The Effects of Commercial Aviation Accidents

A Dynamic Approach

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Abstract

This paper focuses on the query of whether or not aviation accidents have an effect on the financial value of the particular crash-airlines. A time span of twelve years is considered. To assess this impact a Bårdsen Error Correction Model with Newey West Standard Errors is employed, assessing both short – and long run effects of the model.

The model is constructed in such a way to isolate the sole impact of accidents on the airlines' financial value, by employing company, industry and economy indicators. For further depth of the research accidents have been divided into nonfatal and fatal occurrences, whilst assessing also the number of injuries and fatalities of the sampled mishaps. The actual number of fatalities proves to be statistically significant even during a quarter, whilst all other accident indicators used are not.

Keywords: Aviation accidents, fatalities, airlines, share price, stock market, investor sentiment, Bårdsen Error Correction Model, Newey West Standard Errors.

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1. Introduction

Since the first passenger flight in 1913, aviation has endured several changes, most of which were driven by the desire to ensure safety while avoiding accidents. A hundred years later, flying proves to be the safest mode of transportation.

During a press conference, Janet Napolitano, Secretary of Homeland Security said '*nowadays, you can't imagine a world [...] without a safe and secure aviation system; so our job is to keep it this way.*' Aviation today is indeed the safest mode of transportation, regardless of safety measures being taken on a relatively global scale, mishaps still occur. Security measures taken could not have prevented the terrorist attacks of 9/11. It took these devastating events to implement even stricter security measures. The resulting damage and costs were felt not only by the crash-airlines involved, but by the entire industry and society. After the 9/11 attacks the New York Stock Exchange, NASDAQ and several other stock markets were closed for a whole week. However, 9/11 is not the only accident encountered by airlines, yet the most mediatized. Smaller accidents can happen any day, hence the query is if and how do these accidents impact an airline's financial value?

This paper will make an abstraction of the societal costs of an aviation mishap, and will focus on the impact of an accident on the financial value, indicated by share prices of the airline(s) involved. Hence, the research question this paper will analyze is presented as follows:

How are accidents impacting the financial value of crash-airlines?

The focus of this study will solely be on the financial performance of airlines involved in the accident. As for accidents, any mishap that resulted in an injury or a fatality will be considered. The analysis is based on eleven US and Canadian airlines, both Full Service Carriers (FSC) and Low Cost Carriers (LCC).

In order to answer the research question, this study will focus on previous scientific works based on empirical investigations regarding the effects of accidents on the financial performance of airlines. Even though observing a negative impact, scientific literature struggled with finding this negative impact statistically significant for more than a couple of days after accident took place (Chance et al., 1987; Raghavan et al., 2000).

Kaplanski et al. (2010) introduced the notion that a calamity is particularly affecting securities on that specific trading day the most, whilst its impact is diminishing the following days after. To observe the duration of the effect of accidents, this study will consider quarters rather than days. Since the accident variable is a dummy, this paper will go a step further and analyze the impact of the actual number of injuries and fatalities incurred. Having established the relationship between accidents and share prices, the next step is to build a statistical model comprising the effect of accidents on securities. A Bårdsen Error Correction Model (ECM) will be developed explaining the particular relationship. This model will be tested for a series of assumptions to determine its correctitude.

So as to obtain a clear and well-thought-out overview of the topic at hand, this paper will commence with a scientific literature review (*Chapter 2*) on the different aspects of the relationship between accidents and share prices. A small glimpse into recent years of the aviation industry shall be given (*Chapter 2.1*) followed by defining and explaining share prices (*Chapter 2.2*) and accidents (*Chapter 2.3*) separately, which will later aid in determining their relationship (*Chapter 2.4*); having thus, established the theoretical framework of the paper. *Chapter 3* is focused on the data sampled. *Chapter 4* presents the statistical assumptions that need to be met in order for the model employed to be valid and correct; the Bårdsen Error Correction Model is depicted in this section. Having established the model, *Chapter 5* will portray and describe the results of the tests run. Their interpretation and relevance will be presented in the analysis (*Chapter 6*), trailed by the conclusions of the paper (*Chapter 7*), the policy recommendations and limitations (*Chapter 8*).

2. Literature Review

Before digging deeper into the theoretical framework of this paper, it is necessary to define the terminology used, whilst having a look at the scientific literature covering this topic. As mentioned in the introduction, this study will assess the impact of aviation accidents on the financial value of the airlines involved in the mishaps, the so-called crash-airlines. This financial value is analyzed by eyeing the influence of accidents on the share prices of each air carrier during the selected time span of twelve years, from 2000 to 2011.

Scientific literature finds consensus on the fact that, in general, aviation accidents tend to influences airlines' stocks (Kaplanski et al., 2010; Chance et al., 1987; Ho et al., 2011; Oster et al., 2003). The effect of accident is analyzed by scientific literature in different ways, ranging from small-scale mishaps to disastrous events, considering either Full Service Carriers (FSC) or Low Cost Carriers (LCC). There is no debate on the fact that the relationship between aviation accidents and a company's share prices is negative; however this relationship is not always statistically significant. What are the determinants for these findings? Is it is magnitude of the event, the size of the airline, the media coverage of the accidents? There are several factors influencing the relationship between aviation mishaps and the crash-airline's share prices.

This particular relationship will be discussed later in the paper. This chapter will commence by exploring the aviation industry in general, offering a small outlook at the current situation and the challenges being faced. After acquiring insight into this particular industry, this paper will focus on aviation share prices, tailed by a detailed description and explanation of accidents, whilst establishing and assessing the relationship between the two. In order to isolate the impact of aviation accidents on share prices, it is essential to control for company-specific internal factors and market external factors influencing share prices. A complete theoretical framework, combining all the above will be presented.

2.1. The Aviation Industry - A Glimpse

Before looking at imact of accidents on airlines' share prices, it is important to understand the industry this paper is examining. During the late 1970s the aviation industry experienced a boost especially because of the liberalization policies in the US and Europe (Cento, 2009). The 'Open-Skies' policy permitted the liberalization of the international airline industry, reducing governmental control and creating a free-market environment (Debbage, 1994; Durge, 2011). Liberalization led consequently to an increase in air travel demand, fostered further by technological advances, such as the online booking system (Berry et al., 2008).

The airline industry had to cope with a great turmoil during the early 2000's. Precedent growth levels, brought forth by favorable economic conditions during the mid-1990s, could not make up for what was yet to impact the global aviation industry (Cento, 2009).

The airline industry took a terrible blow after the terrorist attacks of 9/11, resulting in restructuring, mergers and acquisitions, strategic alliances and even bankruptcies. The effects of 9/11 were visible on a global scale, with consequences such as decreasing air traffic, reduced revenues and increasing in oil prices (Cento, 2009).

Air traffic is characterized by cyclical movements, after several years of increasing demand for air travel follows regularly a period of slower increase or even decline in demand (Berry et al., 2008). As noted by Berry et al. (2008) the passenger air traffic recovered from the attacks of 9/11 by 2004, increasing thereafter until the recent economic crisis, when it experienced a downturn. Reasons for this recovery were, on the demand side, the increase in passenger traffic coming forth due to stricter security measures at airports and the advancements in technology (Berry et al., 1008). Whilst on the supply one particular development, agreed upon by most scientific literature, affected the profitability of the industry, namely the expansion of Low Cost Carriers (LCC), especially in the US and Europe (Berry et al., 2008; Franke et al., 2011).

The economic crisis of 2008 left the airline industry at an impasse. This crisis represents the second time the aviation industry experienced a negative growth. The economic meltdown in 2008 and the steeply rising oil prices resulted in financial difficulties for air carriers globally. With passenger travel demand decreasing, it was essential to accommodate capacity and resources for the short – and long run appropriately (Franke et al., 2011; Dobruszkes et al., 2011). This was done by limiting frequencies, employing smaller planes or even cancelling routes (Dobruszkes et al., 2011).

Responses to the economic crisis ranged from decreasing fares, scrapping old air crafts, reducing working hours, laying off labor force to strategic answers such as consolidation, in order to reduce costs and share risks (Morrell, 2011). Overall, the key challenges faced were to maintain traffic and yield levels, while trying to cut costs and reduce risks.

The airline industry is highly linked to the global economy, being very susceptible to external shocks (Morrell, 2011; Franke et al., 2011). According to Morrell (2011) the main 'frustrations' the airline industry is facing nowadays, next to recovering from the recent financial crisis, include coping with increasing oil prices, pollution controls and incurring safety lapses. Scientific literature is not clear at what pace the aviation industry will fully recover to precedent growth levels; however, it is important to anticipate external shocks in the future and take specific measures before-hand.

2.2. Share Prices

Share prices give an indication of a company's value (Burkart et al., 1999). A share price can be defined as the worth of a single share issued from a certain number of saleable stocks distributed on the stock exchanges by each company respectively (Lucas et al., 1990). A stock consists of equity stakes of a company's stock holders (Bond et al., 2012).These stocks are also referred to as shares.

Share prices are supposed to function on the assumption that they are being set randomly, however this is not entirely the case for the aviation industry (Praetz, 1972). The reason why share prices are supposed to be set randomly is the fact that agents should act rationally, if they possess perfect information about the company's performance indicators and the surrounding market environment, consequently setting share prices exclusively on future expectations (Fama, 1965). This is of course not the case for the aviation industry, since airlines are tightly linked to one another, cooperating in different strategic alliances, working in the same industry and being influenced by the same factors such oil prices for the use of kerosene or travel demand, functioning under the same economy. Not being set randomly, the model of this study will have to account for internal and external influences.

Scientific literature found evidence of certain variables influencing the set-up of share prices next to future expectations, especially in the case of the airline industry. There are two main concerns here: firstly, share prices depend on their own previous historic values or on calendar-specific trends, and secondly, recent studies in behavioral economics have proven that share prices are sometimes founded on investors' sentiments (Kaplanski et al., 2010; Goedhart et al., 2005). The two market anomalies refer to biases on the financial market that influence to some extent the random setting of securities (Bhardwaj et al., 1992). Historic values tend to give indications about today's or tomorrow's share prices. The most common calendar-specific anomaly is the so-called, 'January Effect' (Thaler, 1987). Share prices increase in January, resulting in investors buying shares before January at lower prices, while selling them in January when their value increases (Bhardwaj et al., 1992). This shows the market is not working efficiently.

The second concern refers to the emotional bias, fostered most of the time by media (Higgins et al., 1992; Kaplanski et al., 2010; Goedhart et al., 2005). Media impacts the decision-behavior of brokers, leading to non-rational, but 'sentimental' decision-making, which can affect not only one particular company, but an entire industry; share prices can, thus, be considered interdependent when governed by the same investment sentiment (Kaplanski et al., 2010). This is particularly the case when media portrays large-scale aviation accidents (Kaplanski et al., 2010). The high number of fatalities broadcasted can lead to a discouragement regarding flying in general, and consequently a negative perception of the airlines involved or even the entire industry (Kaplanski et al., 2010).

2.3. Aviation Accidents

Ranging from operational safety to the prevention of terroristic attacks, safety is a central issue in the aviation industry. With statistics such as one fatality per 7.1 million air passengers, Michaels et al. (2011) establish that the year of 2011 was by far the best year commercial aviation worldwide has encountered regarding safe air travel. Aviation in general is considered to be the safest mode of transportation (Oster et al., 2013).

According to Moses et al. (1990) and Flannery (2001) safety is reflected upon as the absence of an accident. Safety is difficult to measure, thus most scientific literature agrees upon using the number of accidents as proxy for measuring safety (Oster et al., 2013; Barnett, 2000; Lofquist, 2010). Even though the airline industry is considered safe, accidents still happened.

Scientific literature and official organizations find consensus on the universally adopted definition of an aircraft accident. Different attempts of defining such an accident have resulted in the construction of a globally accepted definition by the National Transport Safety Board (NTSB) and the Federal Aviation Administration (FAA). An ***aircraft accident*** is defined as an "*occurrence associated with the operation of an aircraft between the time of boarding until passengers and crew have debarked the aircraft, in which period any person (either inside or outside the aircraft) is fatally or seriously injured or the aircraft receives considerable damage*" (NTBS, 2012). The assumption underlying this definition is centered on the claim that the actual occurrence is not caused on purpose, with the exception of hijacking, by one or more persons leading to the definite damage of the aircraft or the injury of any person on board of the air plane or outside.

In order to clarify the definition, certain terminology needs to be explained. This terminology refers to the degree of injuries and damage to the aircraft. A '*fatal injury'* is considered any injury, which in the timespan of 30 days will result in death (NTSB, 2012). Accordingly, the NTSB (2012) defines a '*serious injury*' as one of the following stances: (1) hospitalization is required for the injured person for more than a couple of days, (2) injuries resulted in bone fractures, hemorrhages, nerve or muscle damage, or in the case of a fire, the injury comprises burns affecting more than 5% of the body surface (NTSB, 2012). Regarding the damage to the aircraft, the NTSB (2012) and the FAA consider a substantial damage to the aircraft the moment the plane can no longer be operated.

According to the NTSB aviation accidents can be categorized as: *nonfatal* – or *fatal* events. Nonfatal events denote occurrences with serious injuries to passengers on board of the aircraft (including personnel) and/or substantial damage incurred to aircraft itself, from the moment of boarding until the disembarking of passengers (Wiegman et al., 2005). Fatal occurrences, on the other hand, refer to the actual fatalities befallen and the damage irretrievability of the aircraft, during the interval between boarding and disembarking.

2.3.1. Causes of Accidents

Four major causes of accidents have been identified: (1) human errors, (2) mechanical failures, (3) weather and (4) hijacking. Next to the causes of accidents, it is imperative to look at the costs and consequences a crash airline has to endure after an accident.

For purposes of better understanding the causes of aircraft accidents, it is advisable to look at the phases of a flight. *Figure 2* shows the flight phases according to the percentage of accidents occurring per phase. According to Castillo (2005) the majority of fatal accidents happen during the landing phase. Even though, landing, takeoff and taxi represent a small portion of the total percentage of a flight, most nonfatal and fatal accidents happen during these particular phases.

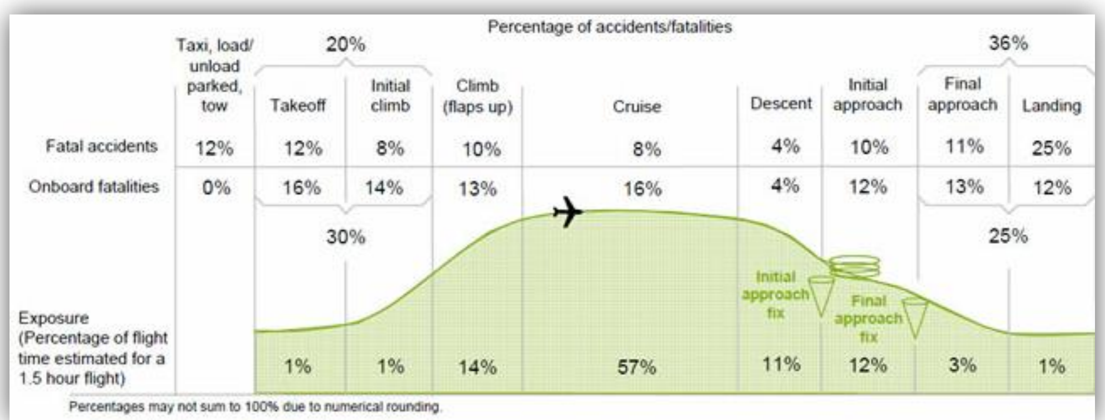


Figure 1: *Source: Boeing: Statistical Summary of Commercial Airplane Accident*

As Lindeberg (2005) suggests, these accidents, even though determined by the operator are considered "unlucky" circumstances, not deliberately set in motion by the pilot (Lindeberg, 2005). Nevertheless, pilot error is one of the most encountered causes of aircraft accidents (Shappell et al., 2004; Wiegmann et al., 2001).

Human Error

About 70% of accidents in aviation are attributed to human error (Shappell et al., 2004). According to Wiegmann and Shappell (2003) four levels of human failure can be identified, building up on each other, one influencing the next. The four levels are: (1) organizational influences, (2) unsafe supervision, (3) preconditions for unsafe acts and (4) unsafe acts.

Organizational influences play an essential role in human errors. Poorly taken managerial decisions, unfriendly working environment and an inefficient operation process can lead to unsafe supervision. Scientific literature (Wiegmann et al., 2001; Sheppell et al., 2004; Johnson et al., 2003; Wiegmann, 2005) agrees that supervisory powers are to blame. The reasons for this can be summed up as: inadequate supervision; inappropriate planning of flights; training failures (Johnson et al., 2003); violations of rules, and corruption (Wiegmann et al., 2001).

Inadequate supervision leads to half of the preconditions of an accident caused by human error (Reason, 1990), the other half is dependent on the individual behavior and capabilities. Preconditions can be divided in two categories, namely the readiness and capabilities of (a) the cockpit and (b) the individual pilots. These 'unsafe' actions taken by the crew can be twofold. Either an error, thus an action taken to not-deliberately sabotage the flight, but rather a good intention with an undesired outcome; or a violation denoting an intentional indifference of rules (Wiegmann et al., 2001; Rouse, 1983).

Mechanical Failure

Human error is not the only cause of accidents, but it is by far the most frequent. Second most recurrent source of aircraft accidents is mechanical failure (Sexton et al., 2000). (a) Pilot errors, (b) ground crew inadequacy or (c) aircraft manufacturers' mistakes can bring upon mechanical failures. Mechanical failures by pilot error result due to misjudgment or ignorance of an occurrence or failing to report difficulties encountered with the aircraft (Sexton et al., 2000; Baker et al., 2001, Wiegmann et al., 2001). Ground crews' inadequacy refers to the inability of the crew to properly inspect the airplane before takeoff, improper supervision of the crewmembers by a supervisory person (Wiegmann et al., 2001), by not respecting regulations or superficial work. Lastly, mechanical failures can be the result of poor design and manufacturing of the airplane or failure to inform their customer about products, thus presenting manuals or warning instructions.

Meteorological Conditions

Weather conditions can cause aircraft accidents. Research has shown that meteorological conditions can be fatal, however accidents due to weather circumstances are rare compared to the previous two causes. The most common variables playing a role in weather related accidents are: wind, visibility and turbulences (Knecht et al., 2010).

Meteorological situations are very closely related to pilots' abilities to cope to certain weather circumstances, thus meteoroidal conditions can be avoided if the flight crew is capable to avoid risk situations. Training, experience and equipment of pilots are keys to success in dangerous meteorological situations (Knecht et al., 2010).

Terrorist Actions

An act of terrorism is, unanimously considered an act of violence against civilization to attain ideological goals (Ruby, 2002; Sharp, 2000; Schmid, 2005). In aviation four tactics (O'Sulivan, 2005) can bring upon terrorist attacks: (1) hijacking, referring to the forceful seize of an aircraft by individuals or a group of individuals (O'Sullivan, 2005), (2) suicide attack on aircraft, (3) external weapons attacking the aircraft and (4) explosive on aircraft. Particularly important for this paper are hijacking, suicide missions and explosive on board of the aircraft.

2.3.2. Costs of Accidents

Having established the causes of an accident, it is insightful to consider the consequences of such a mishap. Not only represent accidents a loss of economic resources both for the airlines involved and the society, but also an irreplaceable loss of human lives. This paper will assume that underlying the costs of accidents are two main assumptions, namely that the airline company is to a certain extent conscious of the risks of possible accidents during each flight, and secondly the company is aware that it will bear the costs (Lindberg, 2005). These costs comprise both the direct and the indirect costs of an expected accident, thus the trip decision is a balance between executing the flight and, hence, gaining revenues, and the possibility of an accident associated with the particular costs. By weighting against each other both revenues related to offering the flight to the expectation of accidents, safety measures can be taken into account.

Companies value a higher probability of not being involved in an accident, due to possible costs arising in the scenario of being part or causing an accident (Lindberg, 2005). According to Lindberg (2005) and Scuffham et al. (2002) the valuation of accidents can be divided into two categories: direct – and indirect costs. The direct costs are quantifiable expenditures incurred directly by the company, ranging from medical and recovery costs of victims, legal costs, and property damage, such as aircraft damage and accidents investigation. Indirect costs according to Lindberg (2005) refer to consequences delaying after the accident. Such costs can vary from company to company and incur differently depending on each case. Indirect costs can be: (1) loss of business, since passengers are likely to switch to other airlines due to perceived safety of the crash airline, (2) image and reputation damage, (3) legal actions towards the airline company by victims' families, (4) increased insurance premiums, with the accident the risk category of the airline increased, and (5) loss of production, if crew is injured, then replacement needs to be found and trained, resulting in time loss and costs, while still paying injured crew members or their families. Due to both direct and indirect costs, companies are willing to invest large amounts in providing safe services for their customers.

So far, this paper has offered a glimpse at the aviation industry; it has defined and described share prices and explained the necessity to avoid accidents. Now, a detailed description of the relationship between accidents and share prices shall be presented, based on previous scientific literature.

2.4. Accidents and Share Prices

The relationship between aviation accidents and the airlines' financial value has been extensively discussed in the scientific literature, resulting in a series of studies and different opinions. Golbe (1986) analyzed US carriers' accident rates and financial records. No statistically significant relationship between an airline's safety measures and its profitability, measured by the net income, was the result of his study. The most important findings were that on a time span exceeding a couple of days, accidents have no influence on the airlines' financial indicators, hence there is no relationship and if there would be a one it would be very weak and insignificant. Common sense, however dictates that an aviation accident should have some significant impact on an airline's financial performance. Chance et al. (1987), just a year later, expanded on Golbe's (1986) research and found there is a negative shock following an unanticipated event, such as an airline accident, when eying the crash-airlines stock prices. Stocks are affected, if an accident occurs, on that particular trading day and the following few days after (Chance et al., 1987). Hence, while assessing the impact of accidents on airlines' revenues on a larger time span, no relationship is found (Golbe, 1986), however when replacing revenues with share prices, a negative relationship stands out, statistically significant for a couple of days (Chance et al., 1987)

There are multiple ways to analyze the effect of an accident on an airline. One is to analyze the risk of fatalities via the length of the route (Barnett et al., 1989). Deregulation has decreased safety, due to the entrance of new competition, however air travel continues to be a safe travel mode. Adapting his study, in 2000, Barnett et al. (2000) assess the impact of air travel fatalities on performance indicators of specific countries, categorizing those countries into three main groups: developed, developing and least developed countries. As expected, airlines in developed countries are safer than airlines in the other two categories, with a one in two million probability of death compared to a one in five hundred thousand probability for developing countries (Barnett et al, 2000). The risk of an accident increases with (1) the length of the route and (2) decreases with higher investments in security measures. Madsen (2011) assess the effect of accidents on profitability, using a Poisson model. He finds that, with increasing profitability, mostly due to an increased number of flights, the risk for a rise in the rate of accidents is present (Madsen, 2011).

There is a significant relationship between an airline's profitability and safety, in which case safety was measured by the number of accidents. Nevertheless, this was solely true for small or medium airlines (Oster et al., 2013).

Another way to look at the relationship between accidents and airlines' financial value is by dividing airlines into national carriers and regional carriers. Raghavan et al. (2005) found a negative and significant relationship only for small regional airlines. A negative relationship was also found when assessing legacy carriers; however, the relationship in this case, even though negative, was statistically insignificant.

An important factor influencing share prices is media, which impacts the investment sentiment of brokers. Kaplanski et al. (2010) introduce the media effects and find that aviation disasters are followed by negative rates of return trailed by a reversal effect two days later. After the impact of an accident has worn out, then share prices reach precedent values. They observe that media impacts the investors behavior, thus with the increased anxiety following aviation disasters there is a short-term decrease in the demand for risky assets, which affects share prices (Kaplanski et al., 2010). Not so much the event itself, but its media exposure influences share prices.

Looking solely at accidents as dummies might not always give enough insight. The next step scientific literature took was to look at the actual number of fatalities befallen in fatal accidents. The company's returns tend to decrease for the crash-airline with increasing fatalities. Thus, there is a negative relationship between accidents and financial indicators. The rival airline suffers the same if the number of fatalities is high (Ho et al., 2010). Hence, they conclude that, if the accident is severe it has repercussions for the entire industry. In the opposite case, meaning if the number of fatalities is low (less than ten), then rivals of the crash-airlines, might gain passengers, thus it has positive effect on their performance. A significant relationship is found when looking at the costs of an accident, hence investment in safety reduce the risk for aviation accidents. Sobieralski et al. (2013) investigate the costs associated with general aviation accidents. They divide those costs into direct and indirect costs, and establish a relationship between accidents and their impact on company performance, via the costs that can incur if such a calamitous event was to take place.

Scientific literature, hence, differs when it comes to evaluating the impact of an accident on the airline's financial performance. As described earlier, there are many approaches to analyzing the impact of accidents on companies' financial values. The size of the airlines sampled, the time unit selected or the duration of the shock, all seem to be relevant when considering the particular relationship between accidents and financial performance of an airline. However, since accidents represent an event on a particular day, scientific literature argues that is highly improbable that the duration of the accident will continue after a couple of days (Chance et al., 1987).

3. Data and Approach

3.1. Approach

This paper will examine the effect of aviation mishaps on the crash-airlines' financial value, projected by each airline's share prices. As established earlier, accidents can significantly impact a firm's value when the airline is either small or medium. The sampled airlines in this study are taken solely from the US and Canada, comprising both FSC and LCC airlines. The analysis is conducted on quarters as time units during 2000 up to 2011.

The *figure* below shows that an airline's financial value, hence its share prices can be influenced by a series of different factors. The first category represents the *internal* or company-specific factors (1), comprising the observations such as the shareholders' equity or the air fare charged. The *external* factors (2) can be divided in two categories, namely industry-specific (2a) and economy-specific (2b) indicators. Industry specific indicators refer to the oil prices or the Consumer Price Index (CPI) to account for inflation, whilst the economy indicator here is the Gross Domestic Product (GDP). All these influence share price, but also impact each other. One such relationship could be between the CPI and the GDP. As noted earlier in *Chapter 2.2* share prices are also depended on their own historic values, hence yesterday's share prices can be a benchmark for today's share prices. On top of this complex relationship, in the event of an accident, via media, accidents impact share prices as well as it was previously noted in *Chapter 2.4*.

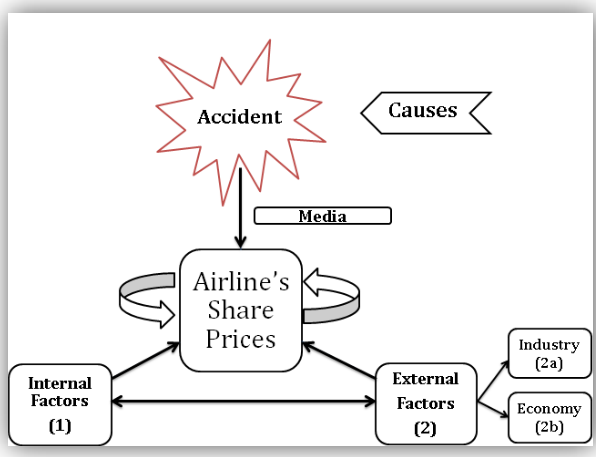


Figure 2: *Theoretical Model*

Scientific literature thrives with potential variables influencing brokers and consequently share prices (Piotroski et al., 2004; Saunders, 1993). Nonetheless, all can be placed into two distinguishable categories: (1) company-specific performance indicators (internal factors), and (2) environment-specific aspects (external factors). It is necessary to establish these influences on the share prices, in order to isolate for the independent effect of the accidents on the share prices.

The first category of control variables presented, are the **internal indicators**. Company-specific performance statements are published quarterly, respectively annually, and provide insight for the investment community into the company's economic outlook (Oswald et al., 1991). This paper will look at figures from periodically-available financial statements. These figures are: the shareholders' equity and the price of air fares. Internal variables have a positive correlation to share prices. If, let's say, the profit of a company increases, then more dividends are distributed to the company's shareholders and, thus, the price of a share rises (Mitchell et al., 2000).

External variables influencing share prices refer to certain macro-economic observations, which impact the economic environment (Wasserfallen, 1989). For this paper, three indicators have been used to account for external influences on share prices: (1) Consumer Price Index (CPI), (2) the oil price and (3) the Gross Domestic Product (GDP). CPI measures changes in the prices of goods and services to consumers (Hobijn et al., 2003). Oil prices were chosen due to the fact that they are receptive and sensitive to market shocks.

Oil prices give an indication of market fluctuations and/or of certain events taking place on a national or international level (Rault et al., 2009). GDP is necessary to account for economic changes.

In the case of aviation operations, which are based on the use of kerosene, oil prices are highly vital, since their actual operation depends on it. Periods with high oil prices result in a reduced number of operations, which reflects in the airliners' revenues and, since a relationship has been established earlier between revenues and share prices, consequently securities will be impacted as well (Rault et al., 2009). Scientific literature has found a significant negative relationship between oil prices and securities.

Adding, **both** the **internal** indicators, as well as the **external** variables, Humpe et al. (2007) showed their combined effects. There is a relationship between the share price and the two types of control variables mentioned, depending on time-specific factors.

The price is, thus, an equation of the sum of the expected values in time t of dividends or other internal variables at their specific time periods as well as the present value of market effects (Humpe et al., 2007).

To sum up, the model investigates whether or not there is a relationship between accidents and an airline's financial value. The share prices of a company are considered as a proxy for the financial value of airline. There are several interconnected factors influencing share prices, hence, in order to isolate the effect of the accidents on share prices, all other influences need to be accounted for. A detailed analysis of the relationship will be presented later in this study.

As seen previously, accidents can have an impact on the company's financial value, considering the magnitude of the event, and other factors such as media exposure or the size of the crash-airline. Thus, for this research only nonfatal and fatal accidents will be used. As proxies for nonfatal respectively fatal events, the actual number of injuries and fatalities will be employed. The financial value, as portrayed earlier in this chapter, can be influenced by own historic values as by external and internal factors. Of course, the emotional bias of the investors is to certain extent present (Kaplanski et al., 2010). The presence of media influencing the investment sentiment will not be part of the statistical model, but one has to keep in mind that media has also an impact on share prices.

This paper will analyze the effects of accidents on airlines' financial value, while controlling for internal and external influences. In the following section the data sampled will be presented and the model employed by the paper is shown. A summary of the relevant scientific literature can be found in *Appendix C.*

3.2. Data

For the purpose of an empirical investigation and in order to assess the impact of aviation accidents on companies' financial performance, secondary data has been gathered from sources such as data bases and company records. The analysis has been carried out in STATA, at a significance level of 5%. Based on North American civil aviation carriers, containing eleven companies according to rankings quality performance, the data assembled is spread over a twelve-year time span, from 2000 to 2011, inclusive. The research is based on the airline industry, whilst the selected airlines are registered either in the United States of America or Canada; this selection came about due to the fact that the information acquired is verifiable and complete, to the extent of the airlines' willingness to publish their records. The air carriers chosen are: Alaska Airlines (ALK), American Airlines (AMR), Air Canada (AC), AirTran Airways (AAI), Delta Air Lines (DAL), Hawaiian Airlines (HA), JetBlue Airways (JBLU), Skywest Airlines (SKYW), Southwest Airlines (LUV), United Airlines (UAL) and US Airways (LCC).

According to Forbes' latest review of the quality of US airlines, the following ranking has been considered for this study, starting from the highest quality airline to the lowest:

Ranking	Airline	FSC	LCC	Remarks
#1	Virgin America (VAI)	•		*Excluded due to lack of data*
#2	JetBlue Airways (JBLU)		•	--
#3	AirTran Airways (AAI)		•	--
#4	Delta Air Lines (DAL)	•		--
#5	Hawaiian Airways (HA)	•		--
#6	Alaska Airlines (ALK)	•		--
#7	Southwest Airlines (LUV)		•	--
#8	US Airways (LCC)	•		--
#9	American Airlines (AMR)	•		--
#10	Skywest Airlines (SKYW)		•	--
#11	United Airlines (UAL)	•		--

Table 1: *Airline Quality Ranking, Forbes.com, 2013*

This ranking is based on the following quality indicators: (1) On-time arrivals, (2) denied boarding, (3) mishandled baggage, and (4) customer complaints (Forbes.com, 2013). The data was obtained from the National Transport Safety Board (NTSB). Additionally, Air Canada (AC) was added to the sample.

The data collected is used for an analysis on a quarter-level according to the twelve-year time span mentioned above. This came about due to the structure of financial records and company-specific indicators, which are published on a quarters. This study will use as dependent variable the share prices of each airline mentioned earlier.

Due to the fact that the stock markets are closed on weekends, national holidays and the immediate week after the terrorist attacks of 9/11, the dataset includes information solely for the remaining working days per week.

Since the data collected includes multiple observations on units (airlines), which are followed over a certain time span, *panel regression* will be used. The collected data can be divided in four main parts: stock records, company-specific indicators, external pointers, and the actual accidents. The stock records have been gathered mainly from the Thomson Reuters database, grounded on information from the New York Stock Exchange (NYSE) and NASDAQ. For validity reasons these records have been compared to the data available at the Wharton Research Data Services Institute, and if need be the missing data has been added to the set. Data on stock records includes the aggregated share prices on quarters for each airline and their respective market value.

The company-specific observations have been assembled using two databases: Thomson Reuters and Orbis, and completed, if necessary, with information form annual – and interim financial reports of the companies. The external variable, namely the price of oil, the consumer price index (CPI) and the Gross Domestic Product (GDP) have been gathered from the OPEC and the Bureau of Labor Statistics, respectively the OECD, IMF and the World Bank.

The accidents of each airline have been collected from the Federal Aviation Administration (FAA) and the National Transport Safety Board (NTSB). Since accidents are registered on days, it was necessary to aggregate them on quarters, and consequently assess their combined impact on the financial value of the air carrier. The accident variable is a dummy, assessing the *presence* of an accident and not the effect of the number of accidents incurred in that particular quarter, hence, if two accidents were to happen in one quarter, only their presence and not their number was noted. The total number of accidents amounts to one hundred, both nonfatal and fatal mishaps. The number of nonfatal events adds up to ninety, whilst fatal events are solely ten occurrences. As mentioned, the event variables are dummies, thus indicating the presence or absence of an event during that particular quarter. The actual number of injuries and fatalities per accident was also collected from the National Transport Safety Board (NTSB).

At this point it is necessary to remember the terminology used; namely according to the NTSB aviation mishaps can be categorized as: nonfatal – or fatal events. Nonfatal events denote occurrences with injuries to passengers on board of the aircraft (including personnel) and/or substantial damage incurred to aircraft itself, from the moment of boarding until the disembarking of passengers. Fatal occurrences refer to the actual fatalities befallen and the damage irretrievability of the aircraft, during the interval between boarding and disembarking (Wiegman et al, 2005).

The effect of accidents will be assessed on the companies' share prices. To individualize the effect of either nonfatal or fatal mishaps, accidents will be divided into nonfatal and fatal events and also according to the actual number of injuries and fatalities. The model will firstly look at the combined impact of accidents on share prices; secondly, it will assess the effects of the presence of either a nonfatal or fatal mishap during a particular quarter; and thirdly, it will look at the effect of the actual number of injuries and fatalities.

In the following section, a Bårdsen Error Correction Model will be developed to assess the impact of accidents on the crash airlines' financial value, whilst solving for nonstationarity and serial correlation issues. Several assumptions will be tested, and if necessary accounted for, in order to validate the final model.

4. Methodology

4.1. Hypotheses

Before looking at the results of the study and the interpretation of the relationship between accidents and share prices, the following three hypotheses will aid in answering the research questions of this paper.

H01: *There is no relationship between* **accidents** *and financial firm value.*
HA1: *There is a negative relationship between* **accidents** *and financial firm value.*

H02: *There is no relationship between* **nonfatal accidents** *and financial firm value.*
HA2: *There is a negative relationship between* **nonfatal accidents** *and financial firm value.*

H03: *There is no relationship between* **fatal accidents** *and financial firm value.*
HA3: *There is a negative relationship between* **fatal accidents** *and financial firm value.*

Thus, the impact of the accumulated number of accidents on share prices will be tested first, followed by the classification of accidents into either nonfatal or fatal events, by analyzing the both the respective dummies as well as the actual number of injuries and fatalities. Before running the tests, it is advised to check several assumptions for the validity and the correctitude of the research.

The model of this paper is based on a Bårdsen Error Correction Model with Newey West Standard Errors, assessing short – and long haul effects, reducing the issue of collinear regressors and decreasing the risk of spuriousness (van Reeven, 2011). The final model of the paper follows a linear path, and looks as per below:

$$\Delta \mathrm{lnshr\_p} = \alpha_0 + (\alpha_1 - 1)\mathrm{lnshr\_p}_{t-1} + \beta_1 \Delta \mathrm{lnshld\_eq} + \beta_2 \mathrm{lnshld\_eq}_{t-1} + \beta_3 \Delta \mathrm{lnfare} + \beta_4 \mathrm{lnfare}_{t-1} + \beta_5 \Delta \mathrm{lncpi} + \beta_6 \mathrm{lncpi}_{t-1} + \beta_7 \Delta \mathrm{lnoil} + \beta_8 \mathrm{lnoil}_{t-1} + \beta_9 \Delta \mathrm{lngdp} + \beta_{10} \mathrm{lngdp}_{t-1} + \beta_{11} \mathrm{accident} + \beta_{12} \mathrm{dummies} + \varepsilon \quad \textbf{\textit{(M.1.)}}$$

Regarding the model above, "Δ" means the difference in the respective variables, "$t-1$" shows the lag of the specific observation in the period $t-1$, "α_0" is the intercept, while "β_n" are the individual coefficients. Both accident dummies as well as the time dummies are represented by "β_{12}dummies".

4.2. Assumptions

Because the data was found to exhibit several theoretical and practical issues impeding panel regression, this paper recommends assessing several assumptions depicted in the following. As determined earlier in the paper, in order to create a valid model for the analysis, certain assumptions need to be tested:

Assumption	Test	Results	Solution
(1) Randomization	--	--	Addition of industry & economy variables
(2) Linearity	--	--	Linear parameters
(3) Exogeneity	• Durbin-Wu Hausman Test	Not Rejected, hence no instrument needed	--
(4) Multicolliearity	• pwcorr, sig • VIF	High correlation between OIL and CPI.	OIL and CPI kept in the model due to **Omitted-Variable-Bias**
(5) Homoscedasticity	• Breusch-Pagan Test • White Test	Rejected → Heteroscedasticity	White's Robust Standard Errors
(6) Normal Distribution	• QQ-Plot • Histogram	Slightly negatively skewed	--
(7) Serial Correlation	• Xtserial	Rejected → Autocorrelation	Newey West Standard Errors
Additionally Testing for:			
(8) Nonstationarity	• Augmented Dickey Fuller Test	Not rejected → Nonstationarity	Error Correction Model (ECM)

Table 2: *Summary of Assumptions*

This section will test, apply and if necessary account for violations of the particular assumptions to follow. In order to assess the impact of accidents on the financial value of companies, the model proposed is based on panel regressions.

Since the data collected includes multiple observations on units (airlines), which are followed over a certain time span, panel regression will be used. Panel regression ensures for a certain degree of ***(1) randomization*** regarding the time span selected. There is a particular interdependence of share prices on the industry level, share prices being governed by the same investor sentiment (Kaplanski et al, 2010). To guarantee a random structure industry-specific (e.g. oil price and CPI) and economic indicators (GDP) will be used. Because of the interdependence of share prices, correlation dummy variables for each trading day, month, and year have been created to account for it. The addition of these shock-dummies to the model safeguards a higher degree of randomization of the sample.

(2) Linearity in parameters is a core assumption that needs to be tested for. Linear regression will be used to model the relationship between the dependent variable, share price, and one or more explanatory variables. The dependent variable y is related to the independent variable x_n and the error ε.

$$f(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$$

All individual terms are summed to yield a final function value. The model must, thus, be linear in parameters. Each independent variable is multiplied by a parameter, whilst there is at most one parameter with no corresponding explanatory variable (Carter Hill et al., 2012).
Before assessing exogeneity, the error term needs to have a *zero population mean*, hence each observation has a random error with a mean of zero. Besides the observations having a random error with a mean equal to zero, it is also advised for the error term at a certain point in time to have a mean of zero, when considering time-series models. Solving for panel structures, each error term of an observation at a specific point in time, needs to be equal to zero $E(\varepsilon_{i_t}) = 0$.

The residuals will influence the dependent variable directly, if $E(\varepsilon_{i_t}) \neq 0$. In order to account for $E(\varepsilon_{i_t}) \neq 0$ a constant (intercept) will be added in the modeling. To reach a zero population mean again, the constant serves as a buffer to add or subtract the difference from zero of $E(\varepsilon_{i_t})$.

(3) Exogeneity refers to the fact that the error term is not correlated with the explanatory variables, thus all observations are determined outside the model (exogenous). For this assumption to be valid in time-series structures, the above formulation needs to be adapted conformingly, accounting for time.

In panel structures one has to justify both for error terms of the observations not being correlated with the explanatory variables and the particular time factor: $E(\varepsilon_{i_t} | X_{i_t}, X_{i_{t-1}}, X_{i_{t-2}}, \dots, X_{i_{t-n}}) = 0$.

If there is a correlation between the error term and the explanatory variables, the estimator will not be valid; therefore, control or instrumental variables need to be added. The Durbin-Wu Hausman Test will be performed to check for endogeneity. This test helps in evaluating whether the model corresponds to the data gathered. In *Table A1*, it can be noted that, with a p-value of 0.5303, the model established cannot be rejected; hence the model cannot be considered endogenous, thus there is no impediment for its further construction regarding exogeneity.

Using more than one independent variable increases the risk of ***(4) multicollinearity*** (Al-Tamimi et al., 2011). Multicollinearity between the dependent and the explanatory variables cannot be present. Multicollinearity arises especially when the explanatory variables are too strongly correlated with each other, hence one variable can be determined from the other, resulting in an undefined least squares estimator (Carter Hill et al., 2012). Drukker (2003) suggests that when there is multicollinearity one of the variables might be dropped, in order for the estimation to be correct. Nevertheless, the omission of a relevant variable can lead to a biased estimator (omitted-variable bias). As long as correlated variables are used as control variables, multicollinearity represents a lesser problem than the omitted-variable bias would. Drukker (2003) describes a limit of the correlation coefficient or a Variance Inflation Factor (VIF). The cut-off, as Drukker (2003) labels it, is around 0.7 for the correlation coefficient or 12 for the VIF.

Table A2a depicts a correlation matrix, while *Table A2b* depicts the results of the Variance Inflation Factor (VIF). The variables, which have a VIF higher than twelve shall not be used in the same regressions; nonetheless this is not the case for this study. The highest correlation (0.8158) is established between the oil price and the consumer price index; however the VIF is not above 12. Nonetheless, due to the "omitted variable bias" both variables will be kept in the model, to ensure randomization of the sample. The residuals (res) were also correlated with the variables in *Table A2a.*

The following assumption that needs to be tested is the presence of ***(5) homoscedasticity***, meaning that $var(\varepsilon_{i_t}) = \sigma^2$ is not violated (Carter Hill et al., 2012). Homoscedasticity shows probability distributions significantly equal, thus the explanatory power of the model is much stronger compared to heteroscedasticity (Drukker, 2003; Wooldridge, 2002).

The problem with heteroscedasticity is that the variances for all observations differ from each other. There are two main tests to check for heteroscedasticity: Breusch-Pagan – and the White test.

The Breusch-Pagan tests for heteroscedasticity in linear regression, by checking whether the variance of the residuals is significantly reliant on the independent variables (Halunga et al., 2011). The general regression model is depicted below:

$$E(lnshr\_p) = \beta_1 + \beta_2 lnshld\_eq + \beta_3 lnfare + \beta_4 lncpi + \beta_5 lnoil + \beta_6 lngdp + \beta_7 accident$$

Because the data collected is cross-sectional and time reliant, the possibility of heteroscedasticity is present.

$$var(lnshr\_p) = \sigma_i^2 = E(e^2) = h(\alpha_1 + \alpha_2 z_{i2} + \cdots + \alpha_N z_{iN})$$

The above-stated formulation implies that a change in the variance of the average share price is dependent on the exogenous explanatory variables z_i (Wooldridge, 2009). The variables z_i are external and are not a direct component of the observations that explain the average share price.

The difference between homoscedasticity and heteroscedasticity lies in the value for α_i. If the variance is constant, then homoscedasticity is present. This happens in the above mentioned case as long as $\alpha_2 = \alpha_3 = \cdots = \alpha_n = 0$. The change in the variance of the average share price is solely reliant on α_1 (Verbeek, 2008). If at least one of $\alpha_2, \alpha_3, \dots, \alpha_n$ is significantly different from zero, then heteroscedasticity prevails.

Table A3 shows the results for the Breusch-Pagan test. The test statistic is significant at the 5% level (p-value of 0.0002) and thus the null hypothesis must be rejected, hence the observations can be considered heteroscedastic.

The problem with the Breusch-Pagan test is its assumption that the z_i variables are known (Verbeek, 2008). This however, is not the case for the study at hand; hence, the White test will be performed. The difference between the two tests lies in the fact that the White test does not assume an understanding of z_i (Drukker, 2003). Baltagi et al. (2009) imply that most of the time the z_i variables are simply the dependent variables of the established model. *Table A4* shows the results of the White test. In accordance with the outcomes of the Breusch-Pagan test, the null hypothesis has to be rejected, as the test statistic is significant at the 5% level (p-value of 0.0128). This implies the existence of heteroscedastic observations.

Having heteroscedastic observations proves to be an impediment. Hence, it needs to be accounted for in the set-up towards the final model. In order to make up for this impairment, Wooldrige (2009) and Carter Hill et al. (2012) propose the use of White's Robust Standard Errors ("robust" option will be used henceforth in STATA). The reason is that these specific standard errors are resistant to heteroscedasticity. Furthermore, taking the logarithm of the model ensures heteroscedastic observations are diminished.

Having established both exogeneity and heteroscedasticity, it is recommended for the variables and the residuals to follow a ***(6) normal distribution*** pattern conditional on the explanatory variables, hence the error term is independent of the explanatory variables and normally distributed, according to the formula: $\varepsilon_{i_t}|X \sim N(0, \sigma^2)$. The QQ-Plot and the histogram in *Graph A1* and *Graph A2* prove a normal distribution. The values are slightly negatively skewed.

Next, it is necessary, especially with time-series to test for ***(7) serial correlation***. As noted in the theoretical framework, stock prices are dependent on their historical values (Chaudhuri et al., 2003). Thus, it can be pointed out that the effects do not incur instantaneously, but are distributed over time (Drukker, 2003). This has implications for the linear regression as the results can be spurious, since $cov(e_{xi}, e_{xj}) \neq 0$. In other words, the value of the standard error in time t is determined by the value of the standard error at time t-1. Share price as the dependent variable, at time t is contingent both with the independent variables at time t and *t-n* as well as on its own values at time *t-n*. Determining the right number of lags, for both the dependent and independent variables can correct for serial correlation.

a. Number of lags

Adding lagged variables reduces the sum of squared errors (SSE), however if too many are added the explanatory power of the model decreases significantly (Carter Hill et al., 2012). The Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC) will be employed to determine the optimum number of lags in the regressions. The number of lags that will be used is when the values for AIC and BIC are smallest (Drukker, 2003).

To clarify the results, the formulas for AIC and BIC are as follows, where ***"t"*** represents the time, ***" l"*** shows the number of lags and ***"SSE"*** stands for the sum of squared errors:

$$AIC = \ln\left(\frac{SSE(l)}{t}\right) + \frac{2(l+1)}{t} \qquad BIC = \ln\left(\frac{SSE(l)}{t}\right) + \frac{(l+1)*lnt}{t}$$

In *Table A5* the results of the AIC and BIC can be seen, thus the optimal value is two lags; this is in accordance with Perasan and Shin (1999), de Boef et al. (2005) and Wooldridge (2009).

b. Testing for Serial Correlation

Serial correlation is always a possibility with time series data. Serial correlation implies a covariance significantly different from zero between the residuals of observations across time. Drukker (2003) proposed a serial correlation test, with following hypotheses.

$$H_0 : cov(e_{xi}, e_{xj}) = 0$$

$$\text{no serial(auto)correlation, where } x_i \neq x_j$$

$$H_1 : cov(e_{xi}, e_{xj}) \neq 0$$

$$\text{serial correlation, where } x_i \neq x_j$$

The test results can be found in *Table A6*. The null-hypothesis needs to be rejected at a 5% significance level with a p-value of 0.0000.

It was previously noted that in order to build a complete model there is a need to use robust standard errors, due to the homoscedasticity violation (Carter Hill et al., 2012). However, since the standard errors also violate the assumption of autocorrelation, Carter Hill et al. (2012) proposes the use of Heteroscedasticity and Autocorrelation Consistent Standard Errors (HAC), also known as Newey West Standard Errors.

The Newey West Standard Errors account for both the autocorrelation, as well as for heteroscedasticity. The “robust” option in STATA will be replaced with the “newey” command. The HAC Standard Errors differ from the robust errors presented earlier to the extent that their variance estimators are equal to those of the latter multiplied by an extra term that accounts for autocorrelation (Carter Hill et al., 2012). Additionally, the assumption is made that the autocorrelations go towards zero as the time difference between the observations increases (Baltagi et al., 2009).

The data collected is characterized by time-series, thus it is necessary to check whether it is ***(8) nonstationary***. Nonstationary data is described by an augmentation over time, resulting in fluctuations in the mean and the variance. The *Graphs A3* to *A13* in the appendix show a random walk. This already hints toward to the presence of nonstationary.

The Fischer test, based on an augmented Dickey Fuller test will be used to check for stationarity. The stock prices of the companies date before the selected starting point, meaning before 2000, therefore an intercept is added.

As noted by Semenick Alam et al. (2012), the economic indicators show certain trends, which can account statistically for nonstationarity. In order to check for the presence of a trend, the Wilcoxon rank-sum test on trend is performed. *Table A7* presents the outcome, pointing out that a certain trend is present in the data at hand, as the null hypothesis must be rejected.

Table A8 presents the result of the Augmented Dickey Fuller test on unit roots. The hypotheses for this test are as follows:

$$H_0 : all\ panels\ have\ unit\ roots$$
$$H_1 : at\ least\ one\ panel\ is\ stationary$$

A trend is added as proven by the Wilcoxon rank-sum test, thus a 'trend' option is added in the Augmented Dickey Fuller test. As can be seen in the results the null hypothesis cannot be rejected (p-value 0.7229), therefore the panels can be considered nonstationary.

4.3. Bårdsen Error Correction Model

Due to non-stationary autoregressive data a dynamic panel model will be employed (de Boef et al., 2005). Autoregressive Distributed Lag Model (ARDL) will be used to account for these concerns. The ARDL model implies that the value of a share price in time ***"t"*** is dependent on its value in time ***"t-1",*** as well as on the independent variables in both time periods (Chaudhuri et al., 2003).

The estimation of the ARDL model will look as follows.

$$y_t = f(y_{t-n}, x_{i,t}, x_{i,t-n}) \qquad \textbf{(ARDL.1)}$$

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{n} (\beta_{i0} x_{it} + \beta_{i1} x_{it-1}) + v_t \qquad \textbf{(ARDL.2)}$$

The estimation of the dependent variable y_t is a function of the intercept β, the two lagged values for y_t $(\alpha_1 y_{t-1} + \alpha_2 y_{t-2})$ as well as the sum of the explanatory variables and their respective lags. The term v_t denotes the HAC Standard Error.

From ARDL, inferences about dynamic behavior can be drawn. However, ARDL models do not specify long run effects (de Boef et al., 2005). Over time, observations tend to reach long run equilibria and if there are any perturbations, the rate of return to the equilibrium state differs in the short – and long run. Long run effects would be especially relevant for this study, in order to assess the duration of the impact of the accidents on the dependent variable.

Therefore, Error Correcting Models (ECM) can be employed in order to check for short – and long run effects, as well as the rate of return to the equilibria, providing a direct estimate of the error correction rate and its standard error (de Boef et al., 2005).

Building on the ARDL model, an ECM will be designed. Considering the ARDL model, firstly the difference of y_t will be taken.

$$\Delta y_t = \alpha_0 + (\alpha_1 - 1)y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + v_t \qquad \textbf{(ECM.1)}$$

The next step is to add and subtract $\delta_0 x_{t-1}$ from the right hand side, resulting in:

$$\Delta y_t = \alpha_0 + (\alpha_1 - 1)y_{t-1} + \beta_0 \Delta x_t + (\beta_0 + \beta_1)x_{t-1} + v_t \qquad \textbf{(ECM.2)}$$

The Bårdsen Error Correction Model, additionally to the ARDL model, reduces the problem of collinear regressors (van Reeven, 2011), as well as the risk of spurious results (van Reeven, 2011). The short run effects are explicitly stated and denoted by$(\alpha_1 - 1)$, β_0 and $(\beta_0 + \beta_1)$. They are different from the normal ARDL coefficients, except β_0. The long run coefficient is shown in the following formula (de Boef et al, 2005): $k_i = \frac{(\beta_1 + \beta_0)}{(1-\alpha_1)}$.

After estimating the ECM short – and long run coefficients, this paper will continue building towards the final model. Regarding the several assumptions, this study now assumes that all issues presented above have been accounted for, hence valid panel regressions can be performed without impediments. In the following sub-section the model investigated throughout this paper is depicted.

The model presented below is based on the previously mentioned assumptions. The purpose of this model is to give an empirical assessment of the impact of accidents on air carriers' financial performance via share prices per air carrier.

$$\Delta \text{lnshr\_p} = \alpha_0 + (\alpha_1 - 1)\text{lnshr\_p}_{t-1} + \beta_1 \Delta \text{lnshld\_eq} + \beta_2 \text{lnshld\_eq}_{t-1} + \beta_3 \Delta \text{lnfare} + \beta_4 \text{lnfare}_{t-1} + \beta_5 \Delta \text{lncpi} + \beta_6 \text{lncpi}_{t-1} + \beta_7 \Delta \text{lnoil} + \beta_8 \text{lnoil}_{t-1} + \beta_9 \Delta \text{lngdp} + \beta_{10} \text{lngdp}_{t-1} + \beta_{11} \text{accident} + \beta_{12} \text{dummies} + \varepsilon$$

(M.1.)

The theory (Angel, 1997; Ferrier et al., 2002; Cragg et al., 1982) behind the model states that share prices are influenced by **internal** and **external** indicators (Cutler et al., 1989; Nandha et al., 2008). Supposing the interrelationship between the two categories above and taking into account the potential effect of accidents on the crash-airlines' financial value, this paper assumes that the mishap in question impacts all factors above.

The shareholders' equity and the air fare will be taken as the main company-specific performance indicator. The next step is to include the external variables, accounting for market effects. The variables used are the oil price during the sampled time period, the consumer price index (CPI) and the Gross Domestic Product (GDP). The oil price accounts, not only for the company's reliance on kerosene, but it also makes up for market shocks, since oil prices are highly susceptible to market fluctuations (Nandha et al., 2008; Cragg et al., 1982). The CPI is used to account for inflation, whilst the GDP is employed to make up for all economic influences. Lastly, the model has to be completed by adding the actual events, since the core of the paper is the effect of aviation accidents on the financial value of the sampled airlines.

5. Results

5.1. Findings

This chapter will present the results of the Bårdsen Error Correction Model (ECM) depicted in the previous section. Thus, using the error correction model mentioned earlier and Newey and West Standard Errors, the impact of aviation accidents on airlines' financial values will be described. Both the short –and the long run effects will be taken under consideration. The output of this study is presented in *Appendix B*. The accumulated impact of all accidents will be considered primarily, followed by the assessment of the presence of a nonfatal respectively a fatal accident, and lastly by the consideration of the impact of injuries and fatalities. The accident variable is a dummy, whilst the injuries and fatalities are not.

This analysis is built on three models assessing the impact of accidents on an airline's financial value via the following internal and external explanatory variables: shareholders' equity, fare, CPI, oil prices and GDP, according to the three hypotheses mentioned earlier. To sum up, this paper will use the following endogenous and exogenous variables:

Dependent Variable	**Endogenous Explanatory Variables**	**Exogenous Explanatory Variables**
Share Price	Shareholders' Equity	Oil Price
	Fare	Consumer Price Index (CPI)
		Gross Domestic Product (GDP)

Table 3: *Summary of Explanatory Variables*

Before looking at the impact of accidents on share prices, it necessary to concentrate on the previously mentioned internal and external factors influencing share prices. This analysis will convey the results based on values identified per quarter. This came about due to the impediment that airlines publish their financial records solely on a quarter, respectively on a yearly basis.

The models are, as specified, based on the Bårdsen Error Correction Model with Newey and West Standard Errors. This solves both the problem of serial correlation and nonstationarity. Additionally, time dummies have been added, for which the results can be seen in *Appendix B*.

Table B1 shows the results of the first model:

$$\Delta \mathrm{lnshr\_p} = \alpha_0 + (\alpha_1 - 1)\mathrm{lnshr\_p}_{t-1} + \beta_1 \Delta \mathrm{lnshld\_eq} + \beta_2 \mathrm{lnshld\_eq}_{t-1} + \beta_3 \Delta \mathrm{lnfare} + \beta_4 \mathrm{lnfare}_{t-1} + \beta_5 \Delta \mathrm{lncpi} + \beta_6 \mathrm{lncpi}_{t-1} + \beta_7 \Delta \mathrm{lnoil} + \beta_8 \mathrm{lnoil}_{t-1} + \beta_9 \Delta \mathrm{lngdp} + \beta_{10} \mathrm{lngdp}_{t-1} + \beta_{11} \mathrm{accident} + \beta_{12} \mathrm{dummies} + \varepsilon$$

(M.1.)

Hence, this model depicts the effect of accidents on share prices via the above-mentioned internal and external variables. The first Bårdsen Error Correction Model tests whether the accumulated aviation mishaps have an effect on share prices via the shareholders' equity, fare, CPI, oil prices and GDP. Ceteris paribus, the interpretation of the variables employed will be similar regarding all models.

	Δlnshr_p		
Number of OBS = **327**			
	Variable	**Coefficient (β_i)**	**p-Value**
Short-Run			
	Δln(SHLD_EQ)	**0.251****	0.001
	Δln(FARE)	0.883	0.078
	Δln(CPI)	**3.579****	0.004
	Δln(OIL)	**-0.823****	0.001
	Δln(GDP)	10.098	0.099
Lagged Variables			
	$\ln(SHR\_P)_{t-1}$	**-0.305****	0.028
	$\ln(SHLD\_EQ)_{t-1}$	0.078	0.078
	$\ln(FARE)_{t-1}$	0.290	0.149
	$\ln(CPI)_{t-1}$	2.301	0.076
	$\ln(OIL)_{t-1}$	**-0.776****	0.017
	$\ln(GDP)_{t-1}$	**0.189****	0.045
Accident Variable			
	Accident (*dummy)*	-0.054	0.385
		*Time Dummies _I**	
Long-Run		**Long-Run Coefficient (k_i)**	**p-Value**
	$\ln(SHLD\_EQ)_{t-1}$	**0.256****	0.000
	$\ln(FARE)_{t-1}$	**0.949****	0.032
	$\ln(CPI)_{t-1}$	7.541	0.151
	$\ln(OIL)_{t-1}$	-2.543	0.088
	$\ln(GDP)_{t-1}$	**0.619****	0.000

Table B1: *Results Model 1* *****Significant at a 5% significance level***

The shareholders' equity shows a positive effect on share prices, being statistically significant at a 5% significance level; hence a 1% increase in shareholder equity means a 0.251% increase in share prices. The price of the air fares influences share prices positively, but is statistically insignificant. CPI is statistically significant with a p-value of 0.004, incurring a positive effect.

Oil prices, as scientific literature predicts, prove to be negatively related to share prices, being statistically significant (p-value of 0.001). The GDP shows a strong influence on share prices; nevertheless, at a 5% significance level it proves to be insignificant. Regarding the lagged variables, the lag of the share prices shows a statistical significance with a p-value of 0.028; this shows the dependence on historic values discussed earlier (Thaler, 1987; Bhardwaj et al., 1992). Besides the lag of share prices, only the lags of the OIL and GDP variables are statistically relevant.

The long run multiplier is calculated according to the formula: $k_i = \frac{(\beta_1 + \beta_0)}{(1-\alpha_1)}$ mentioned in the methodology section. Considering the long run coefficients estimated by the Bårdsen Error Correction Model, the following variables continue to be significant at a 5% significance level: the shareholders' equity (p-value of 0.000), air fare (p-value of 0.032) and GDP (p-value of 0.000).

Accidents have a negative impact on the share prices, however not significant. As Kaplanski et al. (2010) point out a delayed effect can sometimes be expected, due to a reminiscence of the anxiety investors experience towards risky assets. Accidents show no statistical significance at a 5% significance level. Previous literature (Chance et al., 1987; Ho et al., 2011) has argued the prolonged impact of an accident. It is highly improbable for the effect of an accident to be visible for more than a couple of days after the particular event. Thus, in accordance with scientific literature, on a quarterly level, the effect of an accident should not be observable in a company's share prices during a quarter; these reaching previous values in the meanwhile (Chance et al, 1987). The results of first test indicate a negative coefficient which is indeed insignificant (*Table B1*). The results of the first test can be seen in *Appendix B*, *Model 1*. In *Table B2* the results for the second model can be seen, meaning that instead of considering the accumulated impact of accidents on share prices, the effect of injuries will be assessed next.

		Δlnshr_p			
Number of OBS = **327**					
		NONFATAL (*Model 2a*)		INJURIES (*Model 2b*)	
	Variable	**Coefficient (β_i)**	**p-value**	**Coefficient (β_i)**	**p-value**
Short-Run					
	Δln(SHLD_EQ)	**0.251****	0.001	**0.241****	0.002
	Δln(FARE)	0.879	0.079	0.820	0.095
	Δln(CPI)	**3.588****	0.004	**3.699****	0.003
	Δln(OIL)	**-0.823****	0.001	**-0.824****	0.001
	Δln(GDP)	10.093	0.099	10.389	0.087
	ΔINJ	--	--	0.002	0.505
Lagged Variables					
	ln(SHR_P)$_{t-1}$	**-0.305****	0.028	**-0.307****	0.029
	ln(SHLD_EQ)$_{t-1}$	0.077	0.078	0.075	0.090
	ln(FARE)$_{t-1}$	0.290	0.146	0.238	0.206
	ln(CPI)$_{t-1}$	2.308	0.074	2.263	0.079
	ln(OIL)$_{t-1}$	**-0.775****	0.017	**-0.789****	0.015
	ln(GDP)$_{t-1}$	**0.189****	0.044	**0.181****	0.047
	INJ$_{t-1}$	--	--	0.007	0.058
Accident Dummy					
	Nonfatal (*dummy)*	-0.057	0.373	--	--
		*Time Dummies _I**			
Long-Run		**Long-Run Coefficient (k_i)**	**p-value**	**Long-Run Coefficient (k_i)**	**p-value**
	ln(SHLD_EQ)$_{t-1}$	**0.254****	0.000	**0.243****	0.000
	ln(FARE)$_{t-1}$	**0.952****	0.032	0.774	0.068
	ln(CPI)$_{t-1}$	7.566	0.149	7.364	0.152
	ln(OIL)$_{t-1}$	-2.542	0.089	-2.567	0.091
	ln(GDP)$_{t-1}$	**0.618****	0.001	**0.589****	0.000
	INJ$_{t-1}$	--	--	0.021	0.171

Table B2:*Results Model 2a and Model 2b* ***Significant at a 5% significance level*

Regarding the coefficients of the explanatory variables, the shareholders' equity, CPI and the oil prices statistically impact share prices in both *Model 2a* and *2b*. As previously, both the lag variables of the share price, oil price and the GDP are statistically significant. In *Model 2a* the nonfatal events show a negative coefficient, yet insignificant, with a p-value of 0.373. Regarding *Model 2b* similar results are noted for the explanatory variables. Injuries have almost no influence on a company's financial performance. The calculated long run coefficients prove to be strongly statistically significant only for the fare (only *Model 2a*), GDP and the shareholders' equity.

Injuries show a positive coefficient. This positive coefficient can be traced back to the study being conducted on quarters, adding to the fact that injuries are almost never mediatized, implying no influence on the investment sentiment of agents (Kaplanski et al., 2010). Injuries remain statistically insignificant.

The last model replaces the number of injuries with the numbers of fatalities incurred during the accidents sampled. *Table B3* shows the results.

		Δlnshr_p			
Number of OBS = **327**					
		FATAL (*Model 3a*)		FATALITIES (*Model 3b*)	
	Variable	**Coefficient (βi)**	**p-value**	**Coefficient (βi)**	**p-value**
Short-Run					
	Δln(SHLD_EQ)	**0.250****	0.001	**0.249****	0.001
	Δln(FARE)	0.886	0.072	0.897	0.071
	Δln(CPI)	**3.611****	0.004	**3.639****	0.003
	Δln(OIL)	**-0.840****	0.000	**-0.870****	0.000
	Δln(GDP)	10.591	0.080	10.773	0.076
	ΔFAT	--	--	**-0.001****	0.009
Lagged Variables					
	$\ln(SHR\_P)_{t-1}$	**-0.306****	0.029	**-0.305****	0.030
	$\ln(SHLD\_EQ)_{t-1}$	0.076	0.084	0.078	0.075
	$\ln(FARE)_{t-1}$	0.260	0.162	0.273	0.144
	$\ln(CPI)_{t-1}$	2.332	0.070	2.350	0.070
	$\ln(OIL)_{t-1}$	**-0.757****	0.019	**-0.824****	0.012
	$\ln(GDP)_{t-1}$	**0.184****	0.045	**0.185****	0.044
	FAT_{t-1}	--	--	**-0.001****	0.000
Accident Dummy					
	Fatal (*dummy)*	-0.000	1.000	--	- -
		*Time Dummies _I**			
Long-Run		**Long-Run Coefficient (ki)**	**p-value**	**Long-Run Coefficient (ki)**	**p-value**
	$\ln(SHLD\_EQ)_{t-1}$	**0.249****	0.000	**0.256****	0.000
	$\ln(FARE)_{t-1}$	**0.852****	0.040	**0.897****	0.032
	$\ln(CPI)_{t-1}$	7.628	0.145	7.708	0.143
	$\ln(OIL)_{t-1}$	-2.477	0.097	-2.704	0.087
	$\ln(GDP)_{t-1}$	**0.602****	0.000	**0.607****	0.000
	FAT_{t-1}	--	--	**-0.004****	0.050

Table B3: *Results Model 3a and Model 3b* ***Significant at a 5% significance level*

For *Model 3a* and *3b* similar results are noted. As previously mentioned, certain explanatory variables are statistically significant in all models employed. The shareholders' equity seems to strongly influence share prices with a p-value of 0.001 and a positive coefficient of 0.250 (*Model 3a*), respectively 0.249 (*Model 3b*). A similar significance is found when eyeing the results for the CPI and the oil price. A 1% increase in the CPI would eventually lead to a 3.611 % increase in share prices. As before, oil prices are statistically significant and influence share prices negatively; a 1% increase in oil prices would mean a 0.840% decrease in securities. Looking at the lagged variables, next to the shareholders' equity and oil prices, GDP becomes statistically significant with a p-value of 0.045. In the long run the air fare becomes statistically significant in both *Model 3a* and *3b.*

Model 3a looks at the presence of a fatal accident, the fatal accident variable being a dummy. Even if there were to accidents in one quarter, for instance, their presence was noted once. As expected and in accordance with scientific literature (Golbe et al., 1986; Chance et al., 1987; Raghaven et al., 2005) the presence of an accident in a time span exceeding a couple of days, will not be noted in the company's shares, these reaching pre-calamity values short after. Here, the fatal events have a negative coefficient, being with a p-value of 1.000 highly statistically insignificant.

Replacing the presence of a fatal accident with the actual number of fatalities befallen, different results come about. *Model 3b* in *Table B3* shows evidence on the fact that aviation mishaps can be statistically significant at a 5% significance level. As Ho et al. (2011) already discovered, when using the number of fatalities, then, the number of fatalities actually shows significant results, for a couple of days after the event, including the event day (Ho et al., 2011). The obtained results are in concordance with his study, thus statistically significant in the both the short – and the long run, although the effect on share prices is relatively limited (coefficient of -0.001, respectively -0.004).

At a significance level of 5% fatal accidents are statistically significant. This would mean that in the aftermath of a fatal accident, a 1 fatality will result in a 0.1% (0.4% in the long haul) decrease in share prices. Even though highly significant (p-value of 0.009), the negative effect of fatal accidents, on a quarter analysis, is relatively small, as expected. This came about due to the fact that this analysis employs a quarter as unit of measurement and the number of fatal accidents is relatively small, namely ten fatal accidents in total from 2000 to 2011. Not the same can be said about injuries. As Ho et al. (2011) find in their study, injuries have no influence on an airline's financial value. This is also the case with the study at hand. Because injuries are so statistically insignificant, their effect on share prices is irrelevant (*Table B2*).

Looking at the lag of the fatalities variable, here too significance can be noticed. Having described the short run effects of accidents, the Bårdsen Error Correction Model gives insight also into the long run impact of both the explanatory variables as well as the accidents on the independent variable. The number of fatalities, which was significant in the short run, prevails significant in the long run, with a p-value of 0.50 (*Table B3*). Regarding the impact of fatalities and injuries, as before, this study finds a high significance when considering fatalities, nevertheless as discussed earlier the impact on share prices is fairly small fading in the long haul. Compared to the presence of fatal accidents, the number of fatalities befallen if it is high it tends to influence the investors sentiments, via different channels of media (Kaplanski et al., 2010).

5.2. Summary of Outcomes

Overall, it can be said that the results are quite robust, showing similar figures in all tests run. The *Table* below shows the robustness of the explanatory variables. Only in *Model 2b* the fare becomes, in the long run, statistically significant at a 5% significance level. Other changes cannot be noticed.

	Variable	Model 1	Model 2a	Model 2b	Model 3a	Model 3b
Short-Run						
	Δln(SHLD_EQ)	Positive Significant	Positive Significant	Positive Significant	Positive Significant	Positive Significant
	Δln(FARE)	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant
	Δln(CPI)	Positive Significant	Positive Significant	Positive Significant	Positive Significant	Positive Significant
	Δln(OIL)	Negative Significant	Negative Significant	Negative Significant	Negative Significant	Negative Significant
	Δln(GDP)	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant
Lagged Variables						
	ln(SHR_P)$_{t-1}$	Negative Significant	Negative Significant	Negative Significant	Negative Significant	Negative Significant
	ln(SHLD_EQ)$_{t-1}$	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant
	ln(FARE)$_{t-1}$	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant
	ln(CPI)$_{t-1}$	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant
	ln(OIL)$_{t-1}$	Negative Significant	Negative Significant	Negative Significant	Negative Significant	Negative Significant
	ln(GDP)$_{t-1}$	Positive Significant	Positive Significant	Positive Significant	Positive Significant	Positive Significant
Long-Run						
	ln(SHLD_EQ)$_{t-1}$	Positive Significant	Positive Significant	Positive Significant	Positive Significant	Positive Significant
	ln(FARE)$_{t-1}$	**Positive Significant**	**Positive Significant**	**Positive Insignificant**	**Positive Significant**	**Positive Significant**
	ln(CPI)$_{t-1}$	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant	Positive Insignificant
	ln(OIL)$_{t-1}$	Negative Insignificant	Negative Insignificant	Negative Insignificant	Negative Insignificant	Negative Insignificant
	ln(GDP)$_{t-1}$	Positive Significant	Positive Significant	Positive Significant	Positive Significant	Positive Significant

Table 4: *Summary Results*

The analysis is conducted on quarters, including both short – and long haul effects, based on the Bårdsen Error Correction Model with Newey and West Standard Errors. Firstly, share prices are dependent on their previous values. This dependence of share prices on historical values, this is established by the significance of the lagged variable of share prices in all three models. The lag of share prices has a negative coefficient in all tests. Thus, it can be noted that there is an overall decrease in the value of share prices.

The tests have shown that both internal as well as the external control variables used can be significant, in the short run, however it often depends on the modeling of the variables. The shareholders' equity is strongly statistically significant in all tests, influencing share prices to a great deal, this effect prevails in the long run. The air fare is a key component in all models, being the main source of revenue for airline and a component of share prices. In these three tests, in the short run at a 5% significance level, the fare is statistically insignificant. This, however, is not the case for the long run. The CPI show in all tests a statistical significance, up until considering the long run coefficient, when the CPI variable becomes significant. Oil prices are statistically significant in all models, and would be also in the long run if a 10% significance level would have been considered.

Regarding the effect of accidents, thus the sum of nonfatal – and fatal mishaps, it can be remarked that their influence on share prices is limited, being statistically insignificant at a 5% significance level. Similarly, nonfatal events or the number of injuries are completely insignificant. Because injuries do not influence the investment sentiments of brokers and almost never reach the media, can be an explanation of why the coefficients are positive and insignificant.

It is appropriate to assume that the number of injuries during a nonfatal accident does not influence share prices at all. The presence of a fatal event is not influencing a company's share prices. Fatalities show a different story, being statistically significant at a 5% level both in the short as well as in long run. Although scientific literature found that the impact of fatalities lasts no more than a couple of days, this study has proven, that even though small, the impact of a fatal events is still significant in the event-quarter and lagged period.

In the long haul, however, the effect of fatalities becomes less relevant yet still statistically significant; share prices will reach eventually pre-calamity equilibria.

6. Analysis

The outcomes of the tests leave room for interpretation vis-à-vis the actual impact of aviation mishaps on the financial value of airlines. Different barriers arise during the construction of the model and the assessment of the results. In the methodology section, before establishing the final model several assumptions were tested to ensure the validity and correctitude of the model. Even though many assumptions held straight on, some proved to be difficult. If assumptions were violated, solutions were found in order to adjust the model correspondingly. One such violation was the presence of heteroscedasticity. The use of White's Robust Standard Errors, replaced later by Newey and West Standard Errors ensured heteroscedastic observations are diminished and permitted for a stronger explanatory power of the model. A second problem encountered with the data set sampled was the presence of serial correlation. Serial correlation can lead to biased results, hence, parameter estimates of the standard errors are not corresponding to their genuine values, and thus there can be a tendency to reject the null hypothesis even when this is not the case (Carter Hill et al., 2012). The Newey and West standard error make up for the serial correlation problem. Due to the nonstationary autoregressive data, a dynamic model was employed namely the Bårdsen Error Correction Model. The ECM reduces the problem of collinear regressors and the risk of spurious results (van Reeven, 2011). Both short – and long run effects have been estimated to assess the duration of the mishap. To evaluate the results obtained in the previous chapter, it is necessary to review the three main hypotheses of this paper.

Scientific literature found evidence that aviation mishaps affect the financial value of an airline (Raghavan et al., 2005; Ho et al., 2011; Oster et al., 2013). This study has assessed the impact of accidents incurred on the share prices of the crash-airlines. Additionally, all these accidents have been divided into nonfatal and fatal events, by considering also the number of injuries versus the number of fatalities. Adding injuries to the equation is a new factor in this particular research field; however, as expected these prove to be statistically insignificant.

Analyzing the impact of accidents on the financial value of carriers at the quarter-level is risky, due to the fact that there might not be a statistical relevance during a relatively large time span, and considering share prices adjust quickly, nevertheless, for fatalities this proved wrong. Fatalities, in accordance with previous findings, are even on a three-month time span statistically significant.

Nevertheless, there was some disagreement as to what extent this impact would be felt. Raghavan et al. (2005) found that aviation calamities have an impact solely on small regional carriers. Kaplanski et al. (2010) and Ho et al. (2011) established that this was not entirely correct, and that legacy carriers can also be impacted by accidents, when looking at their stock prices on that particular trading day and the following few days after (Kaplanski et al., 2010). Ho et al. (2011) initiated the idea that the impact of an accident can be better judged by using the number of fatalities befallen. Just like Kaplanski et al. (2010) they found the effect of fatalities on the event-day and the following few days after the calamity, while increasing with a rise in the number of fatalities. Neither, however, have analyzed the effect of accidents at a quarter-level and based on this set of airlines.

6.1. Accidents

It was previously assumed that aviation mishaps have a negative effect on share prices, as scientific literature had already found (Oster et al, 2013; Raghavan et al, 2005). Hence, the first hypothesis established was:

H01: *There is no relationship between* **accidents** *and financial firm value.*
HA1: *There is a negative relationship between* **accidents** *and financial firm value.*

Regarding *Model 1* in *Table B1* a statistically insignificant and negative effect of accidents on share prices can be noticed. To isolate for the sole impact of accidents it was necessary to account for internal and external factors. Accidents in the event-quarter are statistically insignificant. Hence, the first null-hypothesis cannot be rejected at a 5% significance level. For the coefficient to be negative is logical, since accidents generate both direct and indirect costs to the crash-airline (Lindberg, 2005). As mentioned earlier, airlines value not being involved in an accident, due to the relatively high costs if involved, hence investing in safety ensures risk reduction (Lindberg, 2005).

There are several reasons for why the presence of an accident in a quarter is insignificant. Firstly, this study has used as 'accidents' both nonfatal and fatal events, where nonfatal events are by far out weighing fatal mishaps. Considering nonfatal events are small – respectively medium scale events, it can be expected that their influence on share prices is small or inexistent.

Media usually doesn't insist on less severe accidents, resulting in investors not being reached by the information, hence any effect can be felt on share prices. As Kaplanski et al. (2010), Chance et al. (1987) and Madsen (2011) have found the effect of an accident lasts only a few days after the event has taken place. The fact that accidents in this study comprise both nonfatal and fatal mishaps, and considering that nonfatal events account for ninety percent of the total number of accidents, whilst there are only ten fatal events, it is reasonable to assume that the impact of accidents can't last for an entire quarter (Ho et al., 2011).

Secondly, previous findings have discussed that many accidents, have only limited effects on a firm's financial value in terms of the time period. Accidents cause mostly a short shock to the firm's share prices, their effect lasting only a couple of days until agents' behavior readapts and, hence, share prices readjust to their short run equilibrium level (Chance et al, 1987). Conformingly, this paper found no statistical evidence that the accumulated number of accidents is statistically significant for the crash-airline on a quarter.

First and foremost, this paper has analyzed the matter at hand on quarterly data, and secondly the number of nonfatal accidents being significantly larger than the number of fatal events, it is safe to accept the fact that the company eventually and relatively quickly recovers after the shock of an accident. As Raghavan et al. (2005) suggest, one other motive for this insignificancy might be the fact that the sampled airlines are all relatively large carriers, thus an accident can be impacting them at a lesser rate than it would small regional carriers. Reasons for this can range from loyalty of customer base; the company offering a series of different services outside the sole scope of transportation, thus different sources of income for the company, to reputational issues (Raghavan et al., 2005). If the event would be extremely severe, then of course the impact can be felt by larger carriers significantly, too.

6.2. Nonfatal Events

Having split the total number of accidents into nonfatal and fatal events, whilst also using injuries, respectively fatalities for further insight, the second hypothesis established sounds as follows:

H02: *There is no relationship between* **nonfatal accidents** *and financial firm value.*
HA2: *There is a negative relationship between* **nonfatal accidents** *and financial firm value.*

Model 2a has proven no statistical significance regarding nonfatal events; however a negative effect was noted. Turing to injuries, the results are presented in *Model 2b*.

To be noted is the fact that the effect of injuries on share prices is very poor with the result showing a positive coefficient albeit the coefficient is highly insignificant both in the short – as well as in the long haul. No inference can be made about the true effects of injuries on share prices. Injuries and nonfatal events, respectively, are of small or no real concern in their effects on share prices. Injuries (*Model 2b)*, exhibit a positive coefficient. Common sense would infer this to be wrong, however a possible explanation for this anomaly can be traced back to the study of Kaplanski et al. (2010) mentioning that only severe calamities are mediatized, hence only severe accidents truly exert an influence on investors' behavior. Injuries almost never reach the media, thus no one can infer to what extent an injury of a person on a flight might or not influence a broker. Injuries and nonfatal mishaps are, thus, statistically insignificant at a 5%.

Henceforth, the second null-hypothesis can't be rejected either, and judging by the slightly abstruse results it can be inferred that injuries, and thus nonfatal accidents, barely matter at all in the relationship between aviation mishaps and share prices.

6.3. Fatal Events

Having discovered that nonfatal accidents are completely insignificant for an airline's performance, the last hypothesis looks at the relationship between fatal accidents and an airline's financial value.

H03: *There is no relationship between* **fatal accidents** *and financial firm value.*
HA3: *There is a negative relationship between* **fatal accidents** *and financial firm value.*

Model 3a shows no statistical evidence that the occurrence of a fatal event in a particular quarter is still impacting the airline's share prices during a relatively large timespan. This is, as expected, logical considering the fact that the number of fatal events is low. When considering only the occurrence of the event the null-hypothesis cannot be rejected.

Scientific research has discovered that, whilst using the actual number of fatalities instead dummies for the occurrence of an accident at that particular point in time, there is strong significant relationship between the number of fatalities and share prices (Kaplanski et al., 2010; Ho et al., 2011). Previous literature has argued that the impact of fatalities on share prices is strongly negative, but this impact is only of short length, lasting solely a couple of days after the mishap (Chance et al, 1987).

As debated by scientific literature (Kaplanski et al., 2010; Chance et al., 1987), this paper has proven that fatalities have a statistically significant negative impact on share prices (*Model 3b)* and consequently the last null-hypothesis must be rejected. Important to note is the fact that this paper has proven the importance and impact of fatalities during an entire quarter, rather than only a few days after the calamity. The effects fatalities exert on a quarter-analysis are relatively small, yet statistically significant. One reason might include the fact that this particular time span is quite vast, including the strong effects of 9/11, whilst comprising all US major carriers, two of which were involved in the devastating events of 9/11 and all had to cope with the aftermath of these calamitous events.

The reason that only the number of fatalities is significant can be attributed to the investors' sentiments being mostly influenced by media and/or other information channels (Kaplanski et al., 2010). The information channels influence investor's behavior strongly and more information leaks whilst a fatal accident occurs, inducing an adversity towards flying and questioning safety issues.

Of course, a fatal accident brings next to direct and indirect costs for the company, also a sometimes irreplaceable reputation loss, reflected by a lower value on the stock market; hence, investors tend to stay away from risky assets, decreasing securities even more (Kaplanski et al., 2010). As Ho et al. (2013) have proven accidents with a higher number of fatalities can bring a larger fear of flying reducing the total number of passengers, thus decreasing demand substantially, which will ultimately be reflected in reducing the value of shares of the entire industry. A less severe accident is any accident where the number of fatalities is a single digit (Ho et al., 2011) or includes solely injuries. Less severe accidents make investors switch companies within the industry, thus indeed the crash-airline loses both regarding reputation, on one side, and, on the other side, risks revenue sources. Due to the 'switching effect' both passengers and investors opt for competitors of the crash-airline (Ho et al., 2011). Hence, indeed in concordance with scientific literature less severe accidents, such as nonfatal events exert no statistically significant influence.

Severe fatal accidents indeed impact the airlines involved, both on an individual level as well as on an industry spectrum. As can be expected even after a severe fatal accident (judged by the high number of fatalities), carriers can still recover, in most cases, from the shocks (Berry et al., 2008; Franke et al., 2011).

Regarding the actual duration of the impact of a calamity, the rather quick readjustment to short run equilibria established by Chance et al. (1987) and Kaplanski et al. (2010) can be linked directly to investor's behavior, with many of them possibly buying shares a couple of days after the fatal mishap and reselling when the prices rise again, if the accidents are not too severe, in which case the investment turns out to be very risk or they completely abstain from buying. This study has proven that the negative impact of fatalities is still statistically significant within a period of three months. Again, a series of reasons are to be considered here: customer loyalty, reputation, the nature of transportation demand, lower fares, etc. This bouquet of reasons makes large legacy carriers recover faster from accidents than regional carriers (Raghavan et al., 2005). An outlier to all the accidents is certainly the event of 9/11, which weighed heavily not just on the aviation industry but on the financial industry as a whole.

Fatal occurrences are not happening every day, as noted earlier, aviation being the safest way to travel (Oster et al., 2013). Injuries can occur even while in taxi, for instance, with information leaking heavier than for fatal accidents. The number of fatal accidents since 9/11 has decreased tremendously, with companies improving the security systems and countering terrorist attacks (Oster et al., 2013; Barnett, 2000; Lofquist, 2010).

Airlines have invested in aviation safety making it one of their primordial interests. Overall, it can be argued that only severe fatal aviation accidents have a negative significant impact on the financial value of companies, due to investor sentiment imprinted by media.

This paper has shown that, even in a time where security measures are accounted for, fatal accidents still happen, and not only do some of these fatal calamities negatively impact an airline's financial value and incur costs to both the airline as well as the society, but all of them represent an irreplaceable loss of human lives.

7. Conclusion

This study has assessed the impact of aviation accidents, injuries and fatalities incurred on the financial value of the crash-airlines. The analysis was conducted on quarters, in order to assess the impact of an accident on a larger period of time. This paper has commenced with a literature review portraying all relevant scientific literature concerning aviation accidents and their effects on the economic performance of airlines. It has established a negative relationship between calamities and financial value, which is statistically significant in the short intervals following an accident (Chance et al., 1987) or whilst considering only small regional airlines (Raghavan et al., 2005) or only when considering fatal accidents (Ho et al., 2011). Furthermore, a model was proposed to assess this particular relationship. The model is based on a Bårdsen Error Correction Model with Newey and West Standard Errors, accounting for share price specific characteristics, such as their trend and their dependence on own historic values, as well as making up for all the violations of time-series and panel assumptions. As control variables, this model has determined both internal and external indicators, and hence considering for potential influences on share prices, while isolating the actual effect of accidents.

Regarding the impact of accidents on share prices, it needs to be noted that the accumulated number of accidents, nonfatal plus fatal events, due to the fact that this research uses a quarter as unit of analysis, show statistically insignificant results. This is also valid for the distinction between nonfatal and fatal mishaps. However, the story changes when considering the actual number of fatalities resulted due to accidents. Here, fatalities show significant results even during a relative extended time span and considering large airlines.

Throughout this paper, the research question proposed in the introduction was the center of this research. The research question, established chapters ago, is the following:

How are accidents impacting the financial value of crash-airlines?

In order to answer the research question, several tests were performed giving an indication of the relationship between the accidents incurred and the financial value of airlines. Supporting this research question, three hypotheses were established.

The first hypothesis described a non-relation between accidents and airlines' securities, in which case with the data sampled was impossible to reject. The results were statistically insignificant, supporting the fact that accidents are not influencing financial performance, on a quarter-level. When all accidents are taken into account, it can be noted that the relationship is negative yet insignificant.

The answer to the research question depends, nonetheless, on the division of accidents according to the number of injuries (nonfatal events) respectively fatalities (fatal events) befallen. Similar results as with the accumulated number of accidents came about when assessing the second hypothesis, here, once more, evidence could not be found that nonfatal events impact companies' financial values. Fatal accidents didn't prove to be statistically significant. The number of fatalities shows a statistically significant relationship. Hence, it can be concluded that the answer to the research question depends on the severity of fatal accidents. For accidents that do not incur fatalities the impact on financial firm value is nil. It is therefore that the impact of severe accidents can be crucial on a firm's financial value if the number of fatalities can measure the severity of the accident. Interestingly and unexpectedly, at the same time, fatalities impact a company's performance even in a time span of a quarter, these effects being still significant in the long run. The table below portrays the results established in this investigation:

Hypotheses	**Model 1**	**Model 2a**	**Model 2b**	**Model 3a**	**Model 3b**
There is no relationship between accidents and financial firm value.	Not Rejected	--	--	--	--
There is no relationship between nonfatal accidents and financial firm value.	--	Not Rejected	Not Rejected	--	--
There is no relationship between fatal accidents and financial firm value.	--	--	--	Not Rejected	Rejected

Table 5: *Summary Hypotheses*

Of course, there are multiple reasons as to why not the accumulated number of accidents, but rather the number of fatalities exerts a statistical significance on companies. As mentioned earlier, the investor sentiment is the key influencing factor of share prices, especially in the case of a two-digit number of fatalities befallen. By information leaking as well as an increase in fear of flying investors tend to stay away from risky assets.

To sum up, this paper find agreements with scientific literature that there is a negative relationship between accidents and the company's financial value, and that, indeed, this effect is only significant when considering the number of fatalities.

Nevertheless, this study has proven that effect of fatalities has an impact on big carriers as well as smaller ones, and compared to previous literature, which has proven this effect to last only for a couple of days, this paper has shown that the effect is significant at least for three months.

This study was able to answer the research question by proving that severe fatal accidents strongly influence the crash-airlines' financial values. Safety is a central and highly debated issue nowadays, and this study has shown that airlines should strive and promote safe air travel, especially after noticing that recovering from an accident incurred, financially speaking, takes time. Of course, factors such as reputation or customer loyalty will suffer from such calamitous events as well. Hence, it is important to stress out that, safety measures should be implemented across all areas of operations. Even though air travel, is considered the safest mode of transportation, accidents still happen and safety negligence still encountered.

8. Policy Recommendations and Limitations

8.1. Policy Recommendations

As noted previously safety is the central issue that companies need to account for before offering a service. When offering such a service the airline is to a certain extent conscious of the risks of possible accidents during each flight, and the company is also aware that it will bear the costs were an accident to happen (Lindberg, 2005). Albeit, solely the severe fatal accidents showed a significant negative effect, one must not forget that fatal accidents in general or even injuries that are considered nonfatal mishaps represent societal costs. Bearing those costs should resolve in an airline's ability to judge the importance of safety and safety measures from both a financial and a social perspective, hence airlines do invest in safety (Scuffham et al., 2002; Lindberg, 2005). Nevertheless, lapses still happen. The query is how to avoid these lapses? This question is very case specific, and a vast array of answers comes to mind. Safety improvements can range from investing in infrastructure and equipment, testing the equipment properly or offering better training for pilots and stricter supervision.

A key aspect sustained by most of the scientific literature and brought up earlier in this study is the role of human error in aviation mishaps. Pilots tend to be stressed or fatigued, confronted with numerous working hours; hence, they tend to underestimate a particular occurrence (Wiegmann et al., 2001; Sheppell et al., 2004). The lack of coordination in the cockpit or the lack to report malfunctions of the plane on time or simply being too stressed or too tired, are factors that weigh in such calamitous events. It is necessary to realize that most common cause for accidents is human errors, thus this is a key aspect for policy makers to work on. Optimizing conditions for pilots, thus reducing the number of hours or creating more shifts, and improving supervisory aspects and team-work during cruise might definitely reduce the risk of accidents, which in turn will not lead to costs for the airlines or the society.

What happens, however, when an accident occurs? With an increased safety it is possible for airlines to counter the shocks of any accident. Nevertheless, if an accident was to occur the best policy recommendations to give would be to firstly cover the costs for the families involved, not only because it means to save bits of the company's reputation, but because it shows compassion.

Secondly, trying to avoid more negative media coverage as much as possible would be a smart move, especially because media influences investors' sentiments, which will tend to stay away from risky investments (Kaplanski et al., 2010), which in the end will reduce not only the airline's financial value, but also inevitably passenger demand.

Thirdly, recover the losses made by working on improving safety, offering better-quality services across the entire spectrum of aviation operations and trying to build customer loyalty.

The best way to avoid the costs resulted in the aftermath of an accidents is to avoid accidents altogether. Hence, the main solution this study is suggesting is improving safety measures and ensuring a client-focused orientation of the company. Investing in safety should be by far the most important lesson of this study.

8.2. Limitations

Regarding the limitations of this research it adds up to four main points that could be elaborated by future studies. As often mentioned, this paper has analyzed the effects of accidents on airline's financial value with data gathered on a quarterly basis. This was done on purpose to assess if accidents still have a significant impact on an airline's securities via financial statements in a three-month time span. Nevertheless, a closer look at this impact could have been obtained if the study would have been carried out on days, since share prices are published on a daily basis. As Chance et al. (1987) and Kaplanski et al. (2010) have shown the effect of an accident is immediately observable on that particular day and the following few days after, reaching equilibrium values. It would be interesting to check for the accidents sampled how long their impact on the daily basis would last, while at the same time employing a Bårdsen Error Correction Model with Newey and West standard errors to account for the multiple statistical issues presented previously.

Furthermore, future studies can differentiate further between the airlines. This study has used a sample of eleven top air carriers from the US and Canada; a sample based on customer satisfaction and financial performance. Of course, this sample could be changed by assessing perhaps only small regional airlines, or low cost companies or even jet services carriers. Additionally, future research can look at the impact an accident has on a particular route for both the crash airline as well as its competitors.

Different characteristics can be added to detail the effect of an accident; such observations can include the cause for the accidents or the distance the plane traveled or the type of aircraft, the weather conditions, or the phase during which the accident happened.

This paper has chosen not to get into such detail, since the focus from the actual research question would have been shifted away, but analyzing accidents into their small details, might definitely offer policy makers the insight they require to provide proper safety management policies.

Lastly, regarding the endogenous and exogenous factors influencing share prices, it is relevant to mention that, even though this study is based on the assumption that media does indeed influence the investment sentiment of agents, no statistical modeling was employed to demonstrate this fact.

This study found no reason to prove this dependency, especially because scientific literature was content with the idea that media has a huge role in investment sentiments of agents. However, assessing or combining the impact of accidents on company performance by looking a media publications, would add to the already existing scientific literature available on this particular topic.

9. Bibliography

9.1. References

- **Abraham** K.G., J.S. Greenlees, B.R. Moulton (1998). Working to Improve the Consumer Price Index. *The Journal of Economic Perspectives*, Vo. 12, No. 1, pp. 27-36
- **Akhtar** S., R. Faff, B. Oliver, A. Subrahmanyam (2011). The Power of Bad: The Negativity Bias in Australian Consumer Sentiment Announcements on Stock Returns. *Journal of Banking and Finance,* Vol. 35, Issue 5, pp. 1239-1249
- **Alderighi** M., A. Cento (2004). European Airlines after September 11. *Journal of Air Transport Management*, Vol. 10, No. 2, pp.97-107, March
- **Al-Tamimi** H.A.H, A.A. Alwan, A.A.A. Rahman (2011). Factors Affecting Stock Prices in the UAE Financial Markets. *Journal of Transport Management*, Vol. 16, No.1
- **Angel** J.J. (1997). Tick Size, Share Prices, and Stock Splits. *The Journal of Finance*, Vol. 52, Issue 2, pp. 655-681, June
- **Ashcraft**, K.L. (2005). Resistance through Consent? Occupational Identity, Organizational Form, and the Maintenance of Masculinity among Commercial Airline Pilots. *Management Communication Quarterly*, Vol. 19, No. 1, pp. 67-90, August
- **Baker** S.P., M.W. Lamb, J.G. Grabowski, G. Rebok, G. Li (2001). Characteristics of General Aviation Crashes Involving Mature Male and Female Pilots. *Aviation, Space, and Environmental Medicine*, Vol. 72, No. 5, pp.447-452
- **Baldwin** N.S., R.E. Rice (1997). Information-Seeking Behavior of Securities Analysts: Individual and Institutional Influences, Information Sources and Channels, and Outcomes. *Morgan Stanley and Co.*
- **Baltagi** B.H., S.H. Song, J.H. Kwon (2009). Testing for Heteroskedasticity and Spatial Correlation in a Random Effects Panel Data Model. *Computational Statistics & Data Analysis*, Vol. 53, No. 8, pp. 2897-2922, June
- **Barnett** A., M.K. Higgins (1989). Airline Safety: The Last Decade. *Management Science* Vol. 35, No. 1, pp. 1-21, January
- **Barnett** A., A. Wang (2000). Passenger-mortality Risk Estimates Provide Perspectives about Airline Safety. *Flight Safety Foundation* Vol. 19, No. 4, April
- **Barros** C.P., J.R. Faria, L.A. Gil-Alana (2008). Persistence in Airline Accidents. *School of Economics and Management – Technical University of Lisbon*

- **Berry** C.J.P. (2008). Policy Change in Aviation Security, Canada and the United States, 1985-2005. *Transportation Research Board*
- **Benner** Jr. L. (1985). Rating Accident Models and Investigation Methodologies. *Journal of Safety Research*, Vol. 16, No.3, pp.105-126
- **Bhardwaj** R.K., L.D. Brooks (1992). The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias. *The Journal of Finance*, Vol. 47, No.2, pp.553-575, June
- **Blanchard** O. (2000). Macroeconomics (2nd edition), *Englewood Cliffs*
- **Borenstein** S., M.B. Zimmerman (1988). Market Incentives for Safe Commercial Airline Operation. *The American Economic Review*, Vol. 78, No. 5, December
- **Boef**, de S., L. Keele (2005). Revisiting Dynamic Specification, *Society of Political Methodology*
- **Bond** P., A. Edmans, I. Goldstein (2012). The Real Effects of Financial Markets. *Annual Review of Financial Economics, Annual Reviews*, Vol. 4, No. 1, pp. 339-360, October
- **Bondt** W.F.M., R. Thaler (1985). Does the Stock Market Overreact? *The Journal of Finance*, Vol. 40, No. 3, pp. 793-805, July
- **Bryan** M.F., S.G. Cecchitti (1993). The Consumer Price Index as Measure for Inflation. *The National Bureau of Economic Research*
- **Burkart** M., D. Gromb, F. Panunzi (1999). Why Takeover Premia Protect Minority Shareholders, *Journal of Political Economy,* Vol. 106, pp. 172-204
- **Cai** Y., R.Y. Chou, D. Li (2009). Explaining International Stock Correlations with CPI Fluctuations and Market Volatility. *Journal of Banking and Finance*
- **Carlsson** F. (2002). Price and Frequency Choice under Monopoly and Competition in Aviation Markets. *Department of Economics, Goteborg University*, June
- **Carter Hill** R., W.E. Griffiths, G. C. Lim (2012). Principles of Econometrics. *John Wiley & Sons, Inc.*
- **Castillo**, C. (2005). Disaster Preparedness and Business Continuity Planning at Boeing: An Integrated Model, *Journal of Facilities Management*, Vol. 3, No. 1, pp. 8-26
- **Cento** A., (2009). Airline Industry: Challenges in the 21st century.
- **Chalk** A.J. (1987). Market Forces and Commercial Aircraft Safety. *Journal of Industrial Economics*, Vol. 36, No, 1, September
- **Chan** W.S. (2003). Stock Prices Reaction to News and No-News: Drift and Reversal after Headlines. *Journal of Financial Economics*, Vol. 70, No.2, pp. 223-260, November
- **Chance** D.M., S.P. Ferris (1987). The Effect of Aviation Disasters on the Air Transport Industry. *Journal of Transport Economics and Policy*. May

- **Chaudhuri** K., Y. Wu (2003). Random Walk versus Breaking Trend in Stock Prices: Evidence from Emerging Markets. *Journal of Banking and Finance*, Vol. 27, No. 4, pp. 575-592, April
- **Chen** N., R. Roll, S.A. Ross (1986). Economic Forces and Stock Market, *Journal of Business*, Vol. 59, No. 3, July
- **Coughlin**, C.C., J.P. Cohen, S.R. Khan (2002). Avaition Security and Terrorism: A Review of Economic Issues, *The Federal Reserve Bank of St. Louis*, September
- **Cragg** J.G., B.G. Malkiel (1982). Expectations and the Structure of Share Prices. *National Bureau of Economic Research*
- **Cutler** D.M., J.M. Poterba, L.H. Summers (1989). What Moves Stock Prices?, *Journal of Portfolio Management*
- **Da** Z., J. Engelberg, P. Gao (2010). The Sum of All FEARS: Investor Sentiment and Asset Prices
- **Debbage** K.G. (1994). The International Airline Industy: Globalization, Regulation and Strategic Alliances. *Journal of Transport Geography* Vol. 2, No.3, pp.190-203, September
- **Dionne** G., R. Gagne, F. Gagnon, C. Vanasse (1997). Debt, Moral Hazard and Airline Safety: Empirical Evidence. *Journalof Econometrics*, Vol. 79, No. 2, pp. 379-402, August
- **Dobruszkes** F., G. van Hamme (2011). The Impact of the Current Economic Crisis on the Geography of Air Traffic Volumes: An Empirical Analysis. *Journal of Transport Geography*, Vol. 19, No. 6, pp.1387-1398, November
- **Drukker** D.M. (2003). Testing For Serial Correlation in Linear Panel-Data Models. *Stata Journal*, Vol. 3, pp. 168-177
- **Durge** S.P. (2011). Global Air Safety and Security Regulations: Current Advancements.
- **Elton** E.J., M.J. Gruber (1973). Estimating the Dependence Structure of Share Prices – Implications for Portfolio Selection, *The Journal of Finance*, Vol. 28, No. 5, pp. 1203-1232, December
- **Engelberg** J.E., C.A. Parsons (2011). The Causal Impact of Media in Financial Markets, *The Journal of Finance*, Vol. 66, No.1, pp. 67-97, February
- **Fama** E.F. (1965). Random Walk in Stock Market Prices, *Financial Analysts Journal*, Vol. 21, No. 5, September
- **Fama** E.F., K.R. French (1988). Permanent and Temporary Components of Stock Prices, *Journal of Political Economy*, Vol. 96, No. 2, April
- **Ferrier** W.J. (2002). Strategic Aggressiveness, Variation and Surprise: How the Sequential Pattern of Competitive Rivalry Influences Stock Market Returns, *Journal of Managerial Issues*, Vol. 14, Issue 2, pp. 162-180

- **Fisher** K.L., M. Statman (2000). Investor Sentiment and Stock Returns. *Financial Analysts Journal*, Vol. 56, No.2, pp.16-23, March
- **Flannery** M.J. (2001). The Faces of 'Market Discipline'. *Journal of Financial Services Research*, Vol.20, No.2, pp.107-119
- **Flannery** M.J., A.A. Protopapadakis (2002). Macroeconomic Factors Do Influence Aggregate Stock *The Review of Financial Studies*, Vol. 15, No.3, pp.751-782
- **Franke** M., F. John (2011). What Comes Next After Recession? – Airline Industry Scenarios and Potential End Games. *Journal of Air Transport Management*, Vol. 17, No. 1, pp. 19-26, January
- **Franses** P.H. (1991). Seasonality, Non-Stationarity and the Forecasting of Monthly Time Series, *International Journal of Forecasting*, Vol. 7, Issue 2, pp. 199-208
- **Geetha** C., R. Mohidin, V.V. Chandran, V. Chong (2011). The Relationship between Inflation and Stock Market: Evidence from Malaysia, United States and China. *International Journal of Economics and Management Sciences*, Vol. 1, No. 2, pp. 1-16
- **Godfrey** M.D., C.W.J, Granger, O. Morgenstern (2007). The Random-Walk Hypothesis of Stock Market Behavior, *Kyklos*, Vol. 17, Issue 1, pp. 1-30, February
- **Goedhart** M., T. Koller, D. Wessels (2005). Do Fundamentals – or Emotions – Drive the Stock Market? *McKinsey Quarterly, Special Edition: Value and Performance*
- **Golbe** D.L. (1986). Safety and Profits in the Airline Industry. *The Journal of Industrial Economics*, Vol. 34, No. 3, March
- **Gordon** M.J. (1963). Optimal Investment and Financing Policy, *The Journal of Finance*, Vol. 18, No. 2, pp. 264-272, May
- **Halunga** A., C.D. Orme, T. Yamagata (2011), A Heteroskedasticity Robust Breusch-Pagan Test for Contemporaneous Correlation in Dynamic Panel Data Models. *Economic Discussion Papers, University of Manchester*, August
- **Hansen** M.M., D. Gillen, R. Djafarian-Tehrani (2001). Aviation Infrastructure Performance and Aviation Cost: A Statistical Cost Estimation Approach, *Transportation Research*, Vol. 37, No. 1, pp. 1-23, March
- **Higgins** R.B., B.D. Bannister (1992). How Corporate Communication of Strategy Affects Share Price. *Long Range Planning*, Vol.25, No.3, pp. 24-35, June
- **Ho** J.C., M. Qiu, X. Tang (2011). The Catalyst in the Air Crash-Stock Market Performance Relationship: The Aviation Disaster Fatality, *Social Science Research Network*, April
- **Ho** J.C., M. Qiu, X. Tang (2013). Do Airlines Always Suffer From Crashes? *Economic Letters*, Vol. 118, No.1, pp.113-117, January

- **Hobijn** B., D. Lagakos (2003). Inflation Inequality in the United States. *Review of Income and Wealth*, Vol. 51, No. 4, pp. 581-606, December
- **Humpe** A., P. Macmillan (2007). Can Macroeconomic Variables Explain Long Term Stock Market Movements? A Comparison of the US and Japan. *Center for Dynamic Macroeconomic Analysis, Working Paper*
- **Jenkins**, B.M. (1989), The Terrorist Threat to Commercial Aviation, *TVI Report,* Vol. 9, No. 1, February
- **Johnson**, C.W., C.M. Holloway (2003). On the Over-Emphasis of Human 'Error' As A Cause of Aviation Accidents: 'Systematic Failures' and 'Human Error' in US NTSB and Canadian TSB Aviation Reports, Dept. of Computing Science, Univ. of Glasgow, Scotland
- **Kahn** A.E. (1988). Surprises of Airline Deregulation. *The American Economic Review*, Vol. 78, No. 2, pp. 316-322, May
- **Kaplanski** G., H. Levy (2009). Sentiment and Stock Prices: The Case of Aviation Disasters, *Journal of Financial Economics* Vol. 95, No. 2, pp. 174-201, February
- **Kasa** K (1992). Common Stochastic Trends in International Stock Markets. *Journal of Monetary Economics*, Vol. 29, No. 1, pp. 95-124
- **Kilian** L., C. Park (2009). The Impact of Oil Price Stocks on the US. Stock Market. *International Economic Review*, Vol. 50, No. 4, pp. 1267-1287, November
- **Knecht**, W.R., M. Lenz (2010). Causes of General Aviation Weather-Related, Non-Fatal Incidents: Analysis Using NASA Aviation Safety Reporting System Data, *Federal Aviation Administration*, Oklahoma City, OK, September
- **Koch** J.V., R.N. Fenili (2013). Using Event Studies to Assess the Impact of Unexpected Events. *Business Economics*, Vol. 48, pp. 58-66, February
- **Kraft** J., A. Kraft (1977). Determinants of Common Stock Prices: A Time Series Analysis. *The Journal of Finance*, Vol. 32, No.2, pp.417-425, May
- **Lagos** A., M. Motevalli, V. Motevalli, N. Sakata (2006). Review and Analysis of the Effects of Major Aviation Accidents in the United States on Safety Policy, Regulation, and Technology. *Journal of Transport Research*, Vol. 45, No. 2
- **Lai** S.L., W. Lu (2005). Impact Analysis of September 11 on the Air Travel Demand in the USA. *Journal of Air Transport Management*, Vol.11, Issue 6, 455-458, November
- **Larcel** D., R. Steckel, S. Mondello, E. Carr, M. Patankar (2011). Aviation Safety Management Systems: Return on Investment Study. *Center for Aviation Safety Research*
- **Lindeberg** G. (2005). Accidents. *Research in Transportation Economics*, Vol. 14, pp. 155-183

- **Lofquist** E.A. (2010). The Art of Measuring Nothing: The Paradox of Measuring Safety in a Changing Civil Aviation Industry Using Traditional Safety Metrics. *Safety Science*, Vol. 48, No. 10, pp. 1520-1529, December
- **Lucas** D.J., R.L. McDonald (1990). Equity Issues and Stock Price Dynamics. *The Journal of Finance*, Vol. 45, No.4, pp. 1019-1043, September
- **Luo** X. (2007). Consumer Negative Voice and Firm Idiosyncratic Stock Returns, *Journal of Marketing*, Vol. 71, No. 3, pp. 75-88
- **Madsen** P.M. (2011). Perils and Profits: A Reexamination of the Link between Profitability and Safety in U.S. Aviation. *Journal of Management,* April
- **Michaels** D., A. Pasztor (2011). Airlines Count Down to Safest Year on Record. *The Wall Street Journal*, December
- **Mitchell** M.L., M.T. Maloney (1989). Crisis in the Cockpit? The Role of Market Forces in Promoting Air Travel Safety. *Journal of Law and Economics*, Vol.32, No.2, pp.329-355, October
- **Mitchell** M.L., Stafford E. (2000). Managerial Decisions and Long-Term Stock Price Performance. *The Journal of Business*, Vol. 73, No.3, pp.287-329
- **Morrell** P., W. Swan (2006). Airline Jet Fuel Hedging: Theory and Practice, *Transport Reviews: A Transnational Transdisciplinary Journal*, Vol. 26, No. 6
- **Morrell** P. (2011). Current Challenges in a 'Distressed' Industry. *Journal of Air Management*, Vol. 17, No. 1, pp. 14-18, Janury
- **Moses** L.N., I. Savage (1990). Aviation Deregulation and Safety: Theory and Evidence. *Journal of Transport Economics and Policy*, Vol. 24, No.2, pp.171-188, May
- **Nandha** M, R. Faff (2008). Does Oil Move Equity Prices? A Global View. *Energy Economics*, Vol. 30, No. 3, pp. 986-997, May
- **Noronha** G., V. Singal (2004). Financial Health and Airline Safety. *Managerial and Decision Economics*, Vol. 25, pp.1-16
- **Nussim** J., A. D. Tabbach (2009). A Revised Model of Unilateral Accidents. *International Review of Law and Economics*, Vol. 29, No.2, pp.169-177, June
- **Nygren** E., K. Aleklett, M. Hook (2009). Aviation Fuel and Future Oil Production Scenarios. *Energy Policy*, Vol. 37, No. 10, pp. 4003-4010, October
- **Oster** Jr. C.V., J.S. Strong, C.K. Zorn (2013). Analyzing Aviation Safety: Problems, Challenges, and Opportunities. *Research in Transportation Economics*.

- **O'Sullivan**, T. (2005). External Terrorist Threats to Civilian Airlines: A Summary Risk Analysis of MANPADS, Other Ballistic Weapons Risks, Future Threats, and Possible Countermeasures Policies, *University of Southern California*, Los Angeles, California, April
- **Oswald** S.L, J.S. Jahera Jr. (2006). The Influence of Ownership on Performance: An Empirical Study. *Strategic Management Journal*, Vol. 12, No.4, pp.321-326, May
- **Piotroski** J.D., D.T. Roulstone (2004). The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices. *The Accounting Review*, Vol. 79, No.4, pp. 1119-1151, October
- **Praetz** P.D. (1972). The Distribution of Share Prices Changes. *Journal of Business*, Vol. 45, No.1, pp. 49-55, January
- **Raghavan** S., D.L. Rhoades (2005). Revisiting the Relationship between Profitability and Air Carrier Safety in the US Airline Industry. *Journal of Air Transport Management* Vol.11, No. 4, pp. 283-290, July
- **Ramdas** K., J.W. Williams, M.L. Lipson (2012). Can Financial Markets Inform Operational Improvement Efforts? Evidence from the Airline Industry, *Social Science Research Network*
- **Randazzo**, M.R. (2008). Reducing Violence and Sabotage in Airports: The Use of Threat Assessment to Manage Employee Threats, *Journal of Airport Management*, Vol. 2, No. 4, pp. 325-335
- **Rault** C., M.El Hedi Arouri (2009). Oil Prices and Stock Markets: What Drives What in the Gulf Corporation Council Countries? *William Davidson Institute, Working Paper No. 960*
- **Reeven** van P. (2011). On the Effectiveness of Pricing Urban Car Usage. *Journal of Transport Economics and Policy*, Vol. 45, No. 3, pp. 367-381, September
- **Reason** J.T. (1990). Human Error. *Cambridge University Press*
- **Riley** Jr. R.A., T.A. Pearson, G. Trompeter (2003). The Value Relevance of Non-Financial Performance Variables and Accounting Information: The Case of the Airline Industry. *Journal of Accounting and Public Policy*, Vol. 22, No. 3, pp. 231-245
- **Roger** S. (1998). Core Inflation: Concepts, Uses and Measurement. *Social Science Research Network*, July
- **Rose** N.L. (1991). Fear of Flying Economic Analysis of Airlines Safety. *Journal of Political Economy*, Vol. 98, No. 5, pp. 944-964, October
- **Rouse**, W.B. (1983). Models of Human Problem Solving: Detection, Diagnosis, and Compensation for System Failures, *Automatica*, Vol. 19, No. 6, pp. 613-625, Great Britain
- **Rubin** R.M., J.N. Joy (2005). Where Are the Airlines Headed? Implications of Airline Industry Structure and Change for Consumers. *Journal of Consumer Affairs*, Vol. 39, No. 1
- **Ruby**, C.L. (2002). The Definition of Terrorism, *Analyses of Social Issues and Public Policy*, pp. 9-14

- **Sandler** R.D. (1988). Market Share Instability in Commercial Airline Markets and the Impact of Deregulation. *The Journal of Industrial Economics*, Vol. 36, No. 3, pp. 327-335, March
- **Saunders** Jr. E.M. (1993). Stock Prices and Wall Street Weather. *The American Economic Review*, Vol. 83, No.5, pp.1337-1345, December
- **Schmid**, A. (2005). Terrorism as Psychological Warfare, Democracy and Security, Vol. 1, No. 2, pp. 137-146, June
- **Scuffham** P., D. Chalmers, D. O'Hare, E. Wilson (2002). Direct and Indirect Cost of General Aviation Crashes. *Original Research*
- **Semenick Alam** I.M., L.B. Ross, R.C. Sickles (2001). Time Series Analysis of Strategic Pricing Behavior in the US Airline Industry. *Journal of Productivity Analysis*, Vol. 16, Issue 1, pp. 49-62, July
- **Sexton** J.B., E.J. Thomas, R.L. Helmreich (2000). Error, Stress, and Teamwork in Medicine and Aviation: Cross Sectional Surveys. *BMJ*, Vol. 18, pp. 745-749
- **Shah** S.A. (2010). Share Price Serves as a Barometer for Business Performance. *Social Science Research Network*, April
- **Shappell**, S.A., D.A. Wiegmann (2003). A Human Error Analysis of General Aviation Controlled Flight Into Terrain Accidents Occurring Between 1990-1998, *Office of Aerospace Medicine*, Washington D.C., March
- **Shappell**, S., D. Wiegmann (2004). HFACS Analysis of Military and Civilian Aviation Accidents: A North American Comparison, *Civil Aviation Medical Institute*, USA, and University of Illinois
- **Sharp**, W.G, Sr. (2000). The Use of Armed Force against Terrorism: American Hegemony or Impotence? *HeinOnline*
- **Shyur** H.J., H. Keng, I.K.I, C.L. Huang (2012). Using Extended Hazard Regression Model to Assess the Probability of Aviation Event. *Applied Mathematics and Computation*, Vol. 218, No. 21, pp.10647-10655
- **Sobieralski** J.B. (2013). The Cost of General Aviation Accidents in the United States. *Transportation Research Part A: Policy and Practice* Vol. 47, pp. 19-27, January
- **Squalli** J., M. Saad (2006). Accidents Airline Safety Perceptions and Consumer Demand. *Journal of Economics and Finance*, Vol. 30, No.3, pp.297-305
- **Sunder** S. (2012). Stationarity of Market Risk: Random Coefficients Tests of Individual Stocks. *The Journal of Finance*, Vol. 35, Issue 4, pp. 883-896, September
- **Thaler** R.H., W.F.M. de Bondt (1987). Further Evidence on Investor Overreaction and Stock Market Seasonality. *The Journal of Finance*, Vol. 42, No.3, pp.557-581, July

- **Tetlock** P.C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, Vol. 62, No. 3, pp. 1139-1168, June
- **Teilelbaum** J.C. (2006). A Unilateral Accident Model under Ambiguity. *American Law & Economics Association Annual Meetings*
- **Verbeek** M. (2008). A Guide to Modern Econometrics. *John Wiley & Sons, Inc.*
- Walker, C., A. Horne (2012). The Terrorism Prevention and Investigation Measures Act 2011: One Thing but Not Much the Other?, *Criminal Law Review*, pp. 421-438
- **Wang** J. (1994). A Model of Competitive Stock Trading Volume. *Journal of Political Economy*, Vol. 102, No.1, pp.127-168
- **Wasserfallen** W. (1989). Macroeconomic News and the Stock Market: Evidence from Europe. *Journal of Banking and Finance*, Vol.13, No. 4-5, pp. 613-626, September
- **Wiegmann**, D.A., S.A. Shappell (2001). A Human Error Analysis of Commercial Aviation Accidents Using the Human Factor Analysis and Classification System (HFACS), *Office of Aerospace Medicine*, Washington D.C., February
- **Wiegmann**, D.A., S.A. Shappell, A. Boquet, C. Detwiler, K. Holcomb and T. Faaborg, (2005). Human Error and General Aviation Accidents: A Comprehensive, Fine-Grained Analysis Using HFACS, *Federal Aviation Administration*, Oklahoma City, OK, May
- **Wooldrigde** J.M. (2009). Introductory Econometrics: A Modern Approach.
- **Yang** F. (2012). A Note on Cointegration Methodology in Studying Stock Market Integration. *Applied Economics Letters*, Vol. 19, No. 16, pp. 1583- 1586

9.2. Websites

- Airlines:
  - ✓Alaska Airlines (AKA): http://www.alaskaair.com/
  - ✓American Airlines (AMR): http://www.american-airlines.nl/
  - ✓Air Canada (AC): http://www.aircanada.com/en/
  - ✓AirTran Airways (AAI): http://www.airtran.com/Home.aspx
  - ✓Delta Air Lines (DAL): http://www.delta.com/
  - ✓Hawaiian Airlines (HA): http://www.hawaiianairlines.com/
  - ✓JetBlue Airways (JBLU): http://www.jetblue.com/
  - ✓Skywest Airlines (SKYW): http://www.jetblue.com/
  - ✓Southwest Airlines (LUV): http://www.southwest.com/
  - ✓United Airlines (UAL): https://www.united.com/
  - ✓US Airways (LCC): http://www.usairways.com/
- Aviation Common Taxonomies, 2011, Phases of Flight, October http://intlaviationstandards.org/Documents/PhaseofFlightDefinitions.pdf (downloaded as of June 26, 2012)
- Boeing: http://www.boeing.com/boeing/
- Bureau of Labor Statistics: http://www.bls.gov/
- Federal Aviation Administration: http://www.faa.gov/
- Forbes: http://www.forbes.com
- International Civil Aviation Organization: http://www.icao.int/Pages/default.aspx
- International Monetary Fund: http://www.imf.org/external/data.htm
- NASDAQ: http://www.nasdaq.com/
- National Transport Safety Board (NTSB): http://www.ntsb.gov/
- New York Stock Exchange: https://nyse.nyx.com/
- OECD: http://www.oecd.org/
- Organization of the Petroleum Exporting Countries (OPEC): http://www.opec.org/opec_web/en/
- Plane Crash Information: http://planecrashinfo.com/
- Research and Innovative Technology Administration Bureau of Transportation Statistics (RITA): http://www.rita.dot.gov/
- Wharton Research Data Services: https://wrds-web.wharton.upenn.edu/wrds/
- World Bank: http://data.worldbank.org/

10. Appendix

10.1. Appendix A

```
. reg lnfare lnor lnshld_eq lnoil lncpi lngdp, robust

Linear regression                                      Number of obs =     366
                                                       F(  5,   360) =  117.42
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5602
                                                       Root MSE      =  .11769

------------------------------------------------------------------------------
             |               Robust
      lnfare |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lnor |    .136837    .007316    18.70   0.000     .1224496    .1512244
   lnshld_eq |   -.046329   .0057236    -8.09   0.000    -.0575849   -.035073
       lnoil |   .0140807   .0192964     0.73   0.466     -.023867    .0520285
       lncpi |   .2280363   .1290482     1.77   0.078    -.0257466    .4818193
       lngdp |    -.14152   .0077299   -18.31   0.000    -.1567213   -.1263186
       _cons |   4.675689   .6839623     6.84   0.000     3.330625    6.020752
------------------------------------------------------------------------------

. ivregress 2sls lnshr_p (lnfare = lnor) lnshld_eq lnoil lncpi lngdp, robust

Instrumental variables (2SLS) regression               Number of obs =     345
                                                       Wald chi2(5)  =  126.43
                                                       Prob > chi2   =  0.0000
                                                       R-squared     =  0.3362
                                                       Root MSE      =  .65484

------------------------------------------------------------------------------
             |               Robust
     lnshr_p |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnfare |   .7928666   .2902121     2.73   0.006     .2240614    1.361672
   lnshld_eq |   .2496454   .0281624     8.86   0.000     .1944481    .3048426
       lnoil |   -.003302   .1130914    -0.03   0.977    -.2249569     .218353
       lncpi |  -2.554161    .763584    -3.34   0.001    -4.050758   -1.057564
       lngdp |   .4943158   .1052035     4.70   0.000     .2881207    .7005109
       _cons |   1.237217   3.836741     0.32   0.747    -6.282657    8.757092
------------------------------------------------------------------------------
Instrumented:  lnfare
Instruments:   lnshld_eq lnoil lncpi lngdp lnor

. estat endogenous

  Tests of endogeneity
  Ho: variables are exogenous

  Robust score chi2(1)          =  .393832  (p = 0.5303)
  Robust regression F(1,338)    =  .392134  (p = 0.5316)
```

Table A1: Durbin-Wu Hausman Test for Endogeneity

```
pwcorr lnshr_p lnshld_eq lnfare lnor lncpi lnoil lngdp res, sig

             |  lnshr_p lnshld~q   lnfare     lnor    lncpi    lnoil    lngdp
-------------+---------------------------------------------------------------
     lnshr_p |   1.0000
             |
             |
   lnshld_eq |   0.4176   1.0000
             |   0.0000
             |
      lnfare |  -0.0167   0.1892   1.0000
             |   0.7305   0.0003
             |
        lnor |   0.2518   0.5878   0.6087   1.0000
             |   0.0000   0.0000   0.0000
             |
       lncpi |  -0.1488   0.0420   0.2776   0.2021   1.0000
             |   0.0017   0.4178   0.0000   0.0000
             |
       lnoil |  -0.1280   0.0399   0.2663   0.2249   0.8158   1.0000
             |   0.0070   0.4416   0.0000   0.0000   0.0000
             |
       lngdp |   0.2325  -0.0783  -0.0748   0.3748   0.0621   0.0846   1.0000
             |   0.0000   0.1305   0.0898   0.0000   0.1542   0.0520
             |
         res |  -0.2007   0.0170  -0.0518  -0.0218  -0.1439  -0.1232   0.0767
             |   0.0003   0.7592   0.3501   0.6941   0.0091   0.0258   0.1665
             |

             |      res
-------------+---------
         res |   1.0000
             |
             |
```

Table A2a: Correlation Matrix

```
. reg lnshr_p lnshld_eq lnfare lncpi lnoil lngdp, robust

Linear regression                                      Number of obs =     345
                                                       F(  5,   339) =   24.97
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3368
                                                       Root MSE      =  .66032

------------------------------------------------------------------------------
             |               Robust
     lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |    .251693   .0283164     8.89   0.000     .1959951    .3073909
      lnfare |   .6714552   .2356601     2.85   0.005      .207915    1.134995
       lncpi |  -2.477175   .7511482    -3.30   0.001    -3.954674   -.9996768
       lnoil |  -.0017192   .1137409    -0.02   0.988    -.2254461    .2220077
       lngdp |   .4887526   .1060145     4.61   0.000     .2802234    .6972817
       _cons |    1.46589   3.903817     0.38   0.708    -6.212864    9.144645
------------------------------------------------------------------------------

. vif

    Variable |       VIF       1/VIF
-------------+----------------------
       lncpi |      3.21    0.311455
       lnoil |      3.09    0.323970
      lnfare |      1.21    0.827874
   lnshld_eq |      1.03    0.970318
       lngdp |      1.03    0.974657
-------------+----------------------
    Mean VIF |      1.91
```

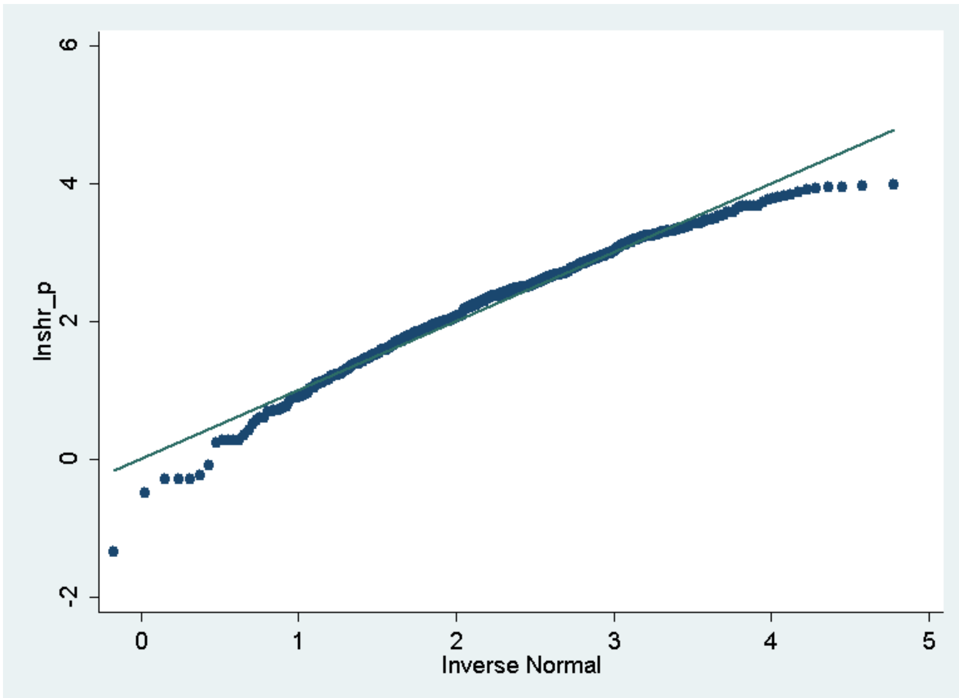
Table A2b: VIF

```
reg lnshr_p lnshld_eq lnfare lncpi lnoil lngdp acc_t

      Source |       SS       df       MS              Number of obs =     345
-------------+------------------------------           F(  6,   338) =   28.65
       Model |  75.1370636     6  12.5228439           Prob > F      =  0.0000
    Residual |  147.731946   338  .437076765           R-squared     =  0.3371
-------------+------------------------------           Adj R-squared =  0.3254
       Total |   222.86901   344  .647875029           Root MSE      =  .66112

------------------------------------------------------------------------------
     lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |   .2501378    .025924     9.65   0.000     .1991451    .3011304
      lnfare |   .6510129   .2256208     2.89   0.004     .2072152    1.094811
       lncpi |  -2.489163    .699808    -3.56   0.000    -3.865691   -1.112636
       lnoil |   .0023847   .1221549     0.02   0.984    -.2378948    .2426642
       lngdp |   .4854585   .0734685     6.61   0.000     .3409453    .6299716
       acc_t |   .0412343   .0974268     0.42   0.672    -.1504049    .2328735
       _cons |   1.684307   3.713717     0.45   0.650    -5.620602    8.989216
------------------------------------------------------------------------------

.
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lnshr_p

         chi2(1)      =    13.71
         Prob > chi2  =   0.0002
```

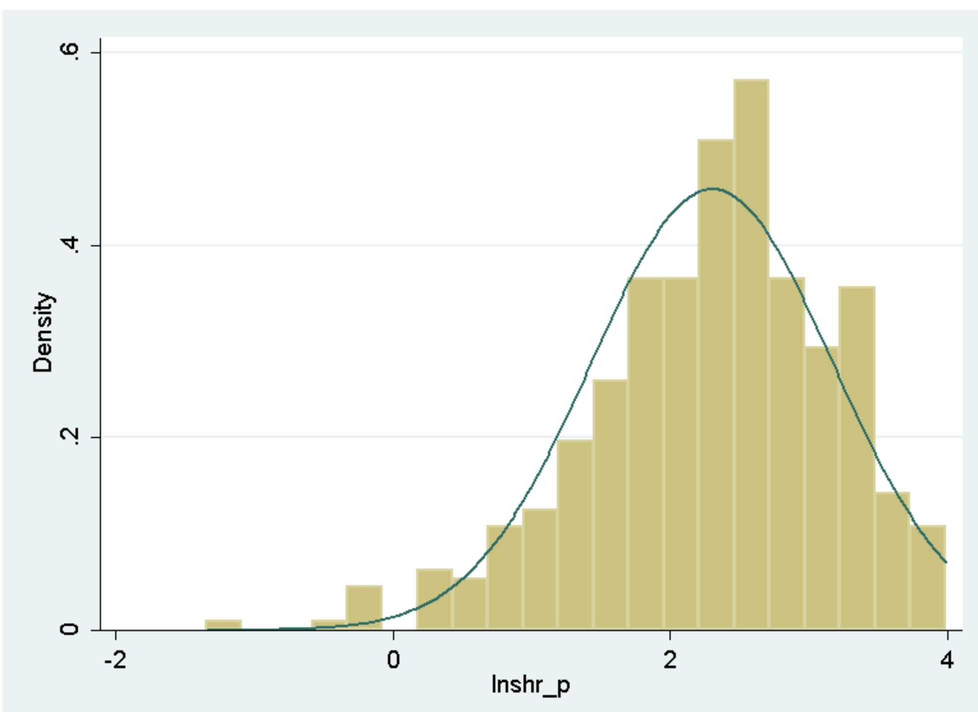
Table A3: Breusch-Pagan Test for Heteroscedasticity

```
reg lnshr_p lnshld_eq lnfare lncpi lnoil lngdp acc_t

      Source |       SS       df       MS              Number of obs =     345
-------------+------------------------------           F(  6,   338) =   28.65
       Model |  75.1370636     6  12.5228439           Prob > F      =  0.0000
    Residual |  147.731946   338  .437076765           R-squared     =  0.3371
-------------+------------------------------           Adj R-squared =  0.3254
       Total |   222.86901   344  .647875029           Root MSE      =  .66112

------------------------------------------------------------------------------
     lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |   .2501378    .025924     9.65   0.000     .1991451    .3011304
      lnfare |   .6510129   .2256208     2.89   0.004     .2072152    1.094811
       lncpi |  -2.489163    .699808    -3.56   0.000    -3.865691   -1.112636
       lnoil |   .0023847   .1221549     0.02   0.984    -.2378948    .2426642
       lngdp |   .4854585   .0734685     6.61   0.000     .3409453    .6299716
       acc_t |   .0412343   .0974268     0.42   0.672    -.1504049    .2328735
       _cons |   1.684307   3.713717     0.45   0.650    -5.620602    8.989216
------------------------------------------------------------------------------

.
. estat imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(26)     =    44.68
         Prob > chi2  =   0.0128

Cameron & Trivedi's decomposition of IM-test

---------------------------------------------------
              Source |       chi2     df      p
---------------------+-----------------------------
  Heteroskedasticity |      44.68     26    0.0128
            Skewness |       9.58      6    0.1437
            Kurtosis |       1.02      1    0.3118
---------------------+-----------------------------
               Total |      55.28     33    0.0089
---------------------------------------------------
```

Table A4: White Test for Heteroscedasticity



Graph A1: QQ-Plot – Entire data sample



Graph A2: Histogram Normal Distrubution

```
. reg lnshr_p lnshld_eq, robust

Linear regression                                      Number of obs =     353
                                                       F(  1,   351) =   68.84
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1744
                                                       Root MSE      =  .72769

------------------------------------------------------------------------------
             |               Robust
     lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |   .2385815   .0287542     8.30   0.000     .1820292    .2951337
       _cons |   -.822174   .3799468    -2.16   0.031    -1.569433   -.0749153
------------------------------------------------------------------------------

.
. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    353   -421.4862   -387.6685      2     779.3369    787.0699
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. reg lnshr_p lnshld_eq l.lnshld_eq, robust

Linear regression                                      Number of obs =     337
                                                       F(  2,   334) =   51.97
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2087
                                                       Root MSE      =  .68886

------------------------------------------------------------------------------
             |               Robust
     lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         --. |   .4222783   .0859126     4.92   0.000     .2532804    .5912762
         L1. |  -.1672564   .0820461    -2.04   0.042    -.3286486   -.0058641
             |
       _cons |  -1.055653   .3402038    -3.10   0.002    -1.724865    -.386441
------------------------------------------------------------------------------

. estat ic

-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    337   -390.5069   -351.0714      3     708.1429    719.6031
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note

. reg lnshr_p lnshld_eq l.lnshld_eq l2.lnshld_eq, robust

Linear regression                                      Number of obs =     322
                                                       F(  3,   318) =   30.57
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1985
                                                       Root MSE      =  .68773

------------------------------------------------------------------------------
             |               Robust
     lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         --. |    .331545   .0916712     3.62   0.000     .1511864    .5119036
         L1. |   .1218886   .1709662     0.71   0.476    -.2144791    .4582564
         L2. |  -.2058582   .1223936    -1.68   0.094    -.4466618    .0349453
             |
       _cons |  -.9775085   .3541443    -2.76   0.006     -1.67427   -.2807465
------------------------------------------------------------------------------

. estat ic
-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    322   -369.9573    -334.341      4      676.682    691.7802
-----------------------------------------------------------------------------
               Note:  N=Obs used in calculating BIC; see [R] BIC note
```

Table A5: AIC and BIC

```
. xtserial dlnshr_p dlnshld_eq dlnfare dlncpi dlnoil dlngdp llnshr_p llnshld_eq llnfare llncpi llnoil llngdp acc_t

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      10) =     76.651
           Prob > F =      0.0000
```

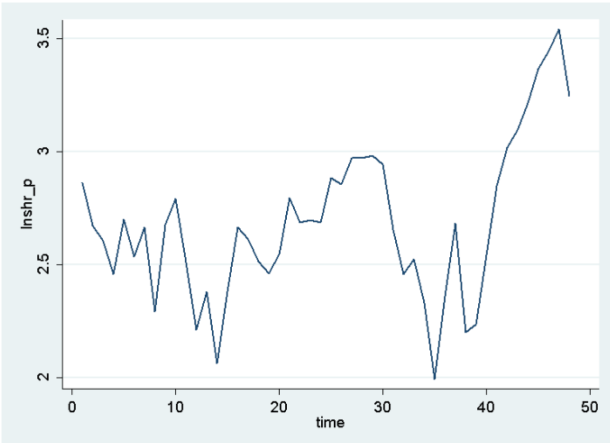
Table A6: Serial Correlation

```
nptrend lnshr_p, by(id)

        id     score       obs      sum of ranks
         1         1        48        7510.5
         2         2        20          2137
         3         3        48         13573
         4         4        48       12081.5
         5         5        48       10469.5
         6         6        48          3637
         7         7        38        7534.5
         8         8        25          5925
         9         9        48       12081.5
        10        10        48       15712.5
        11        11        23          7241

          z  =  5.94
  Prob > |z| = 0.000
```

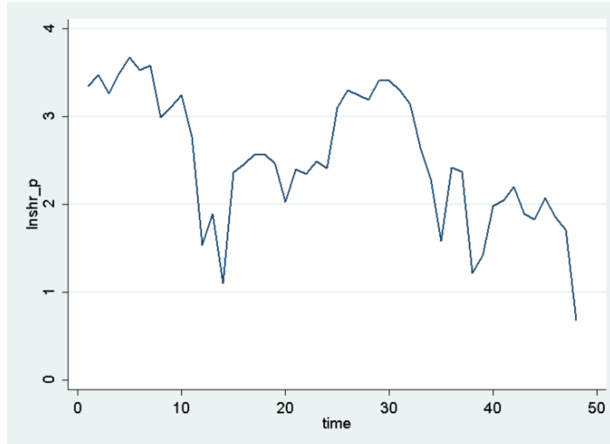
Table A7: Wilcoxon rank-sum test for trend

```
xtunitroot fisher lnshr_p, dfuller trend lag(2)
(86 missing values generated)

Fisher-type unit-root test for lnshr_p
Based on augmented Dickey-Fuller tests
--------------------------------------
Ho: All panels contain unit roots           Number of panels       =     11
Ha: At least one panel is stationary        Avg. number of periods =  40.18

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(22)   P       17.7116       0.7229
 Inverse normal            Z        0.3601       0.6406
 Inverse logit t(59)       L*       0.3200       0.6250
 Modified inv. chi-squared Pm      -0.6465       0.7410
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

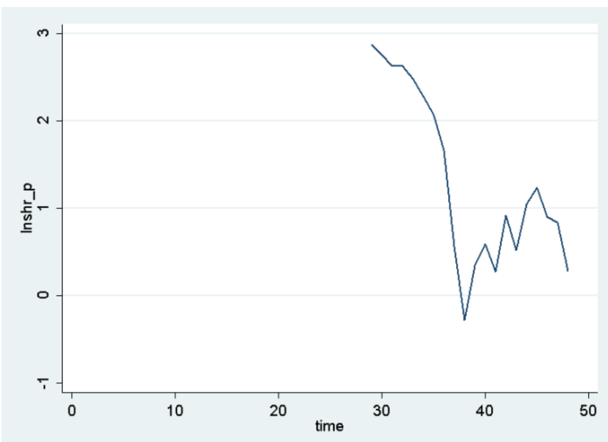
Table A8: Fisher Test Based on an Augmented Dickey-Fuller Test



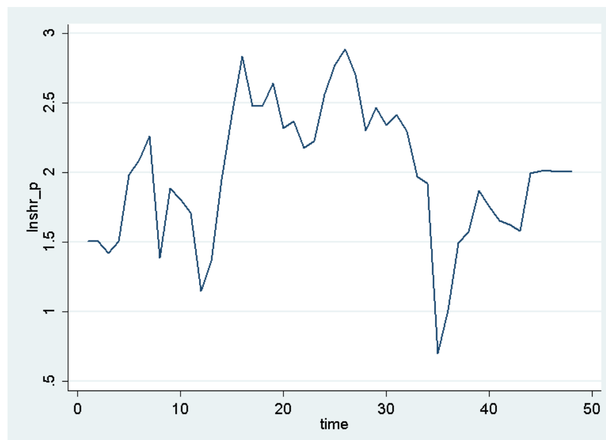
Graph A3: Alaska Airlines (ALK)



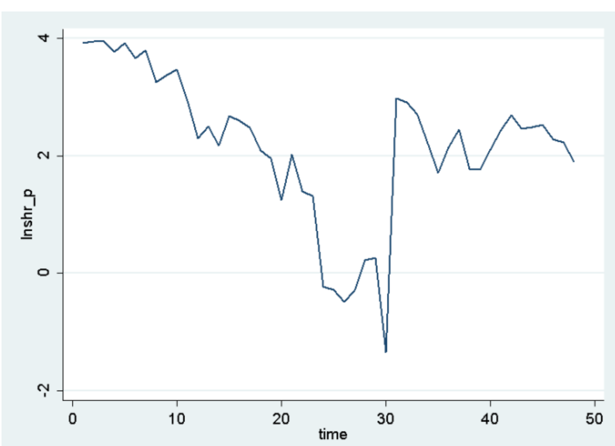
Graph A4: American Airlines (AMR)



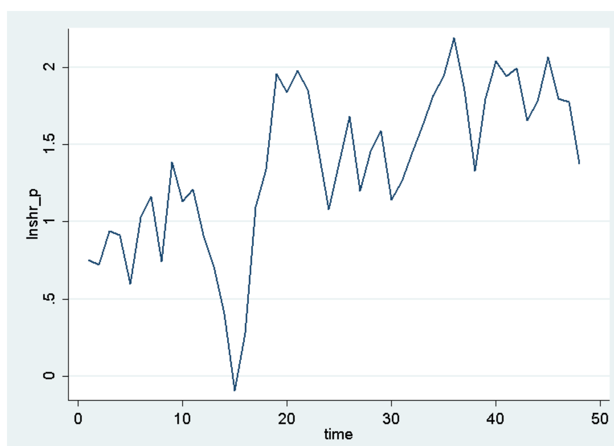
Graph A5: Air Canada (AC)



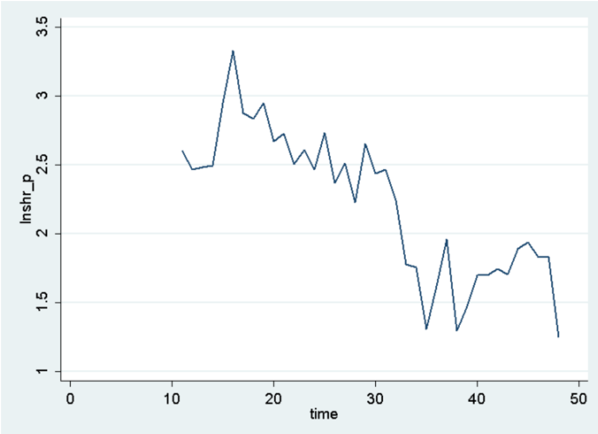
Graph A6: AirTran Airways (AAI)



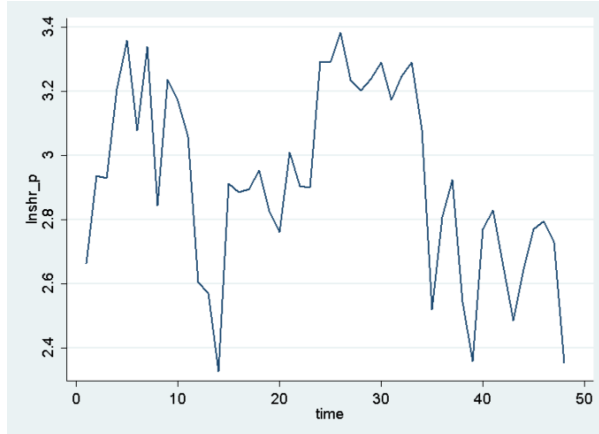
Graph A7: Delta Air Lines (DAL)



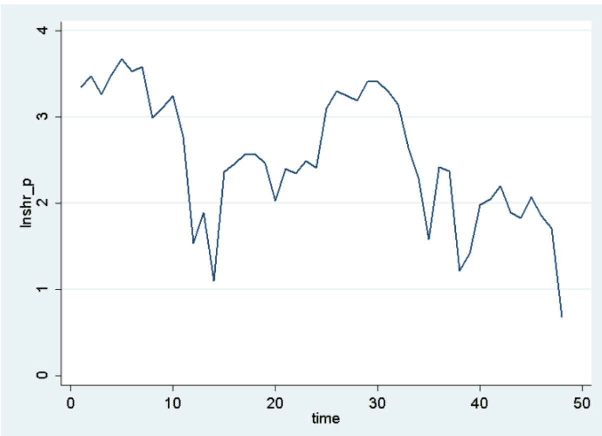
Graph A8: Hawaiian Airlines (HA)



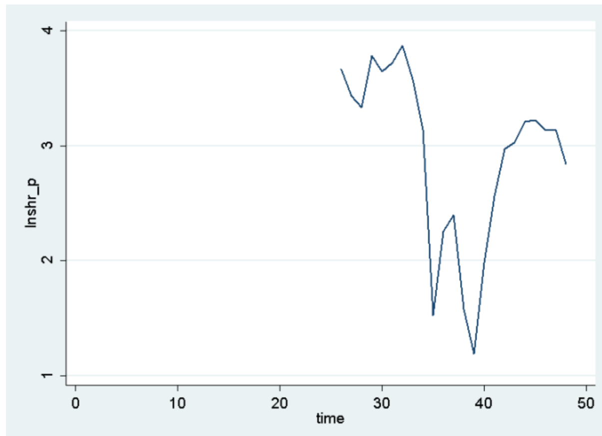
Graph A9: JetBlue Airways (JBLU)



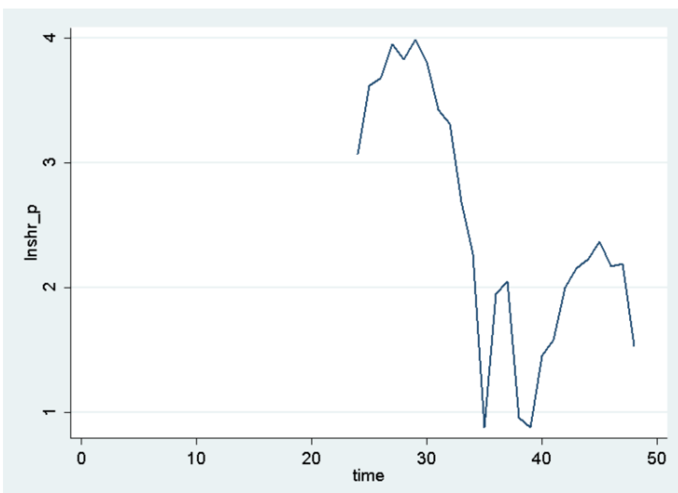
Graph A10: Skywest Airlines (SKYW)



Graph A11: Southwest Airlines (LUV)



Graph A12: United Airlines (UAL)



Graph A13: US Airways (LCC)

10.2. Appendix B

```
. newey d.lnshr_p d.lnshld_eq d.lnfare d.lncpi d.lnoil d.lngdp
l.lnshr_p l.lnshld_eq l.lnfare l.lncpi l.lnoil l.lngdp acc_t _Iy* _Im* _Id*, lag(2) force

Regression with Newey-West standard errors          Number of obs  =       327
maximum lag: 2                                      F( 38,    288)  =      5.09
                                                    Prob > F        =    0.0000

------------------------------------------------------------------------------
             |             Newey-West
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         D1. |   .2514355   .0781159     3.22   0.001     .0976851     .405186
             |
      lnfare |
         D1. |   .8833516   .4991141     1.77   0.078    -.0990223    1.865725
             |
       lncpi |
         D1. |   3.578779   1.235129     2.90   0.004     1.147754    6.009804
             |
       lnoil |
         D1. |  -.8225432   .2354821    -3.49   0.001    -1.286027   -.3590591
             |
       lngdp |
         D1. |   10.09751   6.096914     1.66   0.099    -1.902647    22.09767
             |
     lnshr_p |
         L1. |  -.3051174   .1383709    -2.21   0.028    -.5774638   -.0327709
             |
   lnshld_eq |
         L1. |    .078018   .0440384     1.77   0.078    -.0086599    .1646959
             |
      lnfare |
         L1. |   .2895411   .1999249     1.45   0.149    -.1039582    .6830404
             |
       lncpi |
         L1. |   2.301091   1.291118     1.78   0.076    -.2401336    4.842315
             |
       lnoil |
         L1. |  -.7759658   .3226852    -2.40   0.017    -1.411086   -.1408454
             |
       lngdp |
         L1. |   .1887715   .0935977     2.02   0.045     .0045491    .3729939

       acc_t |  -.0536404   .0616684    -0.87   0.385    -.1750183    .0677374
    _Iyear_2 |  -.0986785   .0950338    -1.04   0.300    -.2857274    .0883704
    _Iyear_3 |  -.2134425   .1240566    -1.72   0.086     -.457615      .03073
    _Iyear_4 |   .0891613   .1259154     0.71   0.479    -.1586699    .3369925
    _Iyear_5 |   .2274938   .1505181     1.51   0.132    -.0687612    .5237488
    _Iyear_6 |   .4190742   .2251153     1.86   0.064    -.0240056    .8621541
    _Iyear_7 |   .6072319   .2918065     2.08   0.038     .0328881    1.181576
    _Iyear_8 |   .6123411   .3085587     1.98   0.048     .0050251    1.219657
    _Iyear_9 |   .3472469   .4334425     0.80   0.424    -.5058698    1.200364
   _Iyear_10 |    .203754   .2784914     0.73   0.465    -.3443827    .7518906
   _Iyear_11 |   .2418906   .3598515     0.67   0.502    -.4663818     .950163
   _Iyear_12 |   .1393796   .4643686     0.30   0.764     -.774607    1.053366
   _Imonth_2 |    -.12758   .1706233    -0.75   0.455    -.4634068    .2082468
   _Imonth_3 |   .1646471   .1022952     1.61   0.109     -.036694    .3659882
   _Imonth_4 |  -.3020718   .2157674    -1.40   0.163    -.7267527    .1226092
   _Imonth_5 |  -.0297521   .1611911    -0.18   0.854    -.3470141    .2875098
   _Imonth_6 |  -.0593656    .114904    -0.52   0.606    -.2855237    .1667925
   _Imonth_7 |   .0319099   .2057485     0.16   0.877    -.3730515    .4368712
   _Imonth_8 |  -.0537826   .1228191    -0.44   0.662    -.2955194    .1879542
   _Imonth_9 |    .019087   .1229911     0.16   0.877    -.2229885    .2611624
  _Imonth_10 |  -.0782315   .1511059    -0.52   0.605    -.3756434    .2191804
  _Imonth_11 |  -.0734692   .1781755    -0.41   0.680    -.4241606    .2772221
  _Imonth_12 |  -.0206199   .1183484    -0.17   0.862    -.2535574    .2123176
     _Iday_2 |   .0155988    .071367     0.22   0.827    -.1248682    .1560658
     _Iday_3 |   .0591974   .0754461     0.78   0.433    -.0892983    .2076931
     _Iday_4 |  -.0458978   .0611175    -0.75   0.453    -.1661914    .0743958
     _Iday_5 |   -.028201   .0796264    -0.35   0.723    -.1849245    .1285225
       _cons |  -14.78535   7.427201    -1.99   0.047    -29.40383    -.166873
------------------------------------------------------------------------------
```

```
. nlcom _b[l.lnshld_eq] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnshld_eq] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2556983   .0593282     4.31   0.000     .1389265    .3724701
------------------------------------------------------------------------------

. nlcom _b[l.lnfare] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnfare] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .9489498   .4398548     2.16   0.032     .0832121    1.814687
------------------------------------------------------------------------------

. nlcom _b[l.lncpi] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lncpi] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   7.541658   5.237679     1.44   0.151    -2.767326    17.85064
------------------------------------------------------------------------------

. nlcom _b[l.lnoil] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnoil] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -2.543171   1.485479    -1.71   0.088    -5.466942    .3805996
------------------------------------------------------------------------------

. nlcom _b[l.lngdp] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lngdp] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .6186848   .1754346     3.53   0.000     .2733882    .9639814
------------------------------------------------------------------------------
```

Table B1: Bårdsen Error Correction Model 1 – Accidents

```
. newey d.lnshr_p d.lnshld_eq d.lnfare d.lncpi d.lnoil d.lngdp
l.lnshr_p l.lnshld_eq l.lnfare l.lncpi l.lnoil l.lngdp nonfatal _Iy* _Im* _Id*, lag(2) force

Regression with Newey-West standard errors          Number of obs  =       327
maximum lag: 2                                      F( 38,   288)  =      5.07
                                                    Prob > F       =    0.0000

------------------------------------------------------------------------------
             |             Newey-West
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         D1. |   .2513787   .0782394     3.21   0.001     .0973853    .4053722
             |
      lnfare |
         D1. |   .8794738   .4989601     1.76   0.079    -.1025971    1.861545
             |
       lncpi |
         D1. |   3.588334    1.23103     2.91   0.004     1.165376    6.011291
             |
       lnoil |
         D1. |  -.8229807   .2351905    -3.50   0.001    -1.285891   -.3600705
             |
       lngdp |
         D1. |   10.09339   6.106557     1.65   0.099    -1.925745    22.11253
             |
     lnshr_p |
         L1. |  -.3049972   .1384444    -2.20   0.028    -.5774884   -.0325061
             |
   lnshld_eq |
         L1. |   .0774696   .0437272     1.77   0.078    -.0085957    .1635349
             |
      lnfare |
         L1. |   .2902636   .1991106     1.46   0.146    -.1016328      .68216
             |
       lncpi |
         L1. |   2.307542   1.287492     1.79   0.074    -.2265451    4.841628
             |
       lnoil |
         L1. |  -.7752707   .3233071    -2.40   0.017    -1.411615   -.1389264
             |
       lngdp |
         L1. |   .1885636   .0933097     2.02   0.044     .0049081    .3722191
             |

             |
    nonfatal |  -.0567921   .0636218    -0.89   0.373    -.1820148    .0684306
    _Iyear_2 |  -.1013323   .0960439    -1.06   0.292    -.2903694    .0877047
    _Iyear_3 |  -.2104321   .1231973    -1.71   0.089    -.4529134    .0320493
    _Iyear_4 |   .0917295   .1241224     0.74   0.460    -.1525726    .3360315
    _Iyear_5 |   .2307889   .1494839     1.54   0.124    -.0634306    .5250084
    _Iyear_6 |    .418821   .2248684     1.86   0.064     -.023773    .8614149
    _Iyear_7 |   .6092313   .2918038     2.09   0.038     .0348928     1.18357
    _Iyear_8 |   .6146874   .3087194     1.99   0.047     .0070549     1.22232
    _Iyear_9 |    .348324   .4337738     0.80   0.423    -.5054448    1.202093
   _Iyear_10 |   .2035461   .2779398     0.73   0.465    -.3435049     .750597
   _Iyear_11 |   .2430998   .3600922     0.68   0.500    -.4656463    .9518459
   _Iyear_12 |   .1396454   .4645076     0.30   0.764    -.7746148    1.053906
   _Imonth_2 |  -.1285868    .170463    -0.75   0.451    -.4640981    .2069244
   _Imonth_3 |   .1650116   .1021896     1.61   0.107    -.0361215    .3661448
   _Imonth_4 |  -.3001626   .2154979    -1.39   0.165    -.7243132     .123988
   _Imonth_5 |  -.0310634   .1606581    -0.19   0.847    -.3472764    .2851497
   _Imonth_6 |  -.0586488   .1146914    -0.51   0.609    -.2843885     .167091
   _Imonth_7 |   .0296946   .2056301     0.14   0.885    -.3750338    .4344229
   _Imonth_8 |  -.0535977   .1227582    -0.44   0.663    -.2952147    .1880192
   _Imonth_9 |   .0181402   .1222701     0.15   0.882     -.222516    .2587965
  _Imonth_10 |  -.0797162   .1507999    -0.53   0.597    -.3765258    .2170935
  _Imonth_11 |  -.0738034   .1779852    -0.41   0.679    -.4241202    .2765133
  _Imonth_12 |  -.0227051   .1176227    -0.19   0.847    -.2542142    .2088041
     _Iday_2 |   .0165972   .0711234     0.23   0.816    -.1233905    .1565849
     _Iday_3 |   .0588206   .0754549     0.78   0.436    -.0896923    .2073336
     _Iday_4 |  -.0444843   .0606558    -0.73   0.464    -.1638692    .0749007
     _Iday_5 |  -.0279391   .0793496    -0.35   0.725    -.1841178    .1282396
       _cons |  -14.81822   7.413511    -2.00   0.047    -29.40975   -.2266832
------------------------------------------------------------------------------
```

```
. nlcom _b[l.lnshld_eq] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnshld_eq] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |    .254001   .0591053     4.30   0.000     .1376678    .3703342
------------------------------------------------------------------------------

. nlcom _b[l.lnfare] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnfare] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .9516926   .4406165     2.16   0.032     .0844557     1.81893
------------------------------------------------------------------------------

. nlcom _b[l.lncpi] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lncpi] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   7.565778   5.228085     1.45   0.149    -2.724323    17.85588
------------------------------------------------------------------------------

. nlcom _b[l.lnoil] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnoil] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -2.541894   1.491316    -1.70   0.089    -5.477155    .3933668
------------------------------------------------------------------------------

. nlcom _b[l.lngdp] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lngdp] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .6182469   .1756143     3.52   0.001     .2725966    .9638971
------------------------------------------------------------------------------
```

Table B2a: Bårdsen Error Correction Model 2a – Nonfatal

```
. newey d.lnshr_p d.lnshld_eq d.lnfare d.lncpi d.lnoil d.lngdp d.inj
> l.lnshr_p l.lnshld_eq l.lnfare l.lncpi l.lnoil l.lngdp l.inj _Iy* _Im* _Id*, lag(2) force

Regression with Newey-West standard errors          Number of obs  =       327
maximum lag: 2                                      F( 39,    287)  =      5.98
                                                    Prob > F        =    0.0000

------------------------------------------------------------------------------
             |             Newey-West
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         D1. |   .2411243   .0786339     3.07   0.002      .0863521    .3958965
             |
      lnfare |
         D1. |    .820279   .4895292     1.68   0.095     -.1432438    1.783802
             |
       lncpi |
         D1. |   3.698828   1.226854     3.01   0.003      1.284055    6.113602
             |
       lnoil |
         D1. |  -.8236084   .2360168    -3.49   0.001     -1.288152   -.3590649
             |
       lngdp |
         D1. |   10.38885   6.054204     1.72   0.087     -1.527421    22.30512
             |
         inj |
         D1. |   .0021772   .0032627     0.67   0.505     -.0042447    .0085991
             |
     lnshr_p |
         L1. |  -.3072908   .1401039    -2.19   0.029     -.5830523   -.0315293
             |
   lnshld_eq |
         L1. |   .0746229   .0438178     1.70   0.090     -.0116221    .1608679
             |
      lnfare |
         L1. |   .2377411   .1877692     1.27   0.206     -.1318382    .6073204
             |
       lncpi |
         L1. |   2.263006   1.283699     1.76   0.079     -.2636524    4.789664
             |
       lnoil |
         L1. |  -.7887699   .3228168    -2.44   0.015     -1.424159   -.1533812
             |
       lngdp |
         L1. |   .1809145   .0905408     2.00   0.047      .0027062    .3591227
             |
         inj |
         L1. |   .0065135   .0034265     1.90   0.058     -.0002308    .0132577
             |
    _Iyear_2 |  -.0539303   .0953635    -0.57   0.572     -.2416309    .1337703
    _Iyear_3 |  -.1678536    .119293    -1.41   0.160     -.4026538    .0669466
    _Iyear_4 |   .1322546   .1189603     1.11   0.267     -.1018907    .3663999
    _Iyear_5 |   .2790799   .1482316     1.88   0.061     -.0126791    .5708388
    _Iyear_6 |   .4741617   .2249285     2.11   0.036      .0314431    .9168803
    _Iyear_7 |    .672012   .2938958     2.29   0.023      .0935473    1.250477
    _Iyear_8 |   .6820272   .3113856     2.19   0.029      .0691381    1.294916
    _Iyear_9 |   .4177514   .4404043     0.95   0.344     -.4490807    1.284583
   _Iyear_10 |   .2521954   .2804101     0.90   0.369     -.2997258    .8041166
   _Iyear_11 |   .3058194   .3663121     0.83   0.404     -.4151796    1.026818
   _Iyear_12 |   .2180598   .4725871     0.46   0.645     -.7121164    1.148236
   _Imonth_2 |  -.1151448   .1710454    -0.67   0.501     -.4518073    .2215178
   _Imonth_3 |    .158956    .104343     1.52   0.129     -.0464186    .3643307
   _Imonth_4 |  -.3039349   .2175191    -1.40   0.163     -.7320699    .1242002
   _Imonth_5 |  -.0207213   .1611419    -0.13   0.898     -.3378911    .2964486
   _Imonth_6 |  -.0637108   .1155495    -0.55   0.582     -.2911428    .1637211
   _Imonth_7 |   .0429155   .2074721     0.21   0.836     -.3654443    .4512753
   _Imonth_8 |  -.0448676   .1252396    -0.36   0.720     -.2913722     .201637
   _Imonth_9 |   .0200772   .1239431     0.16   0.871     -.2238756      .26403
  _Imonth_10 |  -.0733111   .1520738    -0.48   0.630     -.3726324    .2260102
  _Imonth_11 |  -.0593589   .1823654    -0.33   0.745     -.4183022    .2995845
  _Imonth_12 |   -.020895   .1204586    -0.17   0.862     -.2579893    .2161992
    _Iday_2 |    .025329   .0704536     0.36   0.719     -.1133422    .1640003
    _Iday_3 |   .0648944   .0747187     0.87   0.386     -.0821716    .2119605
    _Iday_4 |  -.0401339   .0594193    -0.68   0.500     -.1570869     .076819
    _Iday_5 |  -.0257793     .07801    -0.33   0.741     -.1793235    .1277649
       _cons |  -14.16745   7.415718    -1.91   0.057     -28.76354    .4286458
------------------------------------------------------------------------------
```

```
       _nl_1:  _b[l.lnshld_eq] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2428413   .0599699     4.05   0.000     .1248046     .360878
------------------------------------------------------------------------------

. nlcom _b[l.lnfare] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnfare] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .7736682   .4221917     1.83   0.068    -.0573167    1.604653
------------------------------------------------------------------------------

. nlcom _b[l.lncpi] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lncpi] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   7.364378   5.125665     1.44   0.152    -2.724284    17.45304
------------------------------------------------------------------------------

. nlcom _b[l.lnoil] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnoil] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -2.566852   1.511962    -1.70   0.091    -5.542792     .409089
------------------------------------------------------------------------------

. nlcom _b[l.lngdp] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lngdp] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .5887403   .1634253     3.60   0.000     .2670762    .9104045
------------------------------------------------------------------------------

. nlcom _b[l.inj] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.inj] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .0211964   .0154456     1.37   0.171    -.0092046    .0515974
------------------------------------------------------------------------------
```

Table B2b: Bårdsen Error Correction Model 2b – Injuries

```
. newey d.lnshr_p d.lnshld_eq d.lnfare d.lncpi d.lnoil d.lngdp
l.lnshr_p l.lnshld_eq l.lnfare l.lncpi l.lnoil l.lngdp fatal _Iy* _Im* _Id*, lag(2) force

Regression with Newey-West standard errors          Number of obs  =       327
maximum lag: 2                                      F( 38,   288)  =      5.06
                                                    Prob > F       =    0.0000

------------------------------------------------------------------------------
             |             Newey-West
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         D1. |   .2495839   .0776593     3.21   0.001     .0967322    .4024357
             |
      lnfare |
         D1. |   .8857235   .4907085     1.80   0.072    -.0801063    1.851553
             |
       lncpi |
         D1. |   3.610534   1.228047     2.94   0.004     1.193449    6.027619
             |
       lnoil |
         D1. |  -.8404306   .2337923    -3.59   0.000    -1.300589   -.3802724
             |
       lngdp |
         D1. |   10.59145   6.038006     1.75   0.080    -1.292763    22.47567
             |
     lnshr_p |
         L1. |  -.3057145   .1397295    -2.19   0.029     -.580735    -.030694
             |
   lnshld_eq |
         L1. |   .0762111   .0440047     1.73   0.084    -.0104006    .1628228
             |
      lnfare |
         L1. |     .26041   .1859049     1.40   0.162    -.1054945    .6263145
             |
       lncpi |
         L1. |   2.332141   1.282659     1.82   0.070    -.1924331    4.856714
             |
       lnoil |
         L1. |  -.7571426   .3221673    -2.35   0.019    -1.391244   -.1230417
             |
       lngdp |
         L1. |   .1840793    .091602     2.01   0.045      .003785    .3643736

             |
       fatal |  -.0000549   .1508214    -0.00   1.000    -.2969068    .2967971
    _Iyear_2 |  -.0842168   .0951711    -0.88   0.377    -.2715359    .1031023
    _Iyear_3 |  -.1907482   .1200528    -1.59   0.113    -.4270403    .0455439
    _Iyear_4 |   .1061294   .1211203     0.88   0.382    -.1322638    .3445226
    _Iyear_5 |   .2414204   .1490019     1.62   0.106    -.0518503    .5346911
    _Iyear_6 |   .4252502   .2240087     1.90   0.059    -.0156516     .866152
    _Iyear_7 |   .6075104   .2914146     2.08   0.038     .0339379    1.181083
    _Iyear_8 |   .6157551   .3084358     2.00   0.047      .008681    1.222829
    _Iyear_9 |   .3389015   .4353106     0.78   0.437    -.5178922    1.195695
   _Iyear_10 |   .2042063   .2794016     0.73   0.465    -.3457219    .7541344
   _Iyear_11 |   .2299097   .3626716     0.63   0.527    -.4839133    .9437326
   _Iyear_12 |   .1241749   .4666929     0.27   0.790    -.7943865    1.042736
   _Imonth_2 |  -.1181755   .1724924    -0.69   0.494    -.4576811    .2213302
   _Imonth_3 |   .1653875   .1035548     1.60   0.111    -.0384326    .3692076
   _Imonth_4 |  -.3129083   .2210377    -1.42   0.158    -.7479624    .1221458
   _Imonth_5 |  -.0258198    .160632    -0.16   0.872    -.3419813    .2903417
   _Imonth_6 |  -.0642371   .1148098    -0.56   0.576    -.2902098    .1617355
   _Imonth_7 |   .0305164   .2064643     0.15   0.883    -.3758539    .4368867
   _Imonth_8 |  -.0544369   .1247317    -0.44   0.663    -.2999382    .1910643
   _Imonth_9 |   .0147609   .1230987     0.12   0.905    -.2275263    .2570482
  _Imonth_10 |  -.0801023   .1522425    -0.53   0.599    -.3797514    .2195468
  _Imonth_11 |  -.0721323   .1793579    -0.40   0.688    -.4251509    .2808862
  _Imonth_12 |  -.0296404   .1191251    -0.25   0.804    -.2641067    .2048258
     _Iday_2 |   .0230098    .071046     0.32   0.746    -.1168255    .1628451
     _Iday_3 |   .0640071   .0743577     0.86   0.390    -.0823464    .2103606
     _Iday_4 |  -.0392962   .0600773    -0.65   0.514    -.1575424    .0789501
     _Iday_5 |  -.0227438   .0786773    -0.29   0.773    -.1775992    .1321116
       _cons |  -14.79916   7.399154    -2.00   0.046    -29.36243   -.2358796
------------------------------------------------------------------------------
```

```
. nlcom _b[l.lnshld_eq] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnshld_eq] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2492884   .0601074     4.15   0.000      .130983    .3675938
------------------------------------------------------------------------------

. nlcom _b[l.lnfare] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnfare] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .8518079   .4132032     2.06   0.040     .0385268    1.665089
------------------------------------------------------------------------------

. nlcom _b[l.lncpi] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lncpi] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   7.628492   5.220692     1.46   0.145    -2.647059    17.90404
------------------------------------------------------------------------------

. nlcom _b[l.lnoil] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnoil] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -2.476633   1.489239    -1.66   0.097    -5.407806    .4545399
------------------------------------------------------------------------------

. nlcom _b[l.lngdp] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lngdp] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .6021282   .1706381     3.53   0.000     .2662723    .9379841
------------------------------------------------------------------------------
```

Table B3a: Bårdsen Error Correction Model 3a – Fatal

```
. newey d.lnshr_p d.lnshld_eq d.lnfare d.lncpi d.lnoil d.lngdp d.fat
l.lnshr_p l.lnshld_eq l.lnfare l.lncpi l.lnoil l.lngdp l.fat _Iy* _Im* _Id*, lag(2) force

Regression with Newey-West standard errors          Number of obs  =       327
maximum lag: 2                                       F( 39,   287)  =      7.50
                                                     Prob > F       =    0.0000

------------------------------------------------------------------------------
             |             Newey-West
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lnshld_eq |
         D1. |   .2492084   .0772802     3.22   0.001     .0971005    .4013163
             |
      lnfare |
         D1. |   .8970568   .4949761     1.81   0.071     -.077187    1.871301
             |
       lncpi |
         D1. |   3.639643   1.229732     2.96   0.003     1.219206    6.060081
             |
       lnoil |
         D1. |  -.8696701   .2326922    -3.74   0.000     -1.32767   -.4116704
             |
       lngdp |
         D1. |   10.77376   6.045576     1.78   0.076    -1.125528    22.67305
             |
         fat |
         D1. |   -.000746   .0002844    -2.62   0.009    -.0013058   -.0001862
             |
     lnshr_p |
         L1. |  -.3048131   .1398665    -2.18   0.030    -.5801073   -.0295188
             |
   lnshld_eq |
         L1. |   .0781568   .0437224     1.79   0.075    -.0079005     .164214
             |
      lnfare |
         L1. |   .2733416   .1866715     1.46   0.144    -.0940773    .6407604
             |
       lncpi |
         L1. |   2.349631   1.294122     1.82   0.070    -.1975437    4.896806
             |
       lnoil |
         L1. |  -.8241562   .3255957    -2.53   0.012    -1.465015   -.1832979
             |
       lngdp |
         L1. |   .1848936   .0915324     2.02   0.044     .0047337    .3650535
             |
         fat |
         L1. |  -.0011396   .0002967    -3.84   0.000    -.0017236   -.0005557
             |

             |
    _Iyear_2 |  -.0631378   .0957382    -0.66   0.510    -.2515759    .1253003
    _Iyear_3 |  -.1908518   .1220656    -1.56   0.119    -.4311091    .0494055
    _Iyear_4 |       .108   .1189223     0.91   0.365    -.1260704    .3420705
    _Iyear_5 |   .2597361   .1486712     1.75   0.082     -.032888    .5523602
    _Iyear_6 |    .466356   .2252757     2.07   0.039      .022954     .909758
    _Iyear_7 |   .6609654   .2932445     2.25   0.025     .0837827    1.238148
    _Iyear_8 |   .6684462   .3105524     2.15   0.032     .0571971    1.279695
    _Iyear_9 |   .4202372    .439127     0.96   0.339    -.4440806    1.284555
   _Iyear_10 |   .2540856   .2815306     0.90   0.368    -.3000409    .8082122
   _Iyear_11 |   .2966568   .3666601     0.81   0.419    -.4250271    1.018341
   _Iyear_12 |   .2039506   .4721024     0.43   0.666    -.7252716    1.133173
   _Imonth_2 |  -.1182208   .1742461    -0.68   0.498    -.4611832    .2247416
   _Imonth_3 |   .1651136   .1039051     1.59   0.113     -.039399    .3696261
   _Imonth_4 |  -.3147529   .2203612    -1.43   0.154     -.748482    .1189763
   _Imonth_5 |  -.0176374   .1621587    -0.11   0.913    -.3368086    .3015338
   _Imonth_6 |  -.0619296   .1154518    -0.54   0.592    -.2891692    .1653101
   _Imonth_7 |   .0464154   .2068368     0.22   0.823     -.360694    .4535248
   _Imonth_8 |  -.0484461   .1255369    -0.39   0.700    -.2955358    .1986437
   _Imonth_9 |   .0222444   .1235202     0.18   0.857    -.2208761    .2653648
  _Imonth_10 |  -.0668637   .1537385    -0.43   0.664    -.3694617    .2357343
  _Imonth_11 |  -.0578357   .1810098    -0.32   0.750    -.4141107    .2984393
  _Imonth_12 |  -.0172695   .1203055    -0.14   0.886    -.2540625    .2195236
     _Iday_2 |   .0172759   .0710186     0.24   0.808    -.1225075    .1570594
     _Iday_3 |   .0617045   .0745802     0.83   0.409     -.085089     .208498
     _Iday_4 |  -.0437511   .0594991    -0.74   0.463    -.1608611    .0733589
     _Iday_5 |   -.016743   .0784797    -0.21   0.831    -.1712119    .1377258
       _cons |  -14.78259   7.488871    -1.97   0.049    -29.52267   -.0425183
------------------------------------------------------------------------------
```

```
. nlcom _b[l.lnshld_eq] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnshld_eq] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2564088   .0586228     4.37   0.000     .1410236     .371794
------------------------------------------------------------------------------

. nlcom _b[l.lnfare] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnfare] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .8967515   .4152077     2.16   0.032      .079513     1.71399
------------------------------------------------------------------------------

. nlcom _b[l.lncpi] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lncpi] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   7.708433   5.254059     1.47   0.143    -2.632943    18.04981
------------------------------------------------------------------------------

. nlcom _b[l.lnoil] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lnoil] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -2.703809   1.573329    -1.72   0.087    -5.800537    .3929191
------------------------------------------------------------------------------

. nlcom _b[l.lngdp] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.lngdp] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .6065803   .1717781     3.53   0.000     .2684757    .9446849
------------------------------------------------------------------------------

. nlcom _b[l.fat] /(-_b[l.lnshr_p])

       _nl_1:  _b[l.fat] /(-_b[l.lnshr_p])

------------------------------------------------------------------------------
   D.lnshr_p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |  -.0037387   .0018975    -1.97   0.050    -.0074735   -3.93e-06
------------------------------------------------------------------------------
```

Table B3b: Bårdsen Error Correction Model 3b - Fatalities

10.3. Appendix C

Author	Title	Description	Data		Methodology	Results	Conclusions
			Dependent Variables	**Independent Variables**			
Golbe D.L., (1986)	*Safety and Profits in the Airline Industry*	Model of safety provision, testing whether there is a relationship between safety and US airlines' profits.	(a) Accidents (b) Net Income or Rate of Return	(a) Net income ($prof$), number of departures (dep) and the stage length ($stagel$); (b) Accidents (A), number of departures, stage length and the load factor($load$);	<u>Cross-sectional</u> and <u>time-series analysis</u> (a) $A = \alpha_0 + \alpha_{\alpha 1} prof + \alpha_2 dep + \alpha_3 stagel + \varepsilon_1$ (b) $prof = \beta_0 + \beta_1 A + \beta_2 dep + \beta_3 stagel + \beta_4 load + \varepsilon_2$	*Chance of an accident increases with both the number and length of flights. *No significant relationship between safety and profits.	*No statistical significance. *If there is any relationship it is weak. *More profitable firms may have more accidents.
Chance et al., (1987)	*The Effect of Aviation Disasters on the Air Transport Industry*	Investigates the reaction of share prices on the event day.	Average Unexpected Return (R_t)	Event date, local time, manufacturer, aircraft, location	<u>Cross-section Analysis -Capital Asset Pricing Model -</u> $E(R_t) = R_{ft} + [E(R_{mt} - R_{ft})]\beta$	*Statistically significant negative return on the day of the event. *Largest negative return was -11.4% for Alaska Airline (1971).	*Stock market responds immediately to accident; *impact on trading day and the following few days after.
Barnett et al (2000)	*Passenger-mortality Risk Estimates Provide Perspectives About Airline Safety*	Passenger – mortality rates are analyzed with respect to US carriers and their destinations.	Death risk per flight	(a)Number of Fatalities (b)Safety Scores (c)Incidents (d)Accidents (e)Country indicators	<u>Cross-section Analysis</u> <u>Probability analysis</u> $Q = \frac{\sum_{i=1}^{N} x_i}{N}$ x_i – Proportion of passengers on flights who do not survive the flights. No death$x_i = 0$. Q – death risk	*DEVELOPED WORLD: domestic risk: 1 in 8 million *US domestic: 1 in 2 million *Developing world domestic: 1 in 500000 *International within advanced world: 1 in 5 million *International advanced developing: 1 in 600000 *International developing world: 1 in 400000	*Mortality risks have decreased *General risk for safety when airlines fly to a certain destination *Highest risk for international jets within developing countries. *US no longer the safest.
Raghavan et al., (2005)	*Revisiting the Relationship Between Profitability and Air Carrier Safety in the US Airline Industry*	Examines link between carriers' (small and big) financial performance and safety post-deregulation.	Accident rates	(a) Time (*time)* and post-deregulation time (*dereg)* (b) Accumulated experiences of pilots (*exp)*, average stage length (*avstage)*, and operating profit margin (*opm).*	<u>Using ordinary least squares regression (OLS) – Time Series -</u> (a) $\ln(accident) = \beta_0 + \beta_1 time + \beta_2 dereg + \varepsilon$ (b) $\ln(accident) = \beta_0 + \beta_1 exp + \beta_2 avstage + \beta_3 opm + \beta_4 zerodummy + \varepsilon$	*Decline in accident rate has been slow. *The financial performance measured by OPM has a significant (at the 93% confidence level) negative relationship with accident rates for the regional air carriers (-0.31).	*Significant negative relationship between air carriers' financial performance and accidents, BUT only for small regional carriers.

Kaplanski et al., (2010)	*Sentiment and Stock Prices: The case of Aviation Disasters*	Examination of aviation disasters on stock prices via investor sentiment	Daily rate of return (R_t)	Historic values in period t-i (R_{t-i}), dummy variables for days during the week (D_{it}), the weekend (H_t) and for the first five days of the taxation year (T_t), E_i (i=1,2,3) stands for possible effect and reversal effect variables	Panel analysis $R_t = \gamma_0 + \sum_{i=1}^{5} \gamma_{1i} R_{t-i} + \sum_{i=1}^{4} \gamma_{2i} D_{it} + \gamma_3 H_t + \gamma_4 T_t + \sum_{i=1}^{3} \gamma_{5i} E_{it} + \varepsilon_t$	*Direct and indirect costs for the airline. *Effect of accident on stocks recovers after a view days. *The first-day effect is negative and highly significant, whereas the third-day reversal effect is positive but in most cases insignificant. *Media coverage induces the effect in the stock market (speed of information).	*Aviation disasters are followed by negative rates of return trailed by a reversal effect two days later. *With the increased anxiety there is a short-term reduction in the demand for risky assets.
Ho et al., (2011)	*The Catalyst in the Air Crash-Stock Market Performance Relationship: The Aviation Disaster Fatality*	Investigate the role of the number of fatalities in the impact of aviation accidents on securities for both the crash-airline and its competitors.	(a)Abnormal Return (b)Average Abnormal Return (c)Cumulative Abnormal Return	(a)Market return (R_{it}) (b) return on the S&P 500 stock market index (R_{mt})	(a) estimate expected return of each airline by using OLS regression: $R_{it} = \alpha_t + \beta_t R_{mt} + \varepsilon_{it}$ Panel Analysis: (a)Abnormal Return: $AR_{it} = R_{it} - (\alpha + \beta_i R_{mt})$ (b)Average Abnormal Return: $AAR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N}$ (c)Cumulative Abnormal Return: $CAR_{T1T2} = \frac{\sum_{i=1}^{N} \sum_{t=T_1}^{T_2} AR_i}{N}$ Patell test: the study calculates the post-crash stock returns.	*Negative impact: crash airline stocks lost, on average, 1.58% of the value on the day of the event. *Calamity with single-digit fatalities, the event day average abnormal return of the crash airline is -1.58%. On the contrary, the same figure is negative and statistically significant at the 0.1 percent level when the numbers of fatalities exceed 10.	*Results show that the crash airlines experience deeper negative abnormal returns as the degree of fatality increases. The stock prices of the rival airlines also suffer in large-scale disasters but benefit from the disasters when the fatality is minor.
Madsen, P.M., (2011)	*Perils and Profits: A Reexamination of the Link Between Profitability and Safety in U.S. Aviation*	Examines profitability and safety relationship.	Accumulated accident number	Operating profit margin, operating profit and operating revenue;	Cross Section Analysis Poisson Model $P(n_{it}) = \frac{Exp(-\lambda_{it}) * \lambda_{it}^{n_{it}}}{n_{it}!}$	*Airlines with greater financial slack experience fewer accidents. *Airlines that are undergoing bankruptcy reorganization experience more accidents.	*Organizational profitability impacts safety risks. *Increased profitability leads to more accidents.
Oster et al., (2013)	*Analyzing Aviation Safety: Problems, Challenges, Opportunities*	*Review of scientific literature on aviation safety; *Identifies challenges for aviation safety	*Understanding the safety records of commercial airlines. *The analysis is limited to accidents where there was at least one passenger fatality. *Descriptive statistics ONLY.		Interpretation of statistics from FAA and NTBS.	*Commercial airline safety has improved dramatically: fatalities per mil. enplanements from 0.38 in 2009 to 0.21 in 2011 (non-US)	*Aviation is the safest mode of commercial transportation, even though accidents still happen.