	-14.4	-3.47***

Legend: *** denotes statistical significance at 1%, ** statistical significance at 5% and * statistical significance at 10% level.

Table 22. Airlines stocks' short term beta coefficients vary according to the alternative specifications of the estimation window.

Crash date	**Carrier**	**60-days Beta coefficient**	**90-days Beta coefficient**	**120-days Beta coefficient**	**150-days Beta coefficient**	**180-days Beta coefficient**
1.2.1991	SkyWest Airlines	1.75	1.71	1.17	1.03	1.04
1.2.1991	US Airways	2.97	2.45	2.60	2.59	2.44
5.4.1991	Atlantic Southeast Airlines	1.63	1.67	1.33	1.07	1.41
22.3.1992	US Airways	2.01	2.05	2.66	2.55	2.32
2.7.1994	US Airways	1.77	1.06	0.89	0.91	0.82
8.9.1994	US Airways	1.16	1.12	1.25	0.90	0.90
31.10.1994	American Eagle Airlines	1.88	1.74	1.56	1.50	1.51
11.5.1996	ValuJet	0.31	0.45	1.27	1.43	1.30
17.7.1996	Trans World Airlines	0.59	0.15	0.09	0.60	0.93
9.1.1997	Comair	0.39	0.72	0.12	0.14	0.08
31.1.2000	Alaska Airlines	0.23	0.55	0.57	0.53	0.60
12.2.2009	Colgan Air	0.52	0.59	0.53	0.56	0.56

Hypothesis 1 conclusion: Despite different specifications of the estimation window resulting in varying beta coefficients, the significant negative average abnormal returns in the days after the airplane crash remain statistically significant and are therefore robust to changes in the estimation window length. Hypothesis 1 is confirmed with 99% confidence level at least up to Day 12 after the crash.

6.2.2 Hypothesis 2: Airplane crashes affect stock performance of aircraft manufacturers.

Figure 37. Alternative specifications of the estimation window produce similar changes of cumulative abnormal return for airplane manufacturers in the first days after the crash (a drop and reversal) but then the cumulative abnormal returns start to diverge.

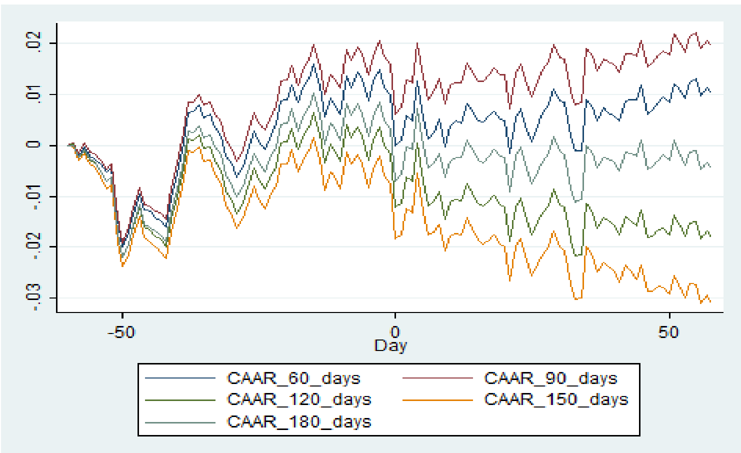


Table 23. Statistical significance of cumulative abnormal return is unchanged under different specifications of estimation window.

Interval of days after the crash	CAAR 90 days (%)	T-statistic 60 days	CAAR 120 days (%)	T-statistic 120 days	CAAR 180 days (%)	T-statistic 150 days
0-1	-1.0	**-2.50	-1.1	***-2.68	-1.1	***-2.80
0-2	-0.9	*-1.55	-1.0	*-1.75	-1.0	**-1.83
0-3	-0.3	-0.47	-0.5	-0.68	-0.5	-0.71
0-4	-0.4	-0.48	-0.6	-0.70	-0.5	-0.71
0-5	0.4	0.47	0.2	0.22	0.2	0.25
0-6	-0.3	-0.28	-0.6	-0.58	-0.5	-0.57
0-7	-0.7	-0.68	-1.0	-0.99	-1.0	-0.98
0-8	-0.5	-0.47	-0.9	-0.84	-0.9	-0.87
0-9	-0.3	-0.24	-0.8	-0.64	-0.8	-0.69
0-10	-0.8	-0.63	-1.3	-1.03	-1.3	-1.08
0-11	-0.4	-0.32	-1.0	-0.74	-1.0	-0.80
0-12	-0.4	-0.26	-0.9	-0.66	-1.0	-0.73
0-13	-0.4	-0.26	-0.9	-0.65	-1.0	-0.72
0-14	0.0	0.00	-0.6	-0.41	-0.7	-0.47
0-15	-0.1	-0.09	-0.8	-0.51	-0.9	-0.58

Legend: *** denotes statistical significance at 1%, ** statistical significance at 5% and * statistical significance at 10% level.

Table 24. Airplane manufacturers stocks' short term beta coefficients are quite stable in the alternative specifications of the estimation window, with the exception of McDonnell Douglas stock around the crash in 1989.

Crash date	Carrier	60-days Beta coefficient	90-days Beta coefficient	120-days Beta coefficient	150-days Beta coefficient	180-days Beta coefficient
21.1.1985	Lockheed	1.29	1.40	1.39	1.45	1.42
2.8.1985	Lockheed	1.52	1.46	1.38	1.57	1.51
6.9.1985	McDonnell Douglas	1.04	1.11	1.16	1.36	1.45
31.8.1986	McDonnell Douglas	0.79	0.86	0.70	0.69	0.75
16.8.1987	McDonnell Douglas	0.87	0.85	0.81	0.77	0.90
15.11.1987	McDonnell Douglas	0.72	0.73	0.73	0.73	0.73
19.7.1989	McDonnell Douglas	0.08	0.22	0.42	0.49	0.52
25.1.1990	Boeing	1.27	1.30	1.37	1.30	1.32
1.2.1991	Boeing	1.79	1.58	1.71	1.69	1.56
3.3.1991	Boeing	1.41	1.48	1.49	1.61	1.59
8.9.1994	Boeing	1.10	0.86	0.83	0.78	0.64
11.5.1996	McDonnell Douglas	0.97	0.89	0.81	0.66	0.76
17.7.1996	Boeing	1.52	1.32	1.32	1.27	1.37
6.8.1997	Boeing	1.10	1.26	1.21	1.22	1.20

Hypothesis 2 conclusion: Negative average abnormal returns after the crash in the case of airplane manufacturers were in base case (estimation window of 120 trading days) statistically significant only in the first two days after the crash; this also holds in alternative lengths of the estimation window. By using alternative specifications of the estimation window we show that the cumulative average abnormal returns beyond Day 2 are not robust to changes in the estimation window. In some specifications they exhibit a rising and in some a declining trend. Hypothesis 2 is confirmed only for Day 1 and Day 2 after the crash with 95% and 90% confidence level, respectively. A reversal effect is observed on Day 3 and Day 5.

6.2.3 Hypothesis 3: Crashes with 50 or more casualties result in higher average absolute abnormal returns of airlines' stocks.

Figure 38: Alternative specifications of the estimation window result in almost identical differences between absolute abnormal returns associated with the group of crashes with less than 50 casualties in comparison to the absolute abnormal returns associated with the group of crashes with more than 50 casualties.

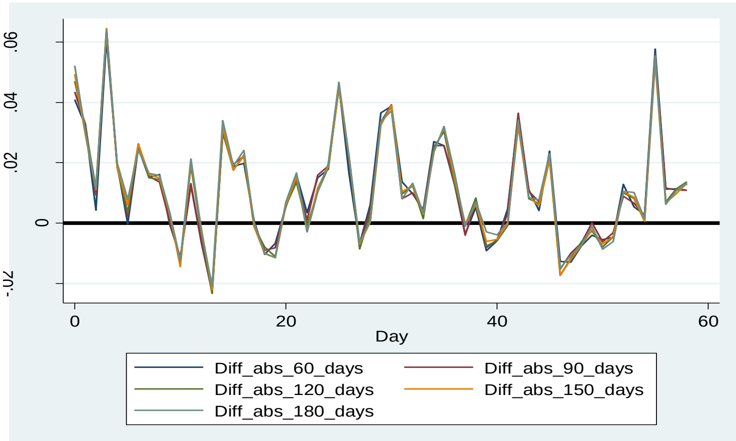


Table 25. Paired t-test results with 60 days long estimation window.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0235	0.0012	0.0096	0.0211	0.0260
over50	60	0.0343	0.0023	0.0177	0.0298	0.0389
diff	60	-0.0108	0.0023	0.0176	-0.0153	-0.0062

Paired t-test **Degrees of freedom = 59** **t = -4.7373** **Significant at p < 0.001.**

Table 26. Paired t-test results with 120 days long estimation window.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0231	0.0012	0.0092	0.0207	0.0254
over50	60	0.0338	0.0023	0.0178	0.0292	0.0384
diff	60	-0.0107	0.0023	0.0180	-0.0154	-0.0061

Paired t-test **Degrees of freedom = 59** **t = -4.6056** **Significant at p < 0.001.**

Table 27. Paired t-test results with 180 days long estimation window.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0226	0.0012	0.0090	0.0203	0.0249
over50	60	0.0340	0.0023	0.0180	0.0294	0.0387
diff	60	-0.0114	0.0023	0.0181	-0.0154	-0.0067

Paired t-test **Degrees of freedom = 59** **t = -4.8767** **Significant at p < 0.001.**

Hypothesis 3 conclusion: Despite different specifications of estimation window, the absolute abnormal returns in the case of crashes with more than 50 casualties are stable and significantly higher than those in the case of crashes with less than 50 casualties. Hypothesis 3 is confirmed at a 99.9% confidence level and is robust relative to the specification of the estimation window.

6.2.4 Hypothesis 4: Competitors of the manufacturer, whose airplane crashed due to mechanical failure, exhibit positive abnormal stock returns.

Figure 39. Alternative specifications of the estimation window produce varying changes of cumulative abnormal return for competing airplane manufacturers (especially after Day 40), further confirming that the competitive effects of airplane crashes in our study are not statistically significant.

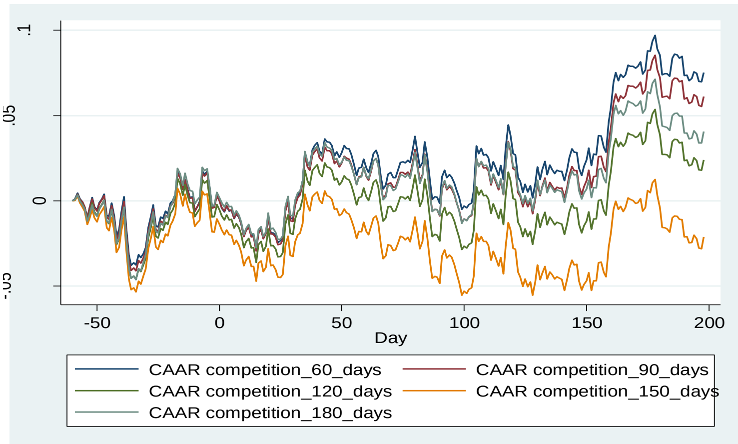


Table 28. Cumulative abnormal returns are also not statistically significant under different specifications of estimation window.

Interval of days after the crash	CAAR 60 days (%)	T-statistic 60 days	CAAR 120 days (%)	T-statistic 120 days	CAAR 150 days (%)	T-statistic 150 days
0-1	-0.3	-0.49	-0.3	-0.49	-0.3	-0.52
0-2	-0.8	-0.77	-0.7	-0.70	-0.7	-0.72
0-3	-1.0	-0.80	-0.9	-0.78	-0.9	-0.82
0-4	-0.7	-0.47	-0.6	-0.46	-0.7	-0.51
0-5	-1.0	-0.60	-0.9	-0.60	-0.9	-0.65
0-6	-0.9	-0.52	-0.9	-0.53	-1.0	-0.59
0-7	-1.4	-0.73	-1.4	-0.78	-1.5	-0.86
0-8	-1.1	-0.55	-1.1	-0.59	-1.3	-0.68
0-9	-1.3	-0.62	-1.4	-0.68	-1.6	-0.80
0-10	-1.7	-0.75	-1.8	-0.83	-2.0	-0.95
0-11	-2.4	-1.03	-2.5	-1.14	-2.8	-1.27
0-12	-2.0	-0.82	-2.2	-0.94	-2.4	-1.07
0-13	-1.8	-0.71	-2.0	-0.82	-2.2	-0.94
0-14	-2.4	-0.89	-2.6	-1.01	-2.8	-1.14
0-15	-2.3	-0.85	-2.5	-0.97	-2.8	-1.11
0-50	2.2	0.43	1.1	-0.24	0.2	0.04
0-100	-0.8	-0.12	-2.6	-0.39	-4.5	-0.68
0-150	1.7	0.19	-1.3	-0.15	-3.8	-0.48
0-200	6.7	0.66	2.1	0.22	-1.6	0.17

Table 29. Competitor stocks' short term beta coefficients in selected estimation windows. Some stocks were extremely volatile with betas above 5 (Lockheed 1991, 1994, McDonnell Douglas 1994).

Crash date	Carrier	60-days Beta coefficient	90-days Beta coefficient	120-days Beta coefficient	150-days Beta coefficient	180-days Beta coefficient
6.9.1985	Boeing	1.84	1.95	2.01	2.06	1.94
6.9.1985	Lockheed	1.47	1.42	1.40	1.42	1.51
3.3.1991	McDonnell Douglas	1.57	1.29	1.04	0.85	8.18
3.3.1991	Lockheed	5.22	6.03	6.39	5.79	6.02
8.9.1994	McDonnell Douglas	9.52	8.87	8.06	6.60	7.57
8.9.1994	Lockheed	9.02	1.05	9.23	8.04	7.69
11.5.1996	Boeing	1.52	1.33	0.13	1.28	1.37
17.7.1996	McDonnell Douglas	0.14	1.45	1.28	1.11	1.12

Hypothesis 4 conclusion: Negative abnormal returns after the crash in the case of airplane manufacturers' competitors were not statistically significant in base case (estimation window of 120 trading days). By using alternative specifications of the estimation window we confirm that they are not statistically significant and are not robust to changes in the estimation window. Some crashes, namely those in 1991 and 1994, happened in a volatile period for the competitors stock, thus possibly obfuscating the event effect. Based on the obtained results, Hypothesis 4 is rejected.

6.2.5 Hypothesis 5: Crashes with 50 or more casualties result in similar average absolute abnormal returns of airplane manufacturers' stocks as those crashes with less than 50 casualties.

Figure 40. Alternative specifications of the estimation window result in almost identical differences between absolute abnormal returns associated with the group of crashes with less than 50 casualties in comparison to the absolute abnormal returns associated with the group of crashes with more than 50 casualties.

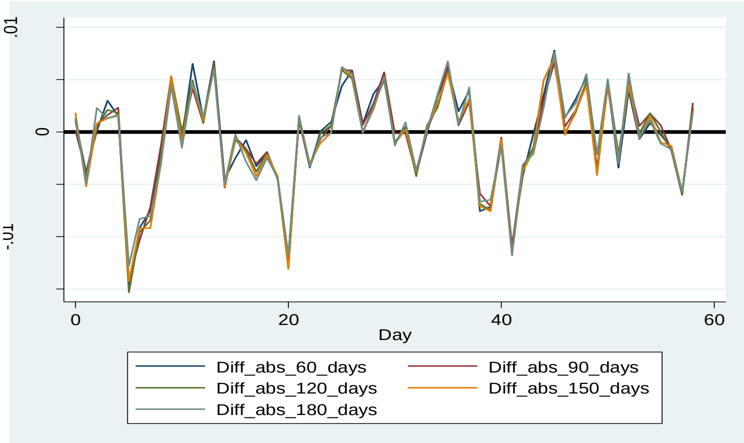


Table 30. Paired t-test results with 60 days long estimation window.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0098	0.00058	0.00449	0.0087	0.0110
over50	60	0.0094	0.00035	0.00269	0.0087	0.0101
diff	60	0.0004	0.00062	0.00484	-0.0008	-0.0017

Paired t-test Degrees of freedom = 59 t = 0.6750 Significant at p < 0.5023.

Table 31. Paired t-test results with 120 days long estimation window.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0098	0.00058	0.00450	0.0086	0.0110
over50	60	0.0092	0.00035	0.00270	0.0085	0.0099
diff	60	0.0006	0.00062	0.00482	-0.0007	-0.0018

Paired t-test Degrees of freedom = 59 t = 0.9280 Significant at p < 0.3572.

Table 32. Paired t-test results with 180 days long estimation window.

Variable	Observations	Mean	Std. Err.	Std. Dev.	[95% confidence interval]	
below50	60	0.0098	0.00057	0.00441	0.0087	0.0109
over50	60	0.0093	0.00037	0.00284	0.0086	0.0101
diff	60	0.0005	0.00061	0.00469	-0.0007	0.0017

Paired t-test   Degrees of freedom = 59   t = 0.7693   Significant at p < 0.4448.

Hypothesis 5 conclusion: Despite different specifications of the estimation window, the average absolute abnormal return for crashes with more than 50 casualties is stable in the range 0.92-0.94% and is not significantly different from the average absolute abnormal return for crashes with less than 50 casualties (0.92-0.93%). Hypothesis 5 is confirmed; difference of the means is at most 0.06% and is not statistically significant in any observed scenario.

CONCLUSION

In this paper we examined the effect airplane crashes have on stocks of U.S. airlines and airplane manufacturers that were involved in the crashes. Our key results are the following:

- **Hypothesis 1:** We confirm the negative influence of the crashes on stock performance up to 13 days after the accident with statistical significance of 99% using one-tailed test. Average first-day abnormal return is -4.3% and the negative effect seems to continue to influence the stock performance up to Day 6 after the accident when the cumulative average abnormal return reaches -12.5%. The results are robust with regards to changes in the estimation window; they are consistent with those obtained by other researchers (Walker et al., 2005, Chance & Ferris, 1987), but the magnitude of the observed effect is much stronger.
- **Hypothesis 2:** We find market reaction in case of airplane manufacturers' stock price to be much less pronounced. The cumulative average abnormal returns do not fall below -1.3% in the first 15 days of trading. The t-statistic is not statistically significant except on Days 1 and 2. Cumulative average abnormal returns beyond Day 2 are not robust to changes in the estimation window. Results are in line with those of Walker et al. (2005) who observed statistically significant declines in intervals 1, 2 and 7 trading days after the crash.
- **Hypothesis 3:** We confirm that crashes, which resulted in more than 50 casualties, are associated with higher average absolute abnormal returns in comparison to those that caused between 20 and 50 casualties (3.4% versus 2.3%). Results are statistically significant and robust to changes in the estimation window.

- **Hypothesis 4:** Our results show negative cumulative average abnormal returns in the first days following the crash, but they are not statistically significant. Longer-term positive cumulative average abnormal returns (also reported in Walker et al. (2005)) are not robust to changes in the length of the estimation window and are not statistically significant.
- **Hypothesis 5:** We confirm that crashes, which resulted in more than 50 casualties, do not result in higher average absolute abnormal returns in comparison to crashes that caused between 20 and 50 casualties (0.93% versus 0.98%). The observed difference is not statistically significant in any observed estimation window scenario.

The results under Hypothesis 1 and Hypothesis 2 suggest that in the first days after the crash the efficient market hypothesis is temporarily violated as investors act (sell) on the same information for a longer period of time. A savvy investor could profit from short-selling the stock of the involved airline (or manufacturer) immediately upon reception of the news and then buying it a few days later. The majority of investors seem to be under the influence of cognitive biases triggered by rare negative events, described by Kahneman (2011, p. 105, 322).These include focus on the existing evidence (media reports) and ignoring absent evidence (available after the official investigation), over-weighting low probabilities (the crash can easily happen again) and diminishing sensitivity to quantity (what is value of a lost plane in comparison to the value of the corporation that owns it?). The findings suggest that if a regulator stopped trading in the involved stock for a few days to prevent the decision making under cognitive biases, the stock price would decrease less dramatically and more in line with the change in economic fundamentals.

The results under Hypothesis 3 suggest that investors consider (consciously or unconsciously) the number of fatalities as an important factor affecting their view on the appropriate price of the relevant airline stock. We speculate that the main reason for this is that they expect a greater negative effect on customer demand (irrational on the side of the customers) or they themselves are subject to irrational decision making. The tests of Hypothesis 5 indicate that the number of casualties does not affect average absolute abnormal returns of manufacturer’s stock in post-crash period. Different sensitivity to the number of casualties in case of airlines (Hypothesis 3) and airplane manufacturers (Hypothesis 5) can be rationally explained and does not provide additional evidence of investors’ cognitive biases.

We acknowledge the limitations of the obtained results. First, the event sample is very specifically defined: it involves only U.S. based airplane crashes in which publicly-traded U.S. airlines or airplane manufacturers were involved. Reactions to airplane crashes in other countries or to other companies may be different. Secondly, the extent of the market reaction to airplane crashes may be dependent on the cause of the crash; disasters caused by terrorists or technical errors may spur stronger reactions by airplane passengers and investors than those caused by bad weather conditions. We are unable to claim that the events in our sample are representative of the general population of airplane crashes in terms of the underlying causes. Our strict definition results in rather limited event samples (data from twelve airplane crashes was used in testing the effects on airlines' stock performance and fourteen crashes in the case of airplane manufacturers), thus putting a constraint on the generalizability of our conclusions.

REFERENCE LIST

1. Abadie, A., Diamond, A., & Hainmueller, J. (2010): Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, *105*(490), 493-505.
2. Acemoglu, D., Johnson, S., Kermani, A., Kwak, J., & Mitton, T. (2013). *The value of connections in turbulent times: Evidence from the United States* (No. w19701). Cambridge: National Bureau of Economic Research.
3. Airline Deregulation Act of 1978, Pub. L. 95-504, 92 Stat. 1705, codified as amended at 49 U.S.C. §§ 1301-1522.
4. *American Airlines Group Overview*. Retrieved August 6, 2014, from www.aa.com/i18n/amrcorp/corporateInformation/facts/americanairlinesgroup.jsp
5. Andrade, G., Mitchell, M.L., & Stafford, E. (2001). New evidence and perspective on mergers. *Journal of Economic Perspectives*, *15*(2), 103-120.
6. Anichebe, T. (2014). Boeing, Airbus rivalry: Lessons in strategic planning. Retrieved August 23, 2014, from http://newtelegraphonline.com/boeing-airbus-rivalry-lessons-in-strategic-planning/.
7. *ASN Aviation Safety Database*. Retrieved August 6, 2014, from http://aviation-safety.net/database/
8. Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of accounting research*, 159-178.
9. Barnett, A. (1990). Air safety: End of the golden age? *New Directions for Statistics and Computing*, *3*(2), 8-12.
10. Basu, S. (1977). Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A test of the Efficient Markets Hypothesis. *Journal of Finance*, *32*(3), 663–682.
11. Bhagat, S., Dong, M. Hirshleifer, D., & Noah, R. (2005). Do tender offers create value? New methods and evidence. *Journal of Financial Economics*, 76, 3-60.
12. Bhagat, S., & Romano, R. (2007). Empirical Studies of Corporate Law. In A.M. Polinsky, & S. Shavell (Eds.), *Handbook of Law and Economics* (pp. 950-951). US: North Holland.
13. Bosch, J.C., Eckard, E., & Singal, J. (1998). The competitive impact of air crashes: stock market evidence. *Journal of Law and Economics*, *41*(2), 503-519.
14. Boyle, K. J., Desvousges, W. H., Johnson, F. R., Dunford, R. W., & Hudson, S. P. (1994). An investigation of part-whole biases in contingent-valuation studies. *Journal of Environmental Economics and Management, 27*(1), 64-83.
15. Brenner, M. (1979). The Sensitivity of the Efficient Market Hypothesis to Alternate Specification of the Market Model. *Journal of Finance*, *34*(4), 915-929.
16. Brown, S., & Warner, J.B. (1980). Measuring Security Price Performance. *Journal of Financial Economics*, *8*(3), 205-258.
17. Campbell, J. Y., Lo, A.W., & MacKinlay, R.H., (1997). *The Econometrics of Financial Markets* (pp. 153-157). US: Princeton University Press.

18. Chan, K. C., Gup, B. E., & Pan, M. (2003). International Stock Market Efficiency and Integration: A Study of Eighteen Nations. *Journal of Business Finance & Accounting, 24*(6), 803-813.
19. *History of Colgan Air*. Retrieved August 6, 2014, from http://www.colganair.com/site/our_company/index.php
20. Chance, D. M., & Ferris, S.P. (1987). The effect of aviation disasters on the air transport industry. *Journal of Transport Economics and Policy*, *11*(2), 151-165.
21. *Current Market Outlook 2014*. Retrieved August 23, 2014, from http://www.boeing.com/boeing/commercial/cmo/
22. Damodaran, A. (2014). Market Efficiency – Definition and Tests, New York. Retrieved August 20, 2014, from http://pages.stern.nyu.edu/~adamodar.
23. Davidson, W. N., Chandy, P.R., & Cross, M. (1987). Large Losses, Risk Management and Stock Returns in the Airline Industry. *The Journal of Risk and Insurance*, *54*(1), 162-172.
24. Demsetz, H. (1968). The cost of transacting. *The quarterly journal of economics*, *82*(1), 33-53.
25. Event study. (n.d.). In *Investopedia*. Retrieved August 19, 2014, from http://www.investopedia.com/terms/e/eventstudy.asp.
26. Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International economic review*, *10*(1), 1-21.
27. Fama, E.F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*(2), 383-417.
28. Fama, E., & French, K. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47, 427–465.
29. Fischer, I. (1930). *The theory of interest*. Clifton: Augustus M. Kelley Publishers.
30. Fisman, R. (2001). Estimating the Value of Political Connections. *The American Economic Review*, *91*(4), 1095-1102.
31. Gibson, G. (1889). *The Stock Markets of London, Paris and New York*. New York: G.P. Putnam's Sons.
32. *Global Commercial Aircraft Manufacturing: Market Research Report*. Retrieved August 24, 2014, from http://www.ibisworld.com/industry/global/ global-commercial-aircraft-manufacturing.html.
33. *Global Market Forecast 2013-2032*. Retrieved August 23, 2014, from http://www.airbus.com/company/market/forecast/
34. Graham, J., Lemmon, M., & Wolf, J. (2002). Does corporate diversification destroy value? *Journal of Finance*, *57*(2), 695-720.
35. Greist, J.H., & Greist, G.I. (1981). *Fearless flying: a passenger guide to modern airplane travel* (pp. 626-628). Chicago: Nelson Hall.
36. Grossman. S. J., & Stiglitz, J.E. (1980). On the impossibility of informationally efficient markets. *American Economic Review, 70*(3), 222-227.
37. Henckels, E. (2011). Airline Industry Overview. Retrieved August 23, 2014, from http://www.columbia.edu/cu/consultingclub/Resources/Airlines_Eric_Henckels.pdf

38. Intriligator, E.F. (1978). *Econometric Models Techniques and Application.* Englewood Cliffs: Prentice Hall.
39. Ito, H., & Lee, D. (2004). Comparing the impact of the September 11 terrorist attacks on international airline demand. *International Journal of the Economics of Business*, 12(2), 225-249.
40. Jensen, M. (1968). The Performance of Mutual Funds in the Period 1945-64. *Journal of Finance, 23*(2), 389-416.
41. Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of Financial Economics 6*(2), 95–101.
42. Kahneman, T. (2011). *Thinking, Fast and Slow*. London: Penguin Books.
43. Kahneman, T., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica (The Econometric Society), 47*(2), 263-291.
44. Kallianiotis, J.N. (2013). *International Financial Transactions and Exchange Rates.* New York: Palgrave Macmillan.
45. Kaplan, S., & Weisebach, M. (1992). The success of acquisitions: evidence from divestitures. *Journal of Finance, 47*(1), 107-138.
46. Kaplanski, G. & Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics*, *95*(2), 174-201.
47. Keynes, J. M. (1923). Some aspects of commodity markets. *Manchester Guardian Commercial: European Reconstruction Series*, 784–786.
48. Klick, J., & Sitkoff, R.H., (2008). Agency costs, charitable trusts, and corporate control: evidence from Hershey's kiss-off. *Columbia Law Review*, *108*(4), 749-838.
49. Klick, J., & Wright, J. D. (2012). *Grocery Bag Bans and Foodborne Illness.* Retrieved August 24, 2014 from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2196481
50. MacCauley, F. R. (1925). Forecasting security prices. *Journal of the American Statistical Association 20*(150), 244–249.
51. MacKinlay, R.H., (1997). Event Studies in Economics and Finance. *Journal of Economic literature*, *35*(1), 13-39.
52. Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives*, *17*(1), 59-82.
53. Mitchell, M. L. & Netter, J. M. (1994). The role of financial economics in securities fraud cases: Applications at the Securities and Exchange Commission. *Business Lawyer*, *49*(1), 545-590.
54. Mitra, G., & Mitra, L. (2011). *The Handbook of News Analytics in Finance.* Chichester: John Wiley & Sons.
55. Mulherin, J.H., & Boone, A.L. (2000). Comparing acquisitions and divestitures. *Journal of Corporate Finance*, *6*(2), 117-139.
56. Nethercutt, L. L., & Pruitt, S.W. (1997). Touched by tragedy: capita market lessons from the crash of ValuJet Flight 592. *Economics Letters*, *56*(3), 351-358.
57. Nicholson, F. (1968). Price-Earnings Ratios in Relation to Investment Results. *Financial Analysts Journal*, *24*(1), 105–109.

58. *NTSB Aviation Accident Database & Synopses*. Retrieved August 6, 2014, from http://www.ntsb.gov/aviationquery/index.aspx
59. *Orders & Deliveries*. Retrieved August 23, 2014, from http://active.boeing.com/commercial/orders/index.cfm
60. *Orders and Deliveries*. Retrieved August 23, 2014, from http://www.airbus.com/company/market/orders-deliveries/
61. Platzer, M. D. (2009). U.S. Aerospace Manufacturing: Industry Overview and Prospects. Retrieved August 23, 2014, from http://fas.org/sgp/crs/misc/R40967.pdf
62. Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive Evidence of Market Inefficiency. *Journal of Portfolio Management*, 13, 9–17.
63. Schimmer, M., Levchenko, A., & Müller, S. (2014). Event Study Tools, St. Gallen. Retrieved August 19, 2014, from http://www.eventstudytools.com.
64. Schwert, G. W. (1981). Using Financial Data to Measure Effects of Regulation. *Journal of Law and Economics*, 24,121-158.
65. Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance*, *21*(1), 937–972.
66. Sewell, M. (2011). *History of the efficient market hypothesis.* Retrieved August 23, 2014, from http://www.cs.ucl.ac.uk/fileadmin/UCL-CS/images/Research_Student_Information/RN_11_04.pdf
67. Singer, E., & Endreny, P. (1987). Reporting hazards: their benefits and costs. *Journal of Communication*, *37*(3), 10-26.
68. *Revenue of the worldwide leading aircraft manufacturers and suppliers in 2013*. Retrieved August 23, 2014, from http://www.statista.com/statistics/264366/revenue-of-the-worldwide-leading-aircraft-manufacturers-and-suppliers/.
69. Surowiecki, J. (2005). *The wisdom of crowds*. New York.: Anchor.
70. Swelbar, W.S. & Belobaba, P.P. (2014). Airline Data Project: The Data. Retrieved August 23, 2014, from http://web.mit.edu/airlinedata/www/Revenue&Related.html
71. *Tailwinds: 2014 airline industry trends*. Retrieved August 23, 2014, from http://www.pwc.com/en_US/us/industrial-products/publications/assets/pwc-tailwinds-the-connected-airline.pdf
72. Taleb, N. N. (2010). *The black swan: The impact of the highly improbable fragility*. New York.: Random House.
73. *US Airways chronology*. Retrieved August 6, 2014, from http://www.usairways.com/en-US/aboutus/pressroom/history/chronology.html
74. Walker, T. J., Thiengtham, D.J. & Lin, M.Y. (2005). On the Performance of Airlines and Airplane Manufacturers Following Aviation Disasters. *Canadian Journal of Administrative Sciences*, *22*(1), 21-34.
75. Wallace, G. (2014). Malaysia Airlines Flight 370: How much will families be paid? Retrieved August 20, 2015, from http://money.cnn.com/2014/03/25/news/companies/malaysia-airlines-compensation/index.html

76. Wong, J. T. & Yeh, W.C. (2003). Impact of flight accident on passenger traffic volume of the airlines in Taiwan. *Journal of the Eastern Asia Society for Transportation Studies*, *5*(1), 471-483.
77. *Wharton Research Data Services*. Retrieved August 14, 2014, from https://wrds-web.wharton.upenn.edu/wrds/index.cfm?

APPENDICES

TABLE OF APPENDICES

TABLE OF TABLES

APPENDIX A: List of frequently used abbreviations

ASN: Aviation Saftey Network

CAR: cumulative abnormal return

CAAR: cumulative average abnormal return

CRSP: Center for Research in Security Prices at the University of Chicago

EDT: Eastern Daylight Time

EMH: efficient market hypothesis

GDP: gross domestic product

M&A: mergers and acquisitions

NTSB: National Transportation Safety Board

NYSE: New York Stock Exchange

SEC: U.S. Securities and Exchange Commission

U.S.: United States

APPENDIX B: Descriptive statistics

Table 1 and Table 2. Descriptive statistics of SKYW (left) and U daily returns in the observation period (right)

Percentiles		SKYW daily returns, 200 days before and after the crash on 1.2.1991	
1st	-0.09		
5th	-0.06		
10th	-0.05		
25th	-0.02		
50th	0.00	**Mean**	0.0006
75th	0.02	**Std. Dev.**	0.0423
90th	0.05	**Variance**	0.0018
95th	0.07	**Skewness**	0.5873
99th	0.10	**Kurtosis**	4.5537

Percentiles		U daily returns, 200 days before and after the crash on 1.2.1991	
1st	-0.09		
5th	-0.05		
10th	-0.04		
25th	-0.02		
50th	0.00	**Mean**	-0.0022
75th	0.01	**Std. Dev.**	0.0330
90th	0.04	**Variance**	0.0011
95th	0.06	**Skewness**	0.6652
99th	0.10	**Kurtosis**	5.4556

Table 3 and Table 4. Descriptive statistics of ASAI (left) and U daily returns in the observation period (right)

Percentiles		ASAI daily returns, 200 days before and after the crash on 5.4.1991	
1st	-0.08		
5th	-0.04		
10th	-0.03		
25th	-0.01		
50th	0.00	**Mean**	0.0020
75th	0.02	**Std. Dev.**	0.0343
90th	0.03	**Variance**	0.0012
95th	0.06	**Skewness**	-2.0695
99th	0.10	**Kurtosis**	28.7313

Percentiles		U daily returns, 200 days before and after the crash on 22.3.1992	
1st	-0.08		
5th	-0.05		
10th	-0.03		
25th	-0.02		
50th	0.00	**Mean**	0.0000
75th	0.01	**Std. Dev.**	0.0329
90th	0.04	**Variance**	0.0011
95th	0.06	**Skewness**	0.8966
99th	0.12	**Kurtosis**	6.3972

Table 5 and Table 6. Descriptive statistics of U daily returns in two different observation periods

Percentiles		U daily returns, 200 days before and after the crash on 2.7.1994	
1st	-0.08		
5th	-0.05		
10th	-0.04		
25th	-0.02		
50th	0.00	**Mean**	-0.0009
75th	0.02	**Std. Dev.**	0.0385
90th	0.04	**Variance**	0.0015
95th	0.06	**Skewness**	1.1213
99th	0.12	**Kurtosis**	11.2394

Percentiles		U daily returns, 200 days before and after the crash on 8.9.1994	
1st	-0.08		
5th	-0.05		
10th	-0.04		
25th	-0.02		
50th	0.00	**Mean**	0.0003
75th	0.02	**Std. Dev.**	0.0406
90th	0.04	**Variance**	0.0016
95th	0.07	**Skewness**	1.0329
99th	0.12	**Kurtosis**	9.5646

Table 7 and Table 8. Descriptive statistics of AMR (left) and VJET daily returns in the observation period (right)

Percentiles		AMR daily returns, 200 days before and after the crash on 31.10.1994	
1st	-0.04		
5th	-0.03		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	0.0002
75th	0.01	Std. Dev.	0.0163
90th	0.02	Variance	0.0003
95th	0.03	Skewness	0.1547
99th	0.04	Kurtosis	3.2502

Percentiles		VJET daily returns, 200 days before and after the crash on 11.5.1996	
1st	-0.14		
5th	-0.06		
10th	-0.05		
25th	-0.02		
50th	0.00	Mean	-0.0030
75th	0.01	Std. Dev.	0.0536
90th	0.05	Variance	0.0029
95th	0.08	Skewness	-1.9155
99th	0.14	Kurtosis	23.2207

Table 9 and Table 10. Descriptive statistics of TWA (left) and COMR daily returns in the observation period (right)

Percentiles		TWA daily returns, 200 days before and after the crash on 17.7.1996	
1st	-0.09		
5th	-0.06		
10th	-0.05		
25th	-0.03		
50th	0.00	Mean	0.0011
75th	0.02	Std. Dev.	0.0453
90th	0.06	Variance	0.0020
95th	0.08	Skewness	0.6638
99th	0.14	Kurtosis	4.6502

Percentiles		COMR daily returns, 200 days before and after the crash on 9.1.1997	
1st	-0.07		
5th	-0.05		
10th	-0.04		
25th	-0.01		
50th	0.00	Mean	0.0008
75th	0.02	Std. Dev.	0.0338
90th	0.03	Variance	0.0011
95th	0.05	Skewness	-1.8811
99th	0.09	Kurtosis	23.7598

Table 11 and Table 12. Descriptive statistics of ALK (left) and PNCL daily returns in the observation period (right)

Percentiles		ALK daily returns, 200 days before and after the crash on 31.1.2000	
1st	-0.06		
5th	-0.04		
10th	-0.03		
25th	-0.02		
50th	0.00	Mean	-0.0011
75th	0.01	Std. Dev.	0.0271
90th	0.03	Variance	0.0007
95th	0.04	Skewness	0.4607
99th	0.07	Kurtosis	7.6394

Percentiles		PNCL daily returns, 200 days before and after the crash on 12.2.2009	
1st	-0.15		
5th	-0.08		
10th	-0.06		
25th	-0.03		
50th	0.00	Mean	0.0012
75th	0.02	Std. Dev.	0.0632
90th	0.06	Variance	0.0040
95th	0.09	Skewness	1.0743
99th	0.26	Kurtosis	10.8484

Table 13 and Table 14. Descriptive statistics of LK daily returns in two different observation periods

Percentiles		LK daily returns, 200 days before and after the crash on 21.1.1985	
1st	-0.04		
5th	-0.03		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	0.0010
75th	0.01	Std. Dev.	0.0176
90th	0.02	Variance	0.0003
95th	0.03	Skewness	0.4709
99th	0.04	Kurtosis	4.6318

Percentiles		LK daily returns, 200 days before and after the crash on 2.8.1985	
1st	-0.035		
5th	-0.025		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	0.0005
75th	0.01	Std. Dev.	0.0159
90th	0.02	Variance	0.0003
95th	0.03	Skewness	0.0982
99th	0.04	Kurtosis	3.0850

Table 15 and Table 16. Descriptive statistics of MD daily returns in two different observation periods

Percentiles		MD daily returns, 200 days before and after the crash on 9.9.1985	
1st	-0.04		
5th	-0.02		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	0.0005
75th	0.01	Std. Dev.	0.0137
90th	0.02	Variance	0.0002
95th	0.02	Skewness	-0.0896
99th	0.04	Kurtosis	4.8536

Percentiles		MD daily returns, 200 days before and after the crash on 2.9.1986	
1st	-0.03		
5th	-0.02		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	0.0000
75th	0.01	Std. Dev.	0.0126
90th	0.02	Variance	0.0002
95th	0.02	Skewness	-0.2376
99th	0.03	Kurtosis	3.9063

Table 17 and Table 18. Descriptive statistics of MD daily returns in two different observation periods

Percentiles		MD daily returns, 200 days before and after the crash on 31.8.1986	
1st	-0.05		
5th	-0.02		
10th	-0.01		
25th	-0.01		
50th	0.00	Mean	-0.0006
75th	0.01	Std. Dev.	0.0157
90th	0.02	Variance	0.0002
95th	0.02	Skewness	-2.8458
99th	0.03	Kurtosis	30.5001

Percentiles		MD daily returns, 200 days before and after the crash on 16.8.1987	
1st	-0.05		
5th	-0.02		
10th	-0.01		
25th	-0.01		
50th	0.00	Mean	-0.0004
75th	0.01	Std. Dev.	0.0151
90th	0.02	Variance	0.0002
95th	0.02	Skewness	-3.2472
99th	0.03	Kurtosis	34.9278

Table 19 and Table 20. Descriptive statistics of MD (left) and BA daily returns in the observation period (right)

Percentiles		MD daily returns, 200 days before and after the crash on 19.7.1989	
1st	-0.06		
5th	-0.02		
10th	-0.01		
25th	-0.01		
50th	0.00	Mean	-0.0009
75th	0.01	Std. Dev.	0.0133
90th	0.01	Variance	0.0002
95th	0.02	Skewness	-1.6139
99th	0.03	Kurtosis	10.0716

Percentiles		BA daily returns, 200 days before and after the crash on 25.1.1991	
1st	-0.07		
5th	-0.03		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	-0.0006
75th	0.01	Std. Dev.	0.0285
90th	0.02	Variance	0.0008
95th	0.03	Skewness	-5.9701
99th	0.05	Kurtosis	65.5753

Table 21 and Table 22. Descriptive statistics of BA daily returns in two different observation periods

Percentiles		BA daily returns, 200 days before and after the crash on 1.2.1991	
1st	-0.07		
5th	-0.03		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	-0.0008
75th	0.01	Std. Dev.	0.0243
90th	0.02	Variance	0.0006
95th	0.03	Skewness	-4.3902
99th	0.05	Kurtosis	53.8375

Percentiles		BA daily returns, 200 days before and after the crash on 3.3.1991	
1st	-0.07		
5th	-0.03		
10th	-0.02		
25th	-0.01		
50th	0.00	Mean	-0.0003
75th	0.01	Std. Dev.	0.0197
90th	0.02	Variance	0.0004
95th	0.03	Skewness	-0.4147
99th	0.05	Kurtosis	6.4843

Table 23 and Table 24. Descriptive statistics of BA (left) and MD daily returns in the observation period (right)

Percentiles		BA daily returns, 200 days before and after the crash on 8.9.1994	
1st	-0.03		
5th	-0.02		
10th	-0.01		
25th	-0.01		
50th	0.00	Mean	0.0009
75th	0.01	Std. Dev.	0.0139
90th	0.02	Variance	0.0002
95th	0.02	Skewness	0.9914
99th	0.05	Kurtosis	7.2192

Percentiles		MD daily returns, 200 days before and after the crash on 11.5.1996	
1st	-0.03		
5th	-0.02		
10th	-0.01		
25th	-0.01		
50th	0.00	Mean	0.0021
75th	0.01	Std. Dev.	0.0144
90th	0.02	Variance	0.0002
95th	0.02	Skewness	1.5559
99th	0.03	Kurtosis	15.9420

Table 25 and Table 26. Descriptive statistics of BA daily returns in two different observation periods

Percentiles		BA daily returns, 200 days before and after the crash on 17.7.1996	
1st	-0.03		
5th	-0.02		
10th	-0.02		
25th	-0.01		
50th	0.00	**Mean**	0.0012
75th	0.01	**Std. Dev.**	0.0154
90th	0.02	**Variance**	0.0002
95th	0.03	**Skewness**	0.4815
99th	0.04	**Kurtosis**	4.2015

Percentiles		BA daily returns, 200 days before and after the crash on 6.8.1997	
1st	-0.04		
5th	-0.02		
10th	-0.02		
25th	-0.01		
50th	0.00	**Mean**	0.0012
75th	0.01	**Std. Dev.**	0.0161
90th	0.02	**Variance**	0.0003
95th	0.03	**Skewness**	0.2291
99th	0.04	**Kurtosis**	4.4840

APPENDIX C: Summary of master's thesis in Slovenian

Uvod

V zadnjih dveh letih je javnost letalskim nesrečam namenjala toliko pozornosti kot po terorističnih napadih septembra 2001. Dve letali svetovno znanega in cenjenega letalskega prevoznika Malaysia Airlines sta strmoglavili v obdobju šestih mesecev. Letalo na letu 370 od Kuala Lumpurja v Peking naj bi bilo ugrabljeno in naj bi pristalo v Indijskem oceanu, vendar glavnine ostankov do danes še vedno niso našli. Drugo letalo na letu 17 iz Amsterdama v Kuala Lumpur so zadeli zaenkrat še neznani predmeti (izstrelki, rakete) nad vzhodno Ukrajino. Marca 2015 pa je kopilot letala družbe Germanwings letalo s 150 potniki in člani posadke usmeril v goro sredi francoskih Alp.

Letalske nesreče so deležne velike pozornosti globalnih medijev: Barnett (1990) je analiziral naslovne strani New York Times-a in ugotovil da pozornost, namenjena letalskim nesrečam bistveno prekaša pozornost, ki je namenjena drugim zgodbam, ki vključujejo izgubo človeških življenj. Število člankov, ki so bili namenjeni letalskim nesrečam je primerjal s tistimi namenjenimi AIDS-u, umorom, avtomobilskim nesrečam in raku. Glede na število žrtev je bila pozornost namenjena letalskim nesrečam izjemno visoka, med 60 in več tisočkrat višja kot v drugih primerih. Singer in Endreny (1987) razlagata, zakaj pride do takšne razlike: »Redka nesreča je za novice bolj zanimiva kot pogosta, nova nesreča je bolj zanimiva kot stara in bolj dramatična nesreča – taka, ki na skrivnosten način ubije več ljudi naenkrat – je bolj zanimiva kot že dolgo znana bolezen.«. Te značilnosti letalskih nesreč naredijo z njimi povezane empirične študije zelo privlačne za ocenjevanje učinkovitosti finančnih trgov pri procesiranju informacij. Omogočajo nam, da ocenimo ali so spremembe cen delnic posledica racionalnega odločanja ali so morda posledica kratkoročnega strahu in negotovosti. Pri tem ocenjevanju zelo pomembno vlogo igra hipoteza o učinkovitosti finančnih trgov.

Hipoteza o učinkovitosti finančnih trgov in njeni kritiki

Hipoteza o učinkovitosti finančnih trgov pravi, da cena vrednostnega papirja nepristransko odraža njegovo resnično vrednost in upošteva vse dostopne informacije (Damodaran, 2014). Fama (1970) je zapisal zadostne pogoje za učinkovitost finančnih trgov:

- pri trgovanju z vrednostnimi papirji ni transakcijskih stroškov,
- vse dostopne informacije so brezplačno dostopne vsem deležnikom na trgu,
- vsi investitorji se strinjajo o pomenu dostopnih informacij na trenutno ceno vrednostnega papirja in o distribuciji bodočih cen za vsak vrednostni papir.

Hipoteza o učinkovitosti finančnih trgov se pojavlja v treh oblikah: šibki, srednje močni in močni, ki se razlikujejo glede na to, katere informacije naj bi že bile upoštevane pri trenutni ceni vrednostnih papirjev. Za študije dogodkov (ki jo izvedemo tudi v tem magistrskem delu) je pomembna srednje močna oblika hipoteze, ki trdi, da naj bi cene vrednostnih papirjev takoj odreagirale na novo dostopne informacije. Ta značilnost naj bi onemogočala možnost doseganja izrednih donosov na podlagi novih javno dostopnih informacij. Posledično tako tehnična kot tudi temeljna analiza vrednostnih papirjev oz. podjetij ne bi vodili do konsistentnega doseganja izrednih donosov. Investitor, ki bi kupil bilančne podatke podjetja in programsko opremo za njihovo analizo, bi bil v povprečju nagrajen z višjimi donosi samo v tolikšni meri, da bi si pokril z analizo povezane stroške.

Empirične raziskave glede učinkovitosti finančnih trgov niso dale nedvoumnih rezultatov, vendar je bila močna oblika hipoteze, ki trdi, da cene odražajo tudi notranje informacije, večinoma zavrnjena (Nicholson, 1968), (Basu, 1977), Rosenberg in drugi, 1985), (Fama & French, 1992), (Chan in drugi, 2003). Klick in Sitkoff (2008) sta zapisala, da se večina finančnih ekonomistov strinja, da je ameriški delniški trg učinkovit v srednje-močnem smislu (odraža vse javno dostopne informacije). V zadnjih letih pa se je povečal dvom v učinkovitost finančnih trgov, predvsem zaradi spoznanj vedenjskih ekonomistov.

Le-ti na podlagi del Kahnemana in Tverskega (1979) in kasnejših odkritij v kognitivni psihologiji trdijo, da so investitorji izpostavljeni različnim kognitivnim omejitvam, pristranskosti in napakam, ki vodijo do sistematičnih odstopanj od racionalnih cen na finančnih trgih. Kritika se navezuje na predpostavko, da smo ljudje racionalni in konsistentni ekonomski subjekti. Kahneman (2011, str. 105) opredeli dva načina (ki ju imenuje 'Sistem 1' in 'Sistem 2'), s katerim ponazori, kako ljudje sprejemamo odločitve. Nekatere karakteristike Sistema 1 nas v tem delu še posebej zanimajo. Sistem 1 na primer:

- poizkuša izpeljati oz. si izmisli vzroke in namene,
- ne upošteva dvoumnosti in odpravlja dvome,
- je nagnjen k potrjevanju,
- je pretirano emocionalno konsistenten,
- se osredotoča na obstoječa in zanemarja neznana dejstva,
- izvede zgolj omejen nabor osnovnih ocen situacije,
- pretirano upošteva majhne verjetnosti in
- je slabo občutljiv na količine.

Če investitorji na finančnem trgu v nekem danem trenutku pri odločanju uporabljajo Sistem 1, je to lahko razlog, da tržne cene odstopajo od tiste vrednosti, ki bi jo pričakovali glede na hipotezo o učinkovitosti finančnih trgov. Investitorji lahko sistematično napačno interpretirajo informacije, kakor je opisano zgoraj, in se na podlagi istih informacij odločajo še v daljšem časovnem obdobju.

Dosedanje raziskave letalskih nesreč

Kako torej investitorji reagirajo na novice o strmoglavljenju letala – redkem dogodku, ki je močno izpostavljen senzacionalističnemu poročanju medijev? Kaplanski in Levy (2010) sta ocenila, da večja letalska nesreča zniža vrednost indeksa NYSE Composite za več kot šestdeset milijard dolarjev, čeprav direktni ekonomski stroški ne presegajo milijarde dolarjev. Katere dodatne vidike naj bi investitorji upoštevali pri določanju ustreznih cen delnic?

Po metodi prostih denarnih tokov, ki jo je prvi zapisal Fisher (1930) cena delnice podjetja predstavlja oceno investitorjev, kolikšne dobičke in denarne tokove je podjetje sposobno generirati v prihodnosti in preko tega odraža zainteresiranost vlagateljev, da podjetju prispevajo kapital. Če cena delnice na dogodek odreagira negativno, to pomeni, da investitorji pričakujejo manjše ali bolj tvegane denarne tokove. Vpliv nesreč na cene delnic letalskih prevoznikov je bil potrjen že v več raziskavah. Posredni negativni učinki, ki vplivajo na ceno delnic so med drugimi spremenjena dinamika konkurence, vpliv na regulacijo in nižje povpraševanje potrošnikov.

Ito in Lee (2005) sta analizirala učinke terorističnih napadov 11. septembra 2001 na povpraševanje po letalskih poletih po svetu. Ugotovila sta, da je prišlo do velikega upada povpraševanja pri mednarodnih poletih med -15% in -38%. Največji učinek je bil zaznan v Evropi in na Japonskem. Več ameriških prevoznikov je po napadih razglasilo bankrot, najpomembnejša med njimi sta bila United Airlines in US Airways. Globalno pa so teroristični napadi prispevali k bankrotom avstralske družbe Ansett, belgijskega prevoznika Sabena in Air Canada (Ito & Lee, 2005).

Wong in Yeh (2003) sta analizirala vpliv letalskih nesreč na potniški letalski promet na Tajvanu. Ob kontroliranju sezonskih in cikličnih faktorjev sta ocenila, da letalska nesreča povzroči 22,1% padec mesečnega prometa za vpletenega prevoznika, negativni učinek pa traja približno dva meseca in pol. Na drugi strani konkurenčna podjetja nekoliko pridobijo zaradi preusmerjenih potnikov, vendar je ta pozitivni učinek še zmeraj manjši kot splošno povečan strah pred letenjem. Kumulativni učinek letalske nesreče na promet pri prevoznikih, ki v nesrečo niso bili vpleteni, je bil ocenjen na -5,6%.

Bosch in drugi (1998) so opazovali reakcije finančnih trgov na letalske nesreče in se pri tem osredotočili na to, koliko se potrošniki nanje odzovejo s prehodom h konkurenci in koliko zares letijo manj. Konkurenčne letalske prevoznike so razdelili na skupine glede na to, koliko se njihovi poleti prekrivajo z vpletenim podjetjem. Odkrili so, da obstaja pozitivna povezava med močjo prekrivanja in porastom delnice konkurenta, kar kaže na učinek preusmeritve. Zaznali so tudi negativen vpliv na delnice letalskih prevoznikov z zanemarljivim prekrivanjem poletov, s čimer so potrdili negativen učinek na splošno povpraševanje.

Walker in drugi (2005) so analizo razširili na ugotavljanje učinkov letalskih nesreč na proizvajalce letal poleg letalskih prevoznikov. Izmerili so povprečen padec za 2,8% pri delnicah prevoznikov in manjši, vendar še vedno značilen padec pri prevoznikih za 0,8%. Ugotovili so, da je sprememba cene delnice letalskega prevoznika negativno povezana z velikostjo podjetja in številom žrtev in da so padci največji, kadar je povod za nesrečo kriminalna dejavnost. Delnice proizvajalcev letal po njihovi raziskavi reagirajo podobno, vendar so najbolj prizadete v primeru, ko so se nesreče zgodile zaradi odpovedi mehanskih delov.

Metodologija študije dogodkov

Za oceno vpliva letalskih nesreč običajno izvedemo študijo dogodka. Študija dogodka je empirična študija vrednostnega papirja, na katerega vrednost je vplival nek pomemben dogodek (Event study, n.d.). Take študije so zelo uporabne, saj lahko ob predpostavki racionalnosti investitorjev zelo hitro ocenimo učinek dogodka. Ekonomski vpliv se da zaznati v relativno kratkem času, medtem ko bi meritve direktnih sprememb v produktivnosti zahtevale nekaj mesecev ali let opazovanja (MacKinlay, 1997).

Vsaka študija dogodka predstavlja skupni test raziskovane hipoteze, izbranega modela pričakovanih donosov in uporabljenih predpostavk iz finančne teorije (Schimmer in drugi, 2014). Če želimo oceniti učinek dogodka na ceno vrednostnega papirja, moramo najprej uporabiti tehnike za ločitev učinkov dogodka od dinamike cene delnice, ki bi lahko nastala zaradi drugih vzrokov.

Da bi ocenili gibanje delnice brez dogodka, po metodologiji študije dogodkov ponavadi uporabimo neko vrsto tržnega modela. Pri uporabi takega modela potrebujemo dve glavni predpostavki (Klick & Sitkoff, 2008): srednje močno obliko hipoteze o učinkovitih finančnih trgih in dejstvo, da je razmerje med gibanjem posamezne delnice glede na tržni indeks kratkoročno stabilno (MacKinlay, 1997). Srednje močna oblika hipoteze o učinkovitosti finančnih trgov implicira, da cena tržnega vrednostnega papirja odraža vse javno dostopne informacije o bodočih denarnih tokovih, ki jih lahko pričakujemo od lastništva tega vrednostnega papirja (Malkiel, 2003). Z uporabo druge predpostavke pa lahko ocenimo abnormalne donose glede na to, koliko je cena vrednostnega papirja odstopala od znanega linearnega razmerja glede na tržni indeks. Ti dve ideji nam omogočata, da lahko ocenimo učinek opazovanega dogodka na ceno izbranega vrednostnega papirja.

Uporaba študije dogodkov kot raziskovalne metodologije je zelo široka: Schimmer (2014) ocenjuje da korpus raziskav obsega več tisoč študij, ki preučujejo najrazličnejša področja (korporativno komuniciranje, pravne postopke v zvezi z vrednostnimi papirji, raziskave in svetovanje v zvezi z združitvami in prevzemi, upravljanje z naložbami in raziskave v politični ekonomiji).

Izbrani pristop

V našem delu smo uporabili standardno metodologijo študije dogodkov, sledeč Davidsonu (1987) in Klicku and Sitkoffu (2008). Izbrana metodologija je sestavljena iz naslednjih korakov:

- Identifikacija dneva dogodka in opredelitev obdobja opazovanja,
- Izbor vrednostnih papirjev, ki jih želimo opazovati,
- Meritev dejanskih donosov izbranih vrednostnih papirjev na opazovane dneve,
- Ocena pričakovanih donosov vrednostnih papirjev na opazovane dneve z uporabo tržnega modela,
- Izračun abnormalnih donosov z odštevanjem pričakovanih od dejansko doseženih donosov,
- Ocena statistične značilnosti dobljenih abnormalnih donosov.

Z izvedbo navedenih korakov je možno oceniti ekonomski vpliv abnormalnega donosa na opazovane dneve.

Panoga letalskih prevoznikov in proizvajalcev letal

V delu na kratko predstavimo obe panogi, v katerih nastopajo podjetja, ki so direktno izpostavljena vplivu letalskih nesreč. Na svetu deluje približno 200 letalskih prevoznikov, ki upravljajo z več kot 23 tisoč letali, ki povezujejo več kot 3700 letališč. Letna rast letalskega prometa v zadnjih tridesetih letih je bila približno dvakrat višja kot rast bruto družbenega proizvoda in je dosegala okrog 5%. Panoga zaposluje okrog pol milijona ljudi, ki omogočijo več kot 30 tisoč poletov na dan. Komercialen letalski promet predstavlja skoraj 8% BDP Združenih držav Amerike (Henckels, 2011).

Panoga je bila zaznamovana z dvema ključnima dogodkoma – deregulacijo in napadi 11. septembra. Od leta 1937 je bil letalski promet reguliran kot javna storitev, dokler ni leta 1978 ameriški kongres sprejev zakon (Airline Deregulation Act of 1978), ki je intenziviral konkurenco in povzročil, da je cena letalskega prevoza ob upoštevanju inflacije upadla za približno tretjino do 90. let prejšnjega stoletja. Teroristični napadi leta 2001 pa so povzročili veliko znižanje povpraševanja in zvišanje varnostnih standardov. Pet velikih ameriških prevoznikov je razglasilo bankrot med letoma 2001 in 2011. Z namenom znižanja stroškov in višje dobičkonosti je prišlo do konsolidacije – predvsem preko združitev Delte in Northwest Airlines leta 2007 in Continental Airlines z United Airlines v letu 2010. (Henckels, 2011). Leta 2013 je panoga letalskih prevoznikov v ZDA ponovno dosegla profitabilnost v skupni višini 11 milijard dolarjev (Swelbar and Belobaba, 2014).

Panoga proizvajalcev komercialnih letal, pomožne opreme in delov letno generira približno 290 milijard dolarjev prometa (Global Commercial Aircraft Manufacturing report: Market Research Report, 2014). Trenutno je trg velikih komercialnih letal duopol med ameriškim proizvajalcem Boeing in evropskim Airbusom, medtem ko na trgu regionalnih letal prevladujeta Bombardier in brazilski Embraer (Platzer, 2009 ter Revenue of the worldwide leading aircraft manufacturers and suppliers in 2013, 2014). Konkurenca med Airbusom in Boeingom je zelo intenzivna že od 90. let prejšnjega stoletja, ko se je zaradi vrste združitev panoga konsolidirala na globalni ravni (Anichebe, 2014). Airbus je začel kot konzorcij evropskih proizvajalcev, medtem ko se je Boeing združil z največjim domačim konkurentom, podjetjem McDonnell Douglas leta 1997. Drugi proizvajalci, kot so Lockheed Martin, British Aerospace in Fokker so le s težavo ohranjali konkurenčnost in nazadnje izstopili iz trga večjih potniških letal (Anichebe, 2014).

Podatki

Analizo vplivov letalskih nesreč smo izvedli na podatkih podatkovnih baz NTSB in ASN (letalske nesreče) in CRSP (cene vrednostnih papirjev). V osnovni vzorec smo zajeli letalske nesreče, ki so se zgodile med 1.1.1983 in 31.12.2013 na ameriških tleh. Po seriji dodatnih omejitev (več kot 20 žrtev, vzrok ni kriminal, vključeno podjetje nastopa na borzi vrednostnih papirjev,...) smo prišli do vzorca 12 letalskih nesreč, kjer nas je zanimal vpliv na ameriške letalske prevoznike in do vzorca 14 letalskih nesreč, kjer nas je zanimal vpliv na ameriške proizvajalce letal (Boeing, Lockheed, McDonnell Douglas).

Analiza in zaključki

V empiričnem delu smo testirali pet glavnih hipotez:

- **Hipoteza 1:** Letalske nesreče negativno vplivajo na donos delnic letalskih prevoznikov.
- **Hipoteza 2:** Letalske nesreče negativno vplivajo na donos delnic proizvajalcev letal.
- **Hipoteza 3:** Letalske nesreče, pri katerih je bilo več kot 50 žrtev, povzročijo višje povprečne absolutne abnormalne donose pri letalskih prevoznikih.
- **Hipoteza 4:** Delnice konkurentov proizvajalca letala, ki je bilo udeleženo v nesreči, izkazujejo pozitivne abnormalne donose.
- **Hipoteza 5:** Letalske nesreče, pri katerih je bilo več kot 50 žrtev povzročijo podobne absolutne abnormalne donose pri proizvajalcih letal kot nesreče, pri katerih je bilo manj kot 50 žrtev.

Naši ključni rezultati so naslednji:

- **Hipoteza 1:** Potrdili smo negative vpliv letalskih nesreč na donose delnic letalskih prevoznikov do trinajstega dneva po nesreči. Statistična značilnost po enostranskem testu je 99%. Povprečen abnormalen donos na prvi dan po nesreči je -4,3%. Negativen vpliv nesreče traja še do šestega dne, ko doseže najnižjo točko, -12,5%. Rezultati so robustni na spremembe v dolžini ocenjevalnega obdobja in so konsistentni z rezultati drugih raziskovalcev (Walker in drugi, 2005, Chance & Ferris, 1987), pri čemer pa je izmerjeni učinek precej večji.
- **Hipoteza 2:** Učinek letalskih nesreč na delnice proizvajalcev letal je manjši. Kumulativni povprečni abnormalni donosi se v prvih 15 trgovalnih dneh ne spustijo pod -1,3%. T-statistika je značilna zgolj na prvi in drugi trgovalni dan po nesreči. Kumulativni povprečni abnormalni donosi niso robustni na spremembe v dolžini ocenjevalnega obdobja. Rezultati so podobni tistim, ki so jih pridobili Walker in drugi (2005). Ti so zaznali statistično značilne padce v obdobjih 1, 2 in 7 trgovalnih dni po nesreči.
- **Hipoteza 3:** Potrdili smo, da nesreče, pri katerih je bilo več kot 50 žrtev, povzročijo višje povprečne absolutne abnormalne donose. Glede na tiste nesreče z manj kot 50 žrtvami, je razlika v povprečnih absolutnih abnormalnih donosih (3,4% v primerjavi s 2,3%) statistično značilna in robustna glede na spremembe v dolžini ocenjevalnega obdobja.
- **Hipoteza 4:** Dobljeni rezultati kažejo na negativne kumulativne abnormalne donose po nesreči, vendar le-ti niso statistično značilni. Dolgoročnejši pozitivni kumulativni abnormalni donosi (o katerih so poročali tudi Walker in drugi, 2005) niso robustni na spremembe v dolžini ocenjevalnega obdobja in niso statistično značilni.
- **Hipoteza 5:** Z analizo smo potrdili, da se letalske nesreče z več kot 50 žrtvami statistično značilno ne razlikujejo glede na izmerjene povprečne absolutne abnormalne donose pri delnicah proizvajalcev v primerjavi s tistimi, kjer je bilo med 20 in 50 žrtev (0,93% oz 0,98%). Zaznana razlika ni statistično značilna v nobenem scenariju različnih dolžin ocenjevalnega obdobja.

Rezultati pri preverjanju Hipoteze 1 in Hipoteze dva nas navajajo k sklepu, da v prvih dneh po letalski nesreči hipoteza o učinkovitih finančnih trgih začasno ne velja, saj investitorji delujejo na podlagi istih informacij še nekaj časa. Spreten investitor bi lahko ta pojav izkoristil tako, da bi takoj ob objavi novice o letalski nesreči na kratko prodal delnico vpletenega prevoznika (proizvajalca) in jo kupil dan oz. nekaj dni kasneje. Glede na rezultate se zdi, da je v tem obdobju večina investitorjev pod vplivom kognitivnih napak ali pristranoskosti, ki jih lahko sprožijo redki, negativni dogodki kot jih je opisal Kahneman (2011, str. 105, 322). Te napake so med drugim: osredotočenost na obstoječa dejstva (medijska poročila) in zanemarjanje neznanih dejstev (ki so rezultat uradne preiskave), precenjevanje nizkih verjetnosti (nesreča se z lahkoto zgodi še enkrat) in zmanjšana občutljivost pri ocenjevanju količin (koliko je vrednost letala v primerjavi s korporacijo, ki ga ima v lasti?). Rezultati kažejo na to, da bi regulator s prekinitvijo trgovanja z delnicami vpletenih podjetij za nekaj dni z namenom preprečitve odločanja pod vplivom kognitivnih napak najverjetneje povzročil, da bi cena delnic padla manj dramatično in bolj v skladu z dejanskimi ekonomskimi spremembami, ki jih povzroči.

Rezultati, povezani s Hipotezo 3 nas navajajo k sklepu, da investitorji pri določanju ustrezne cene delnice letalskega prevoznika upoštevajo (zavestno ali ne) število žrtev nesreče kot pomemben faktor. Domnevamo, da je glavni razlog pričakovan večji negativni učinek na povpraševanje strank po letalskih poletih te letalske družbe, ki pomeni iracionalno vedenje na strani potrošnikov oz. se investitorji sami odločajo neracionalno. Preverjanje Hipoteze 5 nakazuje, da število žrtev ne vpliva na povprečne abnormalne donose delnic proizvajalcev letal. Različno občutljivost investitorjev na število žrtev v primeru letalskih prevoznikov (Hipoteza 3) in proizvajalcev letal (Hipoteza 5) je mogoče racionalno razložiti, tako da rezultati ne prinašajo dodatne potrditve, da so investitorji pod vplivom kognitivnih napak.

Ob koncu dodamo še, da se zavedamo omejitev pri interpretaciji dobljenih rezultatov. Prvič, nabor dogodkov je definiran zelo specifično: vključuje samo letalske nesreče, ki so se zgodili na ameriških tleh in v katere so bili vpleteni zgolj ameriški letalski prevozniki in proizvajalci letal, ki kotirajo na borzi. Reakcije na letalske nesreče v drugih državah ali pri drugih podjetjih bi lahko bile različne. Drugič, moč odziva na letalske nesreče na finančnih trgih je morda odvisen od vzroka; katastrofe, ki jih povzročijo teroristični napadi ali tehnične težave lahko vodijo do močnejših reakcij kot tiste, ki so jih povzročile slabe vremenske razmere. Za naš vzorec ne moremo trditi, da je reprezentativen za splošno populacijo letalskih nesreč kar se tiče vzrokov, ki so do njih pripeljali. Stroge omejitve, ki smo jih upoštevali, vodijo do precej omejenih vzorcev dogodkov (uporabljeni so bili podatki o dvanajstih nesrečah v primeru letalskih prevoznikov in o štirinajstih nesrečah v primeru proizvajalcev letal), kar predstavlja omejitev pri splošnosti predstavljenih ugotovitev.