

The Influence of Aviation Disasters on Engine Manufacturers: An Analysis of Financial and Reputational Contagion Risks

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Abstract

One of the key sub-sectors in the aviation industry includes that of engine manufacturers, who have long led technological advancement and the battle to reduce airline carbon emissions. However, these same companies have been susceptible to a number of issues that have been central to international airlines due to higher costs and competition pressures. When an aviation disaster occurs, there is widespread allocation of blame and responsibility, which has left engine manufacturers exposed until the true cause is identified. This can generate many issues with regards to reputational damage and ability to generate finance. We set out to analyse such interactions over time and region. Our results indicate that engine manufacturers have had to contend with substantial income and financial leverage issues in the aftermath of a major aviation disaster, irrespective of whether they have been identified as a causation factor in the incident itself. Further, we clearly identify that there exists an average one day loss of 1.64% in the immediate aftermath of aviation incidents. Substantial corporate instability is found to persist without the company being in any way responsible for the incident. Shortly thereafter, contagion effects increase as speculation diminishes and more factual evidence arrives. The role of social media is examined as a potential contributory factor.

Keywords: Aviation Disasters; Contagion; Engine Manufacturers; Financial Markets; Reputational Risks; Tourism; Transport.

1. Introduction

In 2018, a record 4.4 billion passengers travelled by air worldwide on 46.1 million flights and the demand for air transport is apparent with almost 82% of all available seats being filled, with 22,000 city pairs connected by direct flights. However the gloss is overshadowed, as there were over 500 fatalities in 2018, which accounted for a fatal accident rate of 0.36 per million flights, or one fatal accident for every 3 million flights, predominantly because of the two 737 Max 8 related accidents, which were subsequently grounded. The previous year had a global fatality rate of 12.2 fatalities per billion passengers, representing the safest year ever on the record for aviation.^{1,2} Airline safety reputation as perceived by passengers plays a substantial role in airline choices (Siomkos [2000]) and flight choices (Molin et al. [2017]). Fatal accidents in commercial aviation remain rare and the safety of commercial passenger aviation services is of major concern for the travelling public and regulatory agencies. Liu and Zeng [2007] found that demand for air travel is likely to fall as the fatality rate increases. Airline accidents trigger instantaneous activity in the financial markets because of their unanticipated and cataclysmic nature. This type of negative rhetoric has caused sharp reductions in the share price of companies throughout the world, but it significantly impacts the aviation industry when compared to other consortiums of commercial enterprises (Kaplanski and Levy [2010]). They can have significant effects on an airline's stock price and profitability (Chance and Ferris [1987]; Borenstein and Zimmerman [1988]; Bruning and Kuzma [1989]; Mitchell and Maloney [1989]; Rose [1992]; Dionne et al. [1997]; Nethercurtt and Pruitt [1997]; Bosch et al. [1998]). Akyildirim et al. [2020] investigated a number of stylised facts relating to the effects of airline disasters on aviation stocks, where results indicate a substantially elevated levels of share price volatility in the aftermath of aviation disasters. Share price volatility appeared to be significantly influenced by the scale of the disaster in terms of the fatalities generated, with evidence suggesting the existence of significant contagion and information flow effects upon the broad aviation sector. Ho et al. [2013] examined the impact of aviation tragedies on the stock prices of the airlines that had encountered a crash together with their rival carriers and found that the afflicted airline experienced deeper negative abnormal returns as the degree of fatality increases. Investigative prognosis by Rose [1990] found that accidents can also have an impact on insurance premiums for airlines. However the financial impacts from the viewpoint of engine manufactures as a result of an accident has not been studied to date. The global engine market is sizeable as the (widebody, narrowbody, regional jets and bizjets) market was worth an estimated \$70 billion in 2018 and is expected to be worth almost \$1 trillion

¹ICAO (2018). Safety report, 999 Boulevard Robert-Bourassa Montreal, QC, Canada H3C 5H7. Available [here](#)

²IATA (2019). More Connectivity and Improved Efficiency - 2018 Airline Industry Statistics Released, July 31. Available [here](#)

when including sales between 2014 and 2023 according to a Rolls-Royce global engine forecast.^{3,4,5}

Therefore, the focus of this research is on this essential linchpin in the aviation value chain in the form of airline engine manufacturers. While social media speculation lingers in the aftermath of an aviation accident, it often encapsulates to scan the wider picture by spreading to all aspects of the commercial operation including engine failure, which triggers a whole set of new interpretations as to what transpired. Engine manufacturers must assert their moral obligation of producing a safe product that is paramount to the commercial success of an aircraft in an industry that is renowned with competitive pressures through cost, efficiency and regulation (Zhang and Gimeno [2016]). While speculation mounts about the cause of the aviation incident, it is very possible that the powerplants were not the cause, however, the engine manufacturers share price could theoretically decline due to combined reputational interlinkages. The research also considers that the engines were responsible for the cause of the accident, and that the engine manufacturer would most likely be held to account, justifying a substantially elevated negative share price response for the engine manufacturer when compared to the airline. But in two independently competitive industries, the reputational damage could be enough to trigger irreparable financial and reputational damage. Such an example was observed in the recent dual loss of MH17 and MH370 which led to the nationalisation of Malaysia Airlines (Corbet et al. [2020]).

This research sets out to answer a number of key questions. First, a thorough analysis of all aviation disasters was conducted through an international database to identify the key statistics associated. The study then focused on the financial stock market interactions between the aircraft companies and their selected engine manufacturer that considered the cumulative abnormal returns after an accident when compared to the market index over a specific time period. Such interactions are then analysed in detail to understand as to whether there exists variation by type of engine and by type of airframe manufacturer, while the volatility of the stock returns is also measured. Finally, a number of robust tests are applied to validate the results.

The results provide a variety of outcomes based on the varying behaviour and interactions between aviation companies in periods of crises. First, when analysing the effects of airline disasters on engine manufacturer's profitability and financing structure, the associated findings reveal that the net income falls sharply in the months following a major aviation disaster that involves an aircraft that utilises an engine created by one of the engine manufacturers in our sample. Further, there is evidence of a dampening effect on financial leverage of the company. These results are found to be robust across a variety of methodological structures, indicating that engine manufacturers have to contend with substantial income and financial leverage issues in the aftermath of a major aviation disaster, irrespective of whether they have been identified as a causation factor in the incident

³BusinessWire (2018). Global \$118 Billion Aircraft Engines Market Forecast Report 2017-2018 to 2026, June 25. Available [here](#)

⁴Bank of America Merrill Lynch (2015). Power On - Commercial aerospace engine primer, Equity research report, 9th June.

⁵Bloomberg (2019). Aircraft Engine Market Size worth USD 97.12 Billion by 2026; Presence of Big Giants in the Aviation Industry to Foster Growth, December 11. Available [here](#)

itself. The second stage of the research focuses on the calculation of cumulative abnormal returns that exist for engine manufacturers in the period after an aviation disaster, where we identify that there exists a sharp one day loss of 1.64% in the aftermath of aviation incidents, and is found to gradually extend such poor performance in each of the following analysed periods thereafter. In the six months thereafter, the calculated CARs of the engine manufacturers of these airlines are found to have under-performed the market index by over 6.5%. In the third stage of the analysis, the changes in stock market volatility are analysed as a result of these disasters. Companies such as General Electric, Rolls Royce, Textron and United Technology Corporation are found to exhibit quite a substantial increase in share price volatility during the period immediately following an aircraft incident that included aircraft using their components. The authors conclude the research by focusing on the interaction between the returns of the engine manufacturers and the aviation sector in the aftermath of the aviation disasters. When focusing on the inherent contagion effects of these incidents, there is evidence to suggest that the largest events relating to companies such as General Electric, Rolls Royce and United Technology Corporation, all of which possess significant links with Airbus and Boeing, are collectively found to possess gradually elevated dynamic correlations with the aviation sector in the sixty day period after such aviation disaster. This suggests that the immediate price volatility particularly targets the designated engine manufacturer as news and speculation develops and spreads about the related tragedy. However, over a brief period of time, there is evidence to suggest that contagion effects take hold as speculation diminishes and more factual evidence arrives.

The rest of this paper is as follows. Section 2 presents a thorough review of the literature relating to the interlinkage between aviation disasters and airline engine manufacturers. Section 3 presents a concise overview of the data used in this research along with the various methodologies employed to capture firm-level volatility, both intra-sectoral and geographic volatility transmission, and indeed contagion effects by type of aviation incident. Section 4 presents a concise overview of the results presented, while Section 5 concludes.

2. Previous Literature

Fuel is an airlines highest cost item representing 23.5% of the total operating costs, whose expenditure amounted to \$180 billion for the industry in 2018. Although substantial, these numbers are in fact already much lower than the historical highs in 2013 (33% and \$231 billion). The wafer thin margins of the airline industry were evident throughout 2018 as it generated just \$6.12 profit per passenger, indicating the importance of efficiency and cost containment of each element of operating an aircraft and particularly that of engine fuel burn as reducing fuel consumption is a unifying goal across the aviation industry.⁶ Engine technology is continuously improving as [Hu et al. \[2018\]](#) found that the average fuel burn of new aircraft fell approximately 45%, or a compound

⁶Pearce, B. (2019). Airline industry outlook update, IATA Annual General Forecast, Seoul, 1-3 June. Available [here](#)

annual reduction rate of 1.3% between 1986 and 2014. The linkages between fuel (or, more generally, operating costs) and an airline profitability have been touched upon through a variety of papers, including [Kang and Hansen \[2018\]](#); [Heshmati and Kim \[2016b\]](#); [Heshmati and Kim \[2016a\]](#); [Kwan and Rutherford \[2015\]](#); [De Poret et al. \[2015\]](#); [Zou et al. \[2014\]](#); [Morrell \[2011\]](#) and [Swan and Adler \[2006\]](#). The Industry has two key manufacturers of large engines, General Electric and Rolls Royce, while three key manufacturers reside in the narrowbody or regional jet market, notably General Electric, Safran and Pratt & Whitney. These power-plants equip the seven original equipment manufacturers in these segments (Airbus, Boeing, Bombardier, Embraer, Mitsubishi, COMAC and Sukhoi). The developmental cost of a new Jet engine is sizeable, costing between \$1 and \$2 billion, while a similar amount is required for plant capital and sales concessions, creating high barriers to industry. Product life cycles tend to be long, at 25 to 35 years in duration, with a stream of services or spares revenues attached to each new engine worth 3 to 5 times of its value. These initial power-plants are typically sold at less than unit manufacturing costs while cash flow remains negative for 10 to 15 years ([Epstein \[2014\]](#)).

Much of the literature encapsulating the economics of airline operations bundles the following entities as one unit of aircraft performance: the airframe type including its aerodynamic envelope; maximum takeoff weight; engine performance; as the overall entity that determines fuel burn, which epitomises its technical cost efficiency. Studies have traditionally sought to establish how technical efficiency and productivity have evolved over time ([Good et al. \[1995\]](#); [Oum and Yu \[1995\]](#)). Other studies investigate airline cost efficiency ([Oum and Zhang \[1991\]](#); [Oum and Yu \[1998\]](#)) or both productivity and cost competitiveness ([Oum and Yu \[2012\]](#); [Windle and Dresner \[1992\]](#); [Windle \[1991\]](#)). The literature dedicated to the analysis of airline financial performance focuses on efficiency and airline productivity ([Schefczyk \[1993\]](#); [Gittell et al. \[2004\]](#); [Tsiriktsis \[2007\]](#); [Barros and Peypoch \[2009\]](#)). The literature is replete with references to airline safety. Airline accidents represent a perilous impass for the involved party, as they have a significant impact on the demand for air travel, which ultimately affects the finances of an airline, compounding its share price volatility. [Borenstein and Zimmerman \[1988\]](#) estimated that the loss in enplanement as a result of a crash accrued to about 10-15% of one months worth of traffic. A majority of extant studies on the effect of profitability on safety takes place in the transportation industries. For example, [Golbe \[1983\]](#) examined the connection between profitability and safety in the US railroad industry and found a positive association between contemporaneous profitability and safety - such that railroads are more profitable when they are involved in fewer accidents. However, [Golbe \[1986\]](#) subsequent analysis of the pre-deregulation US airline industry finds no significant relationship between airline profitability and contemporaneous safety. [Rose \[1990\]](#) revisits the profit-safety link for US airlines, finding a marginally significant positive relationship between airline profitability and safety for all airlines and a stronger positive relationship for smaller airlines. Rose improves on the methods employed by [Golbe \[1983\]](#) and [Golbe \[1986\]](#) by utilising lagged profitability measures, eliminating the possibility of reverse causality whereby the observed relationship between profitability and safety is driven by the effect of an accident on its profitability rather than the effects of profitability on safety processes.

Raghavan and Rhoades [2005] concurs with the findings of Rose. Both Borenstein and Zimmerman [1988] together with Mitchell and Maloney [1989] analysed changes in equity value following accidents and found evidence that airlines that experienced fatal accidents were subsequently penalised by modest profitability declines. Subsequently, the literature on airline safety is highly influenced by event studies assessing the impact of crashes on stock market prices (see for example Bosch et al. [1998], Borenstein and Zimmerman [1988], Chalk [1986]; Chalk [1987]; Mitchell and Maloney [1989]).

The selected hypotheses and methodologies for this investigation are built on a number of disciplines and avenues of research. While considering the interactions between aviation companies, one must consider other types of assets and events that could potentially influence the selected companies and selected methodologies. Stock market volatility because of a shock, structural change or change in conditions can significantly impact the share price of a company and a number of papers have studied this concept. Yun and Yoon [2019] found that there is a return and volatility spillover effect between crude oil price and the stock prices of airlines and that the stock prices of smaller airlines of South Korea and China are relatively more sensitive to the change in oil price. Carvalho et al. [2011] analysed the 2008 case where an six-year old article based on the bankruptcy of United Airline's parent company was mistakenly identified as a new bankruptcy filing, causing a 76% fall in the company's share price, but after the case was identified as an error, the stock remained over 11% below opening prices, as the authors identify that contagion effects would dominate competitive effects. Luo [2007] used longitudinal real-world data set that matches consumer negative voice (complaint records) in the airline industry with firm stock prices, this article finds that higher levels of current consumer negative voice harm firms' future idiosyncratic stock returns. Guzhva et al. [2010] assess the market valuation of airline convertible preferred stocks to suggest that airlines undervalue by approximately 10% when they raise capital by issuing convertible securities. Hung and Liu [2005] use the beta value, an indicator of systematic risk, to estimate the costs of equity and the evaluation of a stock's reasonable price, to find that airline betas are volatile over time and that crashes and stock market trends may also impact them.

A number of previous pieces of research focused on the measurement of share price volatility effects outside of the aviation industry. Such research develops on the work of French et al. [1987] who examined the relation between stock returns and stock market volatility to find evidence that the expected market risk premium (the expected return on a stock portfolio minus the Treasury bill yield) is positively related to the predictable volatility of stock returns. While Schwert [1989] found stock market volatility changed over time, while Campbell and Hentschel [1992] developed a formal model of this volatility feedback effect using a simple model of changing variance to find that volatility feedback normally has little effect on returns, but it can be important during periods of high volatility. Marais and Bates [2006] and Sander and Kleimeier [2003] focused on the contagion effects of the Asian financial crisis of the late-1990s, while Arghyrou and Kontonikas [2012], Kenourgios et al. [2011], Samarakoon [2011], Samitas and Tsakalos [2013] and Philippas and Siriopoulos [2013] focused on the contagion effects from both the US and European elements of the

subprime and European financial crises. [Koutmos and Booth \[1995\]](#) and [Ramchand and Susmel \[1998\]](#) identified that volatility spillovers in a given market are much more pronounced when the news arriving from the last market to trade is bad, while the correlations between the US and other world markets are on average 2 to 3.5 times higher when the US market is in a high variance state as compared to a low variance regime. [Veronesi \[1999\]](#) found that in equilibrium, investors' willingness to hedge against changes in their own 'uncertainty' on the true state makes stock prices overreact to bad news in good times and under-react to good news in bad times. [Bekaert and Wu \[2000\]](#) found evidence of volatility feedback when investigating the market portfolio and portfolios with different leverage constructed from Nikkei 225 stocks. [Andrei and Hasler \[2015\]](#) investigated the joint role played by investors' attention to news and learning uncertainty in determining asset prices, both theoretically and empirically showing that both attention and uncertainty are key determinants of asset prices.

Focusing on the use of methodologies to specifically analyse the contagion effects of such airline disasters and the interactions between the airlines and the engine manufacturers, the authors of this paper developed a preferred analysis while considering a number of previous works. [Forbes and Rigobon \[2002\]](#) were amongst the first to tests for contagion based on correlation coefficients which they defined as a significant increase in market comovement after a shock to one country. Such correlation coefficients were found to be conditional on market volatility, where the authors identify a high level of market comovement during periods of crisis. [Bae et al. \[2003\]](#) based their measure of contagion by capturing the coincidence of extreme return shocks across countries within a region and across regions find that contagion is predictable and depends on regional interest rates, exchange rate changes, and conditional stock return volatility in emerging markets during the 1990s.

Such contagion was found not just to be identified in stock markets. [Longstaff \[2010\]](#) identified contagion effects in markets for subprime asset-backed collateralised debt obligations (CDOs) and their contagion effects on other markets, while [Sadorsky \[2012\]](#) found evidence of correlations and volatility spillovers between oil prices and the stock prices of clean energy companies. [Swidan and Merkert \[2019\]](#) investigated the relative effect of operational hedging on airline operating costs, presenting evidence of reduced operating costs, but also providing the caveat that such decision-making does not, in isolation, provide an optimal strategy to manage jet fuel risk exposure. [Berghöfer and Lucey \[2014\]](#) studied the extent of operational and fuel hedging in airlines, identifying that neither financial nor operational hedging is effective and that fleet diversity matters greatly. [Corbet et al. \[2020\]](#) investigated the effects of negative WTI on hedging and portfolio dynamics. [Hsu et al. \[2008\]](#) proposed a class of new copula-based GARCH models for the estimation of the optimal hedge ratio and compare their effectiveness with that of other hedging models, including the conventional static, the constant conditional correlation (CCC) GARCH and DCC-GARCH to find performance improvements in comparison to other dynamic hedging models. [El Hedi Arouri et al. \[2011\]](#) used a generalised VAR-GARCH approach to examine the extent of volatility transmission between oil and stock markets in Europe and the United States at the sector-level to identify the existence of significant volatility spillover between oil and sector stock returns.

3. Data and Methodology

3.1. Data

The analysis initiated by constructing a concise list of airline disasters that can then be utilised in a thorough and robust methodological investigation with engine manufacturers corporate accounts and stock market performance. The authors establish as to whether there exist specific speculative financial punishment for engine manufacturers in the aftermath of an airline disaster. As earlier hypothesised, broad speculation based on the cause of such an airline disaster can manifest through many forms, but direct financial punishment due to investor perceptions can present a number of damaging side-effects for the broad aviation sector. To develop such a dataset, a number of strict rules are developed in an attempt to standardise the process across major international financial markets. The first implemented rule is that the specified company must be a publicly traded company with an available stock ticker between the period June 1, 1995 and May 31, 2019. This specific time period is identified due to the relative absence of concise financial market in the period before.

There are two specific methodological approaches developed within this research. Firstly, an investigative approach is instigated to determine if there exists a direct effect within the company as measured by its internal financial performance across a number of theoretically supported, robust methodologies, while also considering the manner in which the financial performance of the engine manufacturers change. Secondly, there is a focus on the financial performance and investor perceptions of the events through a thorough analysis of share price volatility of the same manufacturers, along with a thorough analysis of the contagion effects of such volatility as sourced from the airline industry upon the manufacturers of aviation engine technologies. The selected corporate account data is taken from Bloomberg. Stock price data is taken from Thomson Reuters Eikon. The second news selection rule is based on the source of the data. The authors develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords relating to aviation disasters. For added robustness of the developed dataset, the authors leverage upon that of the National Transportation Safety Board (available at: <https://www.nts.gov>), the International Civil Aviation Organisation, ICAO (available at: <https://www.icao.int>) and the Aviation Safety Reporting System (available at: <https://asrs.arc.nasa.gov>). To obtain a viable observation, a single observation must be present across each of the selected search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. Forums, social media and bespoke news websites were omitted from the search. Finally, the selected observation is based solely on the confirmed news announcements being made on the same day across all of the selected sources. If a confirmed article or news release had a varying date of release, it was omitted due to this associated ambiguity. All observations found to be made on either a Saturday or Sunday are denoted as active on the following Monday morning. All times are adjusted to GMT, with the official end of day closing price treated as the listed observation for each comparable company when analysing associated contagion effects.

The associated summary statistics for the selected engine and engine component manufacturers are presented in Table 1. Three control variables have been selected to act as a representation of international effects. The Dow Jones International Average (DJIA) is used to control for financial market performance during the period under investigation. While considering a number of international airlines and engines manufacturers, the study also accounts for financial growth and crises during the period. This is further accounted for through the use of West Texas Intermediate (WTI) oil prices and the S&P500 Aviation Index. The aviation sector is found to present the largest mean returns during the period between 1995 and 2019. WTI is found to possess the largest standard deviation of returns (0.0231) of the selected independent variables along with the two most extreme one-day price increase and decrease of 17.83% and 15.25% respectively. The aviation index is found to be the most negatively skewed (-0.1486) and also possess the largest level of kurtosis (9.1538). While focusing on the examined engine manufacturers, there are a number of particularly significant events and results. The largest mean return is exhibited by MTU Aero Engines (+0.0008), while Textron exhibits the largest standard deviation with regards to the selected companies (+0.0241). The largest one-day fall in the share price of an engine manufacturer was experienced by that of Safran (-33.3%), closely followed by that of Textron (-31.6%). The largest one-day price increase was experienced by Textron (+48.9%), presenting evidence of the particularly volatility behaviour of this share price. The second largest one-day share price increase was experienced by Honeywell International (+26.2%). The most negatively skewed company returns are that of BAE Systems (-0.6965), while the most positively skewed are that of Textron (+0.5876). Textron also possesses the largest kurtosis of any of the selected engine manufacturers (+42.38), while Leonardo SpA experienced the lowest kurtosis of returns (+6.07)

Insert Table 1 about here

Figure 1 outlines the geographical dispersion of the identified accidents while both Table 2 and Figure 2 make reference to the number of fatalities by year of the same accidents. Some Countries stand out such as Brazil, the United States, Russia, China, Nigeria and Indonesia as they were amongst the worst hit in terms of domiciled companies that were attributed to the cause of such aviation disasters. There appears to be no discernible pattern in the number of total fatalities between 1995 and 2018. The largest number accidents including fatalities occurred in 1996 where 1,339 people died in fifty major airline disasters related to publicly traded companies. This included the largest aviation disaster in the sample where 312 persons perished when a Boeing 747-100 belonging to Saudi Arabian Airlines crashed in New Delhi. Overall, 12,692 fatalities occurred across 610 accidents during the period analysed.

Insert Figure 2 and Table 2 about here

Table 3 shows the number of incidents on a company-by-company basis. Three substantial outliers are identified within the group of publicly traded companies. American Airlines has eight

individual accidents that account for 588 fatalities. The eight American Airlines disasters occur between December 1995 and December 2005. The largest incident occurred on 12 November 2001, one month after the 9/11 terrorist attacks, when 262 people perished in another catastrophe in New York. Boeing directly supplied the aircraft in seven of the eight incidents, while the other aircraft type was a McDonnell Douglas MD-82. Next, Malaysia Airlines experienced two substantial incidents that led to the loss of 537 persons. These incidents refer to the loss of MH17 and MH370, where the former was lost after being struck by a missile in the Ukraine, while the latter has yet to be found despite going missing in 2014. Both of these incidents occurred within five months of each other and in both cases a Boeing 777-200 was lost. Finally, China Airlines experienced 428 fatalities in three separate incidents. The first referred to the loss of an Airbus A300-600 in 1998 in Taipei resulting in 203 fatalities. The second case referred to the loss of 225 persons in Taiwan in 2002 during the loss of a Boeing 747-200, while the final case referred to a serious incident involving a Boeing 737-800 in February 2007.

Insert Tables 3 and 4 about here

Considering that the market for airline travel is an extremely competitive industry, any broad error of substantial loss of credibility and reputation can lead to quite a disastrous financial outcome. Table 4, represents a list of airlines that are no longer in operation today, in the aftermath of a substantial aviation disaster. It is also quite important to note that there are also a number of such companies that have actually experienced multiple events. Adamair is found to have had three substantial events leading to the lost of 102 passengers. Prior to the crash of Adamair Flight 574, it was the fastest growing low-cost carrier in Indonesia. On March 16, 2007, the Indonesian government grounded the carrier as it was deemed mismanaged which was further compounded by embezzlement proceedings. Hewa Bora Airways also experienced three separate incidents before operations were suspended after flight 952 crashed in 2011. This carrier had undergone a series of mergers and management changes (FlyCongo, Compagnie Africaine d'Aviation, Zaire Airlines, and Congo Airlines). The third company that experienced three incidents that forced its grounding was that of Rico Linhas Aereas S/A, which was a Brazilian regional airline authorised to operate scheduled passenger and cargo services in the Amazon region. Table 5, details the summary statistics of the crashes that led to fatalities based on the cohort of aircraft type that crashed. In terms of frequency, the three most frequently involved aircraft with engines developed by publicly traded engine manufacturers were the De Havilland DHC-6 Twin Otter, the Boeing 737-200, the Cessna 208 Caravan, and the Britten-Norman Islander. In terms of fatalities, the larger planes such as the Boeing 727-200, Boeing 737-200, Boeing 737-800, Boeing 747-100, Boeing 777-200, Airbus A320, Airbus A300-600, Airbus A310 and McDonnell Douglas MD-83 resulted in the most severe crashes.

Insert Tables 5 and 6 about here

Table 6, denotes the summary statistics for each major crash associated by engine manufacturer that was attached to downed airliner. United Technologies Corporation and Rolls Royce are found to be the leading engine manufacturer for 160 and 157 of the identified accidents respectively, obtained during the analysis. Furthermore, General Electric provide leading engines for use in the CF6 engine-series which were mounted on the wings of Airbus A300, A310, A330, B747 and B767, while the GE90 series are used in B777 and the next generation of engines, termed the GENx series are fitted on the Boeing 787 and 747-8i, which collectively accounted for 30 significant accidents that resulted in the deaths of 1,269 passengers. Pratt & Whitney's main engines (United Technologies Corporation is the associated parent company) include the JT8D series which were the powerplants for early Boeing 737s, the JT9D series were attached to Airbus A300, A310, Boeing 767, 747, the PW2000 series thrust the Boeing 757, while the PW4000 series were used in Airbus A300, A310 and A330 as well as the Boeing 767, 747 and 777, while the smaller PW6000 series powered the Airbus A318. Meanwhile Rolls-Royce produced the RB200 series engine which was used in Boeing 747 and 757, the Trent 500 series was used in later Airbus A340, the Trent 700 series powered the Airbus A330, while the Trent 800 series were used in Boeing 777, the Trent 970 series was attached to the Airbus A350 and A380, while the newer Trent 1000 series is used in Boeing 787s.

Between these three companies, there has also been a number of joint-venture collaborations that have been at the forefront of engine manufacturing development. Firstly, the CFM International joint venture between General Electric and Safran colluded to produce the CFM56 series widely used in Airbus A318/A319/A320/A321, early A340, and later Boeing 737s. Secondly, the Engine Alliance was a joint venture between General Electric and Pratt & Whitney which produced the GP7000 series that is used for the Airbus A380. Finally, one of the largest Joint ventures was based on that of International Aero Engines, who formed a consortium that encompassed Pratt & Whitney, Rolls-Royce, Japanese Aero Engine Corporation and MTU. This engine was used in the IAE V2500 series and powered the Airbus A319/A320/A321. Other significant engine component manufacturers that experienced severe aviation disasters were that of BAE systems, Lockheed Martin and Textron.

3.2. Methodology

While it is of course expected that the airline that has been directly affected by a major disaster would have substantial financial ramifications, both in terms of immediate internal monetary damage through loss of earnings through reduced passenger flows and by the exceptional costs associated thereafter, without any direct evidence of potential causality, the engine manufacturers would be expected to be somewhat buffered from such attributed responsibility. Any evidence of a substantial financial shock to engine manufacturers without firm evidence provided would be considered to be generated by highly speculative investor behaviour. This very situation could potentially generate broad financial repercussions for the aviation sector at large through increased costs, regulatory misalignment and increased exposure to external shocks due to excessive competitive pressures. There are several ways through which the unfortunate aviation disaster experienced by a company could have an impact on that company's financial variables, both on the book-value, and more immediately in the financial markets. In particular, perceptions of reduced future sectoral growth

by the airline sector would manifest in quite a negative outlook for the engine manufacturers, which would be subsequently reflected through decreased profitability and leverage on the financial statements of the company. Moreover, due to the substantial negative publicity and perceptions of wrong-doing, which could possibly be present without due cause, the company's share price might experience dramatic decreases in the short through medium term. This could be expected to manifest in sharp increases in stock market volatility and interactions with other market variables through the spread of financial market contagion. Contagion effects are also considered as this can be the source of inter-sectoral risk transfer between the aviation sector and that of engine manufacturers. All these arguments will be analysed thoroughly in the rest of the paper using the following methodologies.

3.2.1. The impact of aviation disasters on firms' profitability and financing structure

In this part of the analysis, the authors aim to investigate as to whether engine manufacturer's next term profitability has directly been influenced by aviation disasters. Furthermore an examination seeks to determine if the firms have had to manipulate their use of financial leverage so as they can mitigate such financial difficulties. Both of these scenarios are investigated with emphasis on the fact that the engine manufacturer has not been held responsible in any way for the related airline disaster with the exception that they had supplied the downed airline with its engines and is perceived by investors to be potentially responsible. The motivation for these hypotheses comes from the fact that the company is potentially about to enter a highly speculative and sensitive period of time where blame could indeed be attributed. Therefore, profitability of the company might fall substantially and its access to debt financing might become substantially more difficult to obtain as lenders observe substantially elevated levels of risk. To work on the above mentioned hypotheses, quarterly balance sheet and income statement data are used for the period between Q3 of 1995 and Q2 of 2019, adding up to twenty-eight quarters in total. All data comes from Thomson Reuters Datastream. FL_t represent financial leverage calculated by company's debt to equity at the end of quarter t and NI_t represents the net income in quarter t . Control variables are constructed subject to three sets of stock characteristics. All variables are updated every quarter unless otherwise stated.

The first set is associated with historical return patterns; (i) Size: Natural logarithm of the firm's market capitalisation by the end of last quarter, (ii) Book to Market (B/M) Ratio: Book-to-market ratio by the end of last quarter, (iii) MOM_{-1Q} : Cumulative return over the last quarter, (iv) $MOM_{[-4Q,-1Q]}$: Cumulative three quarters' return preceding the last quarter, and (v) Beta: Beta obtained from the regression of the firm's monthly returns over the last 2 years on the monthly market returns over the same period; i.e., $r_i - r_f = \alpha + \beta(r_M - r_f) + \epsilon$. The second set is associated with liquidity and transaction costs; (vi) Price: Natural logarithm of the stock price by the end of each quarter, (vii) Turnover (TRN): Turnover ratio over the last quarter, and (viii) Amihud: Amihud ratio over the last quarter. Finally, the third set of stock characteristics is associated with prudence; (ix) Age: Natural logarithm of the number of quarters that the company is listed on the exchange, (x) Dividend Yield (DY): Dividend yield over the last quarter, (xi) Index: A

dummy variable equal to 1 if the firm is included in the benchmark index and 0 otherwise, and (xii) Volatility (VOL): Standard deviation of monthly returns in the last 2 years. Therefore, 12 stock characteristics are used as control variables in total.

To examine the effects of such incidents on a company’s profitability (H_1) and financial leverage (H_2), the authors run the following panel regressions in equation (1) through equation (3) using two-way clustered standard errors:

$$Y_{t+1} = \alpha + \beta_1 Hist_t + \gamma Incident_t + \epsilon_t \quad (1)$$

$$Y_{t+1} = \alpha + \beta_2 Liq_t + \gamma Incident_t + \epsilon_t \quad (2)$$

$$Y_{t+1} = \alpha + \beta_3 Prud_t + \gamma Incident_t + \epsilon_t \quad (3)$$

In this model, Y is either the NI or FL and X_t is the vector of 12 stock characteristics described above, as separated as $\beta_1 Hist_t$ for the group relating to historical return patterns, $\beta_2 Liq_t$ which represents the variables analysing liquidity and transaction costs, and $\beta_3 Prud_t$ which analyses corporate prudence. On the other hand, $Incident_t$ is i) a dummy variable taking the value unity in the period after the accident in quarter t . In each of the twenty-eight quarters, the authors winsorize all variables at the level of 95% (both dependent and independent) with the exception of the index and incident dummies in the cross-section by two levels from both upper and lower tails to eliminate the outlier effect without removing any observations.

3.3. Does there exist an engine manufacturer share price discount due to aviation disasters?

The analysis is elongated by conducting a thorough investigation of the cumulative abnormal returns for each company and the average cumulative abnormal returns in the aftermath of a airline incident leading to injury or fatality. Abnormal returns are calculated as the companies’ returns less that of the exchange on which the company trades (as used by [Akyildirim et al. \[2020\]](#), [Corbet and Gurdgiev \[2019\]](#) and [Corbet et al. \[2020\]](#)). The analysis is partitioned by each publicly traded company that provided engines to the airlines of interest. It is also of interest to examine as to whether there exists persistence of any identified share price discounts in such circumstances. We select a variety of time-frames on which to analyse such effects. The authors investigate the 1-, 5- 10-, 20-, 30-, 60-, 90- and 180-day periods after each identified events to identify as to whether such engine manufacturer share price discounts persist while the investigation into the cause of the airline disaster takes place, or indeed, as to whether such effects are found to dissipate within this time-frame. Evidence of such a share price discount is particularly damaging across a number of areas. First, it must be noted that engine manufacturers are heavily reliant on external financing while researching and developing future engine technology. The impact of such financial pressures and reputational damage in the aftermath of such airline incidents can greatly reduce the availability of such financing. Further, the existence of such a share price discount would also strongly indicate that engine manufacturers have been greatly influenced by speculative investors, who are most likely attempting to invest on ‘potential’ developing stories rather than on a factual basis. Such

speculative investment is by no means illegal, but it has been dealt with in a variety of manners over time, such as the implementation of ‘short-sale bans’ on banking shares during the most stressful and volatile periods of the most recent international financial crisis.

3.3.1. The volatility effects of aviation disasters within the sector for engine manufacturers

GARCH-based methodologies are found to be one of the primary mechanisms through which one can observe direct volatility effects in financial markets, allowing for both comparison and scalability of parameters. Developing from key analyses that focused on issues such as the GARCH(1,1) quasi-maximum likelihood estimator (Lee and Hansen [1994]) and the consistency and asymptotic normality of such models (Lumsdaine [1996]), Tse and Tsui [2002] were the first to propose a multivariate generalised autoregressive conditional heteroscedasticity (MGARCH) model with time-varying correlations which retained the intuition and interpretation of the univariate GARCH model and yet satisfies the positive-definite condition as found in the constant-correlation and Baba-Engle-Kraft-Kroner models. Garcia et al. [2005] provided estimations of GARCH to act in a forecasting ability to predict day-ahead electricity prices. Hansen and Lunde [2005] compared 330 ARCH-type models in terms of their ability to describe the conditional variance to find no evidence that a GARCH(1,1) is outperformed by more sophisticated models in their analysis of exchange rates. Whereas the GARCH(1,1) is clearly inferior to models that can accommodate a leverage effect in their analysis of IBM returns. Kristjanpoller and Concha [2016] found a strong positive influence of fuel price fluctuation and airline stock returns using GARCH-family methodologies. Corbet et al. [2019] found that airline traffic flows fall quite sharply despite significant fare reductions as a result of terrorist incidents in Europe using a seasonally-adjusted ARMA-GARCH methodology. Such terrorism impacts were also found to be both significant and substantial when considering the persistence of their effects at both sectoral and national levels (Kolaric and Schiereck [2016]; Carter and Simkins [2004]; Kim and Gu [2004]; Corbet et al. [2018]).

In this analysis, we undertake specific investigation is undertaken to determine if there exists a substantial change in stock price volatility of the engine manufacturers due to their direct association with the airline company that has experienced a severe accident. Analysis is conducted to decipher if the associated volatility in the periods both before and after the designated announcement of a crash presents evidence of substantial change. Firstly, statistical tests are applied to determine if there is an increase in unconditional variance of the company stocks’ daily returns (and the corresponding excess returns over the market they are traded in) after announcements for various time periods by utilising a common variance inequality test. Secondly, more penetrative scrutiny is enforced by building upon the GARCH-family to understand the volatility dynamics of crypto-exuberance based on naming behaviour in the conditional variances. At this stage, a number of goodness-of-fit testing procedures identified the EGARCH(1,1) model as the best selected to identify specific volatility changes in the companies’ returns, thus we exercise our analysis using this model.⁷ The variance

⁷EGARCH exploits information contained in realised measures of volatility while providing a flexible leverage function that accounts for return-volatility dependence. While remaining in a GARCH-like modelling framework

equation of our EGARCH model is expressed as follows:

$$\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t \quad (4)$$

Here, an additional D_t term is included in equation (4) in the analysis to provide a coefficient relating to the observed volatility in the subsequent days following each event for each of the investigated companies. Before proceeding with the EGARCH analysis, exogenous effects are migrated which can be completed through the inclusion of the returns of traditional financial products in the mean equation of the EGARCH(1,1) methodology as displayed in equation (5).

$$R_t = a_0 + b_1R_{t-1} + b_2DJIA_t + b_3WTI_t + b_4AVI_t + \varepsilon_t \quad (5)$$

The volatility sourced in shocks that are incorporated in the returns of traditional financial markets are therefore considered in the volatility estimation of the selected structure. In equation (5), R_{t-1} represents the lagged value of the observed company returns. $DJIA_t$ is the returns of the benchmark index where the stock is traded, and represents the interaction between the selected company returns and the corresponding market index. WTI_t represents the interactions between the selected company and the market for West Texas Intermediate (WTI) oil. Such interactions are very much of interest from a methodological standpoint due to the observed interactions between the market for oil and international crisis and instability. Therefore, the selection of WTI in this methodological structure allows the GARCH-family methodologies to incorporate and account for such instability. Similarly, the addition of the variable AVI_t incorporates broad trends and periods of instability within the broad aviation sector.

3.3.2. Analysing potential contagion effects: A DCC-EGARCH methodology

The final stage of our selected analysis develops on the channels through which such airline sector volatility influences that of the engine manufacturers in the periods after such incidents. While no particular causality has been identified throughout a number of the selected cases in our above analysis, it is very much of interest in this section to identify and observe as to whether engine manufacturers are found to experience direct contagion flows from the airline industry, and indeed, as to how long these particular periods of contagion persist. It is important to identify as to whether companies who had traditionally little or no direct involvement with such incidents had observed structural changes in their previously outstanding interactions. For example, a company who had changed their name from that which did not identify as a blockchain or cryptocurrency-related company to one that does thereafter, could therefore theoretically experience a sharp change

and estimation convenience, the model allows independent return and volatility shock and this dual shock nature leaves a room for the establishment of a variance risk premium. In our selection, other competitive models included EGARCH, TGARCH, Asymmetric Power ARCH (APARCH), Component GARCH (CGARCH) and the Asymmetric Component GARCH (ACGARCH). The optimal model is chosen according to three information criteria, namely the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ).

in dynamic correlations, perhaps also indicative that the company is being treated differently by investors in the aftermath of changed perceptions of corporate risk-tolerance (Corbet et al. [2020]). For example, it is important to specifically analyse if these investors, who could perceive that these companies have changed in terms of their perceived high-risk behaviour. To consider the contagion effects, the popular dynamic conditional correlation (DCC) model of Engle [2002] is applied. The authors firstly let $r_t = [r_{1,t}, \dots, r_{n,t}]'$ be the vector of financial time series returns and $\varepsilon_t = [\varepsilon_{1,t}, \dots, \varepsilon_{n,t}]'$ be the vector of return residuals obtained after some filtration. Let $h_{i,t}$ be the corresponding conditional volatilities obtained from a univariate EGARCH process.

Assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, \dots$. The asset conditional covariance matrix H_t can be written as

$$H_t = D_t^{1/2} R_t D_t^{1/2} \quad (6)$$

where $R_t = [\rho_{ij,t}]$ is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by $D_t = \text{diag}(h_{1,t}, \dots, h_{n,t})$. Engle [2002] models the right hand side of Eq.(6) rather than H_t directly and proposes the dynamic correlation structure

$$\begin{aligned} R_t &= \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2}, \\ Q_t &= (1 - a - b)S + a u_{t-1} u_{t-1}' + b Q_{t-1}, \end{aligned} \quad (7)$$

where $Q_t \equiv [q_{ij,t}]$, $u_t = [u_{1,t}, \dots, u_{n,t}]'$ and $u_{i,t}$ is the transformed residuals i.e. $u_{i,t} = \varepsilon_{i,t}/h_{i,t}$, $S \equiv [s_{ij}] = E[u_t u_t']$ is the $n \times n$ unconditional covariance matrix of u_t , $Q_t^* = \text{diag}\{Q_t\}$ and a, b are non-negative scalars satisfying $a + b < 1$. The parameters of the DCC model are estimated by using the quasi-maximum likelihood method with respect to the log-likelihood function, and according to the state two-step procedure.

4. Results

4.1. Impact of airline disasters on firms' profitability and financing structure

The estimated coefficients are reported of equation (1) through equation (3) for the cases of net income (NI) and financial leverage (FL) with respect to the influence of such aviation disasters on the corporate accounts of engine manufacturers. For each of the explained variables, the authors separately regress the selected control variables that represents i) historical return patterns (M1 column); ii) liquidity and transaction costs (M2 column), and iii) prudence (M3 column) as shown in Table 7. Finally, the column representing M_{all} present the results when all control variables are used for explanatory purposes.

Insert Table 7 about here

In Table 7, it is noticeable that whether a sub-group of control variables is applied or all applied at the same time, there is consistency in the signs of the explanatory variables with a few exceptions for both net income and financial leverage analysis. This shows the reliability of the results. According to the M_{all} analysis, except the insignificant market cap and short-term momentum variables, effect of all variables on profitability differ with respect to either sign or insignificance between the types of incident. In this analysis, the main variable of interest is the dummy variable γ and according to our findings, the coefficient of this dummy indicates that net income falls sharply in the aftermath of the months following a major aviation disaster that involves an aircraft that utilises an engine created by one of the engine manufacturers in our sample. Further, there is evidence of a dampening effect on financial leverage of the company. This is quite an interesting result, as in the majority of the cases sampled, there is no distinct evidence provided during this time period to indicate that the engines on the aircraft were in fact responsible for the accident. Regarding the determinants of financial leverage, both methodological structures present common factors. For example, according to the M_{all} column, variables such as market cap, book-to-market ratio, short-term momentum, beta, stock price, age and volatility have no significant impact on the leverage; whereas turnover and Amihud ratio are both significant and have impact in the same direction.

4.1.1. Robustness tests based on profitability and financing structure results

To check the robustness of the finding above, the authors try alternative variations of equations (1) through (3) and start with estimating the following equations (8) through (10). The motivation is to bring a dynamic perspective to the analysis by focusing on not the levels but the change in the levels of net income and leverage.

$$\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta_1 Hist_t + \gamma Incident_t + \epsilon_t \quad (8)$$

$$\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta_2 Liq_t + \gamma Incident_t + \epsilon_t \quad (9)$$

$$\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta_3 Prud_t + \gamma Incident_t + \epsilon_t \quad (10)$$

The robustness analysis is taken to another level and instead of a separate analysis for the combined financial effects, an analogous regression is employed of equations (1) through (3) and (8) through (10) in the new equations (11) and (12), respectively. The results are presented in Table 8. These models allow for control of the multiple types of financial effects at the same time in the aftermath of the identified aviation disasters. Significant results would indicate that there exist corporate financial effects on engine manufacturers without any evidence or allocation of responsibility.

Insert Table 8 about here

At this stage, the authors solely focus on the main variable of interest and discuss the findings on the main control variables for the accounts of the engine manufacturers. Accordingly, the findings

strongly support our earlier presented results whether we use only a sub-group or all control variables at the same time to explain the changes in the dependent variables of quarterly net income change or leverage change. In both cases, γ remains significantly negative for each of the sub-models tests as M1, M2 and M3 present results of -0.483, -0.481 and -0.442 for the change in net income and -0.358, -0.357 and 0.334 for the change in financial leverage as shown in Table 8.

At this stage, to verify the existence of effects on the profitability and financial structure of engine manufacturer companies, the expectations of the dummy coefficient signs in the last two equations above are the same as in the previous analysis, and the findings almost perfectly fit. In the case of equation (11), without an exception, all dummy coefficients are significantly negative for both income and the leverage.

$$Y_{t+1} = \alpha + \beta_1 Hist_t + \beta_2 Liq_t + \beta_3 Prud_t + \gamma Incident_t + \epsilon_t \quad (11)$$

$$\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta_1 Hist_t + \beta_2 Liq_t + \beta_3 Prud_t + \gamma Incident_t + \epsilon_t \quad (12)$$

Further verification is provided through the inclusion of equation 12 in Table 8 which provides the full specification methodology using first-differenced net income and financial leverage data for the analysed engine manufacturers, which, despite presenting results that are somewhat below the same analysis results for net income and financial leverage (-0.711 and -0.455 respectively), pertaining to the regression testing and when comparing this to the results of the robustness testing procedure, -0.475 and -0.286 respectively, we find that both outcomes produce the same size and scale, providing substantial support as to the selected methodological procedures used in this analysis. The findings indicate that engine manufacturers have to content with substantial income and financial leverage issues in the aftermath of a major aviation disaster, irrespective of whether they have been identified as a causation factor in the incident itself.

4.2. Cumulative abnormal returns (CARs) for engine manufacturers in the aftermath of airline disasters

Next an attempt is formulated to establish how influential aviation disasters were upon the share price performance of the analysed engine manufacturers. To examine this effect we calculate the cumulative abnormal returns (CARs) which are presented in Table 9. First focusing on the overall average of CARs, we clearly identify that there exists a sharp one day loss of 1.64% in the aftermath of aviation incidents. This result is largely driven by the sharp initial one-day fall in the price of BAE Systems (-9.16%), Honeywell International (-2.84%) and Leonardo SpA (-2.38%). Substantial corporate instability is found to persist without the company being in any way responsible for the incident. Shortly thereafter, contagion effects increase as speculation diminishes and more factual evidence arrives.

Insert Table 9 about here

There is evidence of a sharp deterioration in the calculated CAR approximately ten days after the event (-1.64%) and this excess loss over the market average continues up to one-hundred and twenty-five days after the event where the calculated CAR is -8.14%. Only in the period thereafter does the calculated CAR improve to approximately -5.4%, but in the subsequent three month period, the market performance deteriorates further in comparison to the market average. One hundred and eighty days after each of our analysed aviation disasters, the calculated CARs of the engine manufacturers of these airlines are found to have under-performed the market index in excess of 5%. While a broad variety of results exist, there exist two companies that out-perform the market index in the six months after the average of the incidents that are analysed.

Insert Figure 3 about here

A graphical representation of the daily estimate of the CARs for the overall sample is illustrated in Figure 3. For the overall sample there are multiple distinct, yet sharp periods of deterioration in the performance of the companies when compared to the market index, the first in the forty-five days after the event which is found to result in a loss of 5% approximately. The share price performance falls quite substantially once again between four and six months after the event leading to a point in time estimated loss in excess of 8% when compared to the related domestic market index.

4.3. Firm-level volatility by type of airline disaster

The level of conditional volatility on a case-by-case basis is presented with significant results in Table 10. With regards to specific companies, General Electric, Rolls Royce, Textron and United Technology Corporation present evidence of the largest number of significant volatility events during the period analysed. There is also an interesting observation to be made in the wide-ranging reduction in the number of statistically significant volatility events within the designated time period under observation. It is apparent that while each company with the exception of Rockwell Automation experience significant effects for a number of aviation disasters in an exceptionally short time-frame (such as the day on which the news was announced), the effects appear to subside in the weeks that follow, as evident in the reduced number of statistically significant volatility changes in the periods throughout twenty, forty and sixty days after.

Insert Table 10 about here

One particularly interesting observation is made when considering these results based on the dates on which the most significant observations have occurred. While considering that the sample incorporated all events identified between June 1995 and May 2019, there are only eight significantly positive conditional volatility increases in excess of +0.05 since January 2010. This is of particular interest. While one particular explanatory theory surrounds the role that social media could potentially play in influencing investor perceptions of fault or indeed attributing blame to

one particular cause or party, the above results somewhat diminish this view. While considering the Facebook, Instagram and Twitter are primarily used for dissemination of information, it is the latter that is broadly used for the dissemination of news, whether positive, negative or indeed true or false. While Twitter has been in existence since March 2006, it experienced quite a sharp growth in the number of continuous monthly users in period after 2009 and 2010. In Q1 2010, Twitter possessed 30 million monthly users. This increased to 302 million monthly users in Q1 2015 and 330 million monthly users in Q1 2019. While engine manufacturers are largely found to not portray evidence of detrimental effects in the day immediately after the incident, conditional volatility is then found to increase somewhat in the sixty-day period thereafter as more robust news continues to disseminate. On a case-by-case analysis, this finding also holds as the largest cases of conditional volatility are not found to be as frequent in the period after the rapid growth of this social media technology. This could indicate that the existence of better quality information could in fact be changing the manner in which volatility and contagion interact between companies.

4.4. Volatility transmission between the aviation sector to the engine manufacturer

to conclude the research, the paper focuses on the interaction between the returns of the engine manufacturers and the aviation sector in the aftermath of the aviation disasters. In these selected samples, there has not been any official announcement as to whether there exist a relationship between the engines on the aircraft and the cause of the incident itself. While the aviation sector at large can be susceptible to sharp decreases in valuation in the days following a significant incident, it is quite alarming from the viewpoint of a provider and developer of engine components to be susceptible to such volatility, particularly due to influence that such perceptions and reputational risk can have on the continued development of the associated companies.

Insert Table 11 about here

When considering the short term period after the individual event, a selection of multiple time frames is considered including that of the 1-, 5-, 10-, 20-, 40- and 60-day periods.⁸ The final column presented in both Table 10 and Table 11 represent the entire period in the aftermath of aviation disasters. When considering the stock return's conditional variance, it can be seen that there are substantially fewer significant results in the period. When analysing the results of the interactions between the dynamic correlations between engine manufacturers and the broad aviation section, one finds evidence of both elevated and consistent relationships between the sample of incidents and the aviation sector throughout the entire sixty-day period after. The results indicate that while a broad number of companies exhibit elevated dynamic correlations, it is those relating to General Electric, Rolls Royce and United Technologies Corporation that are found to generate substantial

⁸For brevity, only sector average results have been presented. Individual results are available from the authors on request.

sector-wide volatility effects. However, when considering only significant results it returns some very interesting findings. In the one-day period after the aviation incident, only 30 events, or 4.7% of engine manufacturer events analysed exhibit elevated levels of dynamic correlation with the aviation sector. Within the five-day period, this increases to 7.0% and then increases again to almost one-quarter of the sample ten days after the event (9.7%). This figure is at its largest at twenty days after the event, representing 11.1% of the sample. One potential explanation for this outcome is based on the slow dissemination of news in the aftermath of the events. While the airline stocks themselves are sharply effected by the negative sentiment and reputational damage, it would appear that initially that the engine manufacturers do not experience the same influence. However, within ten days, this decoupling effect subsides and there is a substantial positive correlation identified between the engine manufacturers and the aviation industry. Moreover, this effect tends to be permanent as it does not disappear mostly after a quarter and even longer periods than that.

5. Concluding Comments

The continued evolution of the aviation sector relies on technological development, with particular emphasis surrounding the response of the industry to the growing calls to immediately deal with the carbon emissions disaster that has been escalating in recent years. While structural design and efficiency improvements will support such efforts, much of the weight of the task will be borne by engine manufacturers. However, one must understand their role within the sector when considering the presence of the effects of contagion risks due to accidents involving the airlines to which these manufacturers supply and the subsequent attributed responsibility for injury and fatality. These manufacturers are not responsible for the many identified shortcomings that have been identified in the sector in recent years with regards to poor maintenance which has been attributed to cost-cutting effects in an extremely competitive environment. However, when an aviation disaster occurs, there is widespread allocation of blame and responsibility until the true cause is identified. It is very much of interest to understand as to how such contagion effects influence engine manufacturers and as to how effects relating to asymmetric information and moral hazard can influence their profitability and potential for growth.

The results provide a variety of explanation based on the varying behaviour and interactions between these companies in periods of crises. First, when analysing the effects of airline disasters on engine manufacturer's profitability and financing structure, the findings reveal that net income falls sharply in the aftermath of the months following a major aviation disaster that involves an aircraft that utilises an engine created by one of the engine manufacturers in our sample. Further, there is evidence of a dampening effect on financial leverage of the company. These results are found to be robust across a variety of methodological structures, indicating that engine manufacturers have to contend with substantial income and financial leverage issues in the aftermath of a major aviation disaster, irrespective of whether they have been identified as a causation factor in the incident itself. The second stage of our research focuses on the calculation of cumulative abnormal returns that exist for engine manufacturers in the period after an aviation disaster. Focusing on the overall

average of CARs, it clearly identifies that there exists a sharp one day loss of 1.64% in the aftermath of aviation incidents. However, the stock price remains substantially below the market average in the five days following the disaster. It is very much of interest to note that one hundred and eighty days after each of the analysed aviation disasters, the calculated CARs of the engine manufacturers of these airlines are found to have under-performed the market index by over 6.5%.

In the third stage of the analysis, the authors evaluated the changes in stock market volatility as a result of these disasters. Companies such as General Electric, Rolls Royce, Textron and United Technology Corporation are found to exhibit quite a substantial increase in share price volatility during the period immediately following an aircraft incident that included aircraft using their components. There is also an interesting observation to be made in the wide-ranging reduction in the number of statistically significant volatility events within the designated time period under observation. One potential explanation for this outcome is based on the slow dissemination of news in the aftermath of the events. While the airline stocks themselves are sharply effected by the negative sentiment and reputational damage, it would appear that initially that the engine manufacturers do not experience the same influence. However, within ten days, this decoupling effect subsides and there is a substantial positive correlation identified between the engine manufacturers and the aviation industry. Moreover, this effect tends to be permanent as it does not disappear mostly after a quarter and even longer periods than that. When focusing on the inherent contagion effects of these incidents, there is evidence to suggest that the largest events relating to companies such as General Electric, Rolls Royce and United Technology Corporation, all of which possess significant links with Airbus and Boeing, are found to possess gradually elevated dynamic correlations with the aviation sector in the sixty day period after such aviation disaster. This suggests that the immediate price volatility particularly targets the designated engine manufacturer as news and speculation develops and spreads about the related tragedy. However, over a brief period of time, there is evidence to suggest that contagion effects take hold as speculation diminishes and more factual evidence arrives.

The changing role of social media must be observed as a significant contributory factor to the presented results. While considering that the sample incorporated all events identified between June 1995 and May 2019, there is strong evidence to indicate strong changing dynamics since January 2010, where a fewer significant interactions have been unidentified in recent times. This is of particular interest. While one particular explanatory theory surrounds the role that social media could potentially play in influencing investor perceptions of fault or indeed attributing blame to one particular cause or party, the above results somewhat diminish this view. Twitter has been in existence since March 2006, it experienced quite a sharp growth in the number of continuous monthly users in period after 2009 and 2010. While engine manufacturers are largely found not to portray evidence of detrimental effects in the day immediately after the incident, conditional volatility is then found to increase somewhat in the sixty-day period thereafter as more robust news continues to disseminate. On a case-by-case analysis, this finding also holds as the largest cases of conditional volatility are not found to be as frequent in the period after the rapid growth of this social media technology. This could indicate that the existence of better quality information could

in fact be changing the manner in which volatility and contagion interact between companies.

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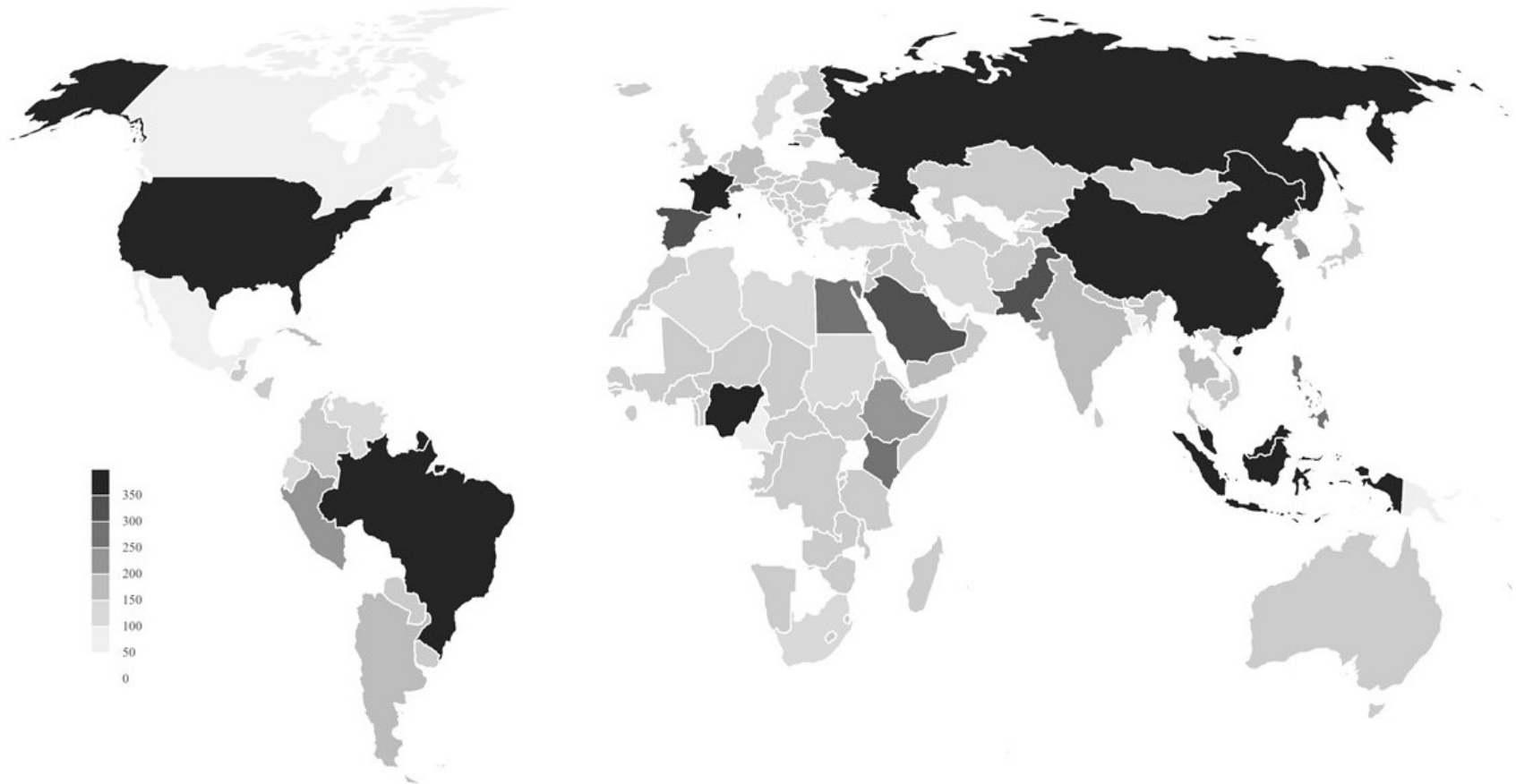
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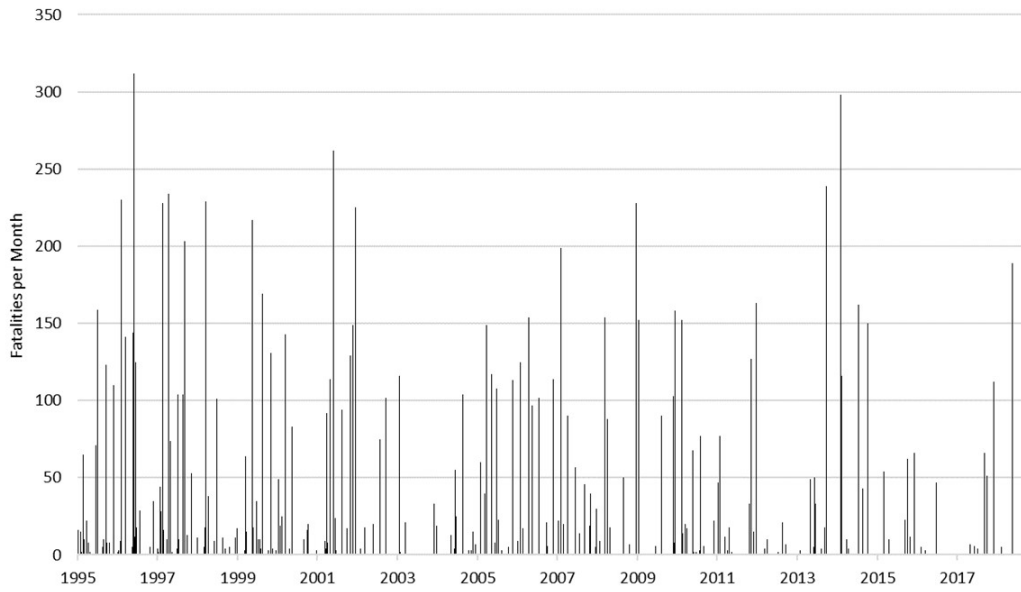
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Figure 1: Geographic dispersion of fatalities by domicile country of airline, 1996-2019



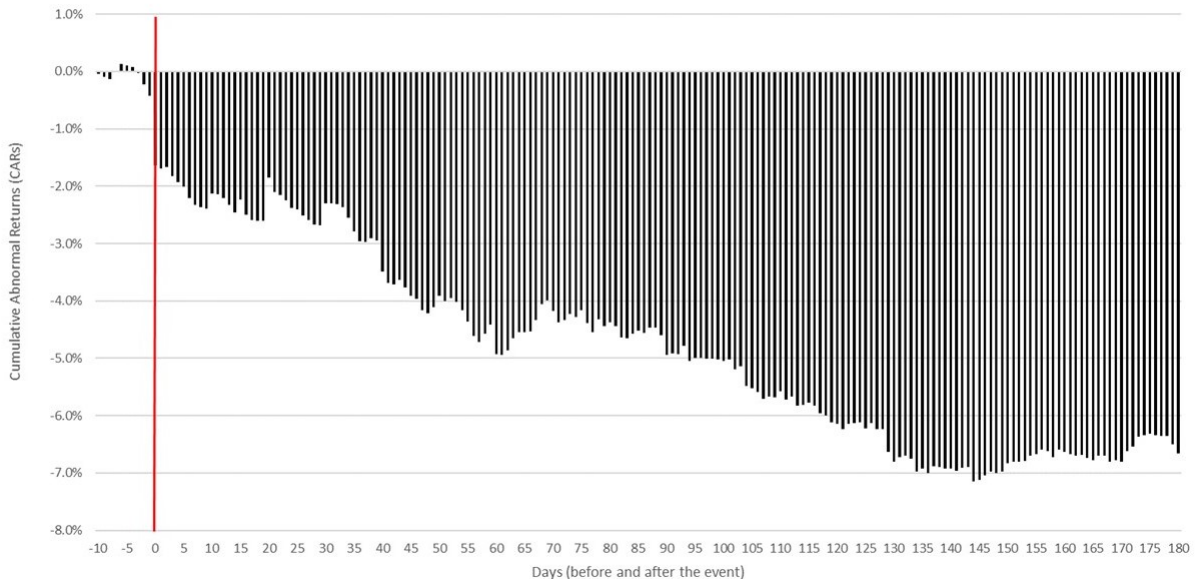
Note: The above figure presents the geographic dispersion of airline fatalities as represented by the domicile company of the airline that experienced the crash. Data is between the period 1996 and 2019.

Figure 2: Number of fatalities per month, 1996-2019



Note: The above figure presents the monthly frequency of airline fatalities. Data is between the period 1996 and 2019.

Figure 3: Overall Cumulative Abnormal Returns (CARs) in the 180 days after each event



Note: The above figure shows the Cumulative Abnormal Returns (CARs) in the 180 days after each event. The red line represents the date on which the event occurred.

Table 1: Summary statistics for the identified engine manufacturers, engine component suppliers and military engine suppliers

Variable	Mean	Std. Deviation	Minimum	Median	Maximum	Skewness	Kurtosis
DJIA	0.0003	0.0109	-0.0787	0.0003	0.1108	-0.0179	8.6229
West Texas Intermediate	0.0004	0.0231	-0.1525	0.0000	0.1783	0.1415	4.4492
Aviation Index	0.0005	0.0115	-0.0751	0.0007	0.1028	-0.1486	9.1538
BAE Systems*	0.0004	0.0194	-0.2458	0.0000	0.1250	-0.6965	12.7372
General Electric	0.0002	0.0187	-0.1279	0.0000	0.1970	0.3071	8.3537
Honeywell International	0.0005	0.0190	-0.1737	0.0000	0.2616	0.0784	12.7131
Leonardo SpA*	0.0003	0.0237	-0.2155	0.0000	0.1996	0.2424	6.0656
Lockheed Martin [#]	0.0005	0.0161	-0.1376	0.0000	0.1469	-0.0035	7.9517
MTU Aero Engines	0.0008	0.0207	-0.1519	0.0003	0.1636	0.1720	6.3797
Northrop Grumman [#]	0.0005	0.0158	-0.1462	0.0000	0.2377	0.4670	15.2816
Rolls-Royce	0.0005	0.0211	-0.2243	0.0000	0.1558	0.2509	8.8424
Safran	0.0007	0.0223	-0.3327	0.0000	0.2034	-0.2644	14.2370
Textron	0.0005	0.0241	-0.3165	0.0000	0.4885	0.5876	42.3786
United Technology Corp.	0.0005	0.0164	-0.2825	0.0000	0.1365	-0.6637	18.4291

Note: * indicates a corporation denoted as a component supplier, while [#] indicates a company that is primarily operational in military engine supply. We establish the above list noting that each company must be publicly traded with an available stock ticker between the period June 1, 1995 and May 31, 2019. This specific time period is identified due to the relative absence of concise financial market in the period before. Stock price data is taken from Thomson Reuters Eikon.

Table 2: Summary statistics of the largest included aviation incidents in the selected sample

Year	Number of In- cidents	Standard Deviation of Fatalities	Largest Number of Fa- talities in One Crash	Total Fatalities
1995	23	36.513	159	385
1996	50	63.812	312	1,339
1997	44	51.642	234	904
1998	33	55.991	229	802
1999	25	44.019	217	431
2000	30	47.656	169	747
2001	33	51.441	262	758
2002	27	58.487	225	791
2003	22	34.734	116	318
2004	18	15.438	55	149
2005	32	40.728	149	650
2006	20	50.391	154	523
2007	21	53.269	199	631
2008	31	33.345	154	499
2009	22	56.993	228	470
2010	28	46.171	158	648
2011	32	20.254	77	278
2012	20	44.602	163	356
2013	23	15.436	50	184
2014	16	95.614	298	906
2015	25	32.070	150	259
2016	14	24.279	66	220
2017	8	2.875	7	19
2018	12	60.451	189	425
Totals	610	47.786	312	12,692

Table 3: Summary statistics of the largest included aviation incidents in the selected sample

Company	Count	Fatalities	Company	Count	Fatalities	Company	Count	Fatalities	Company	Count	Fatalities
ACES Colombia	1	14	Cameroon Airlines	2	71	Lao Airlines	1	49	Shangri-La Air	1	18
Adamair	3	102	Cebu Pacific Air	1	104	Lapa	1	64	Silkair	1	104
ADC Airlines	4	242	China Airlines	3	428	Laser	1	14	Singapore Airlines	1	83
Aereo Ruta Maya	1	10	China Northern Airlines	1	112	Lion Air	7	214	Skyline Airways	2	14
Aero Servicio Guerrero	1	14	China Southern Airlines	2	35	Lumbini Airways	1	18	SOL Lineas	1	22
Aerocaribbean	2	87	China Yunnan Airlines	1	55	Malaysia Airlines	2	537	Sosoliso Airlines	1	108
Aeroflot	2	88	Comair	2	78	Manaus Aero Taxi	1	24	Spanair	1	154
Aeroperlas	3	20	Continental Connection	1	50	Mandala Airlines	2	149	Sudan Airways	1	116
AeroPeru	1	70	Conviasa	1	17	Merpati	7	31	Sudan Airways	1	30
Aeroservicios Empresariales	1	16	CrossAir	2	34	Milne Bay Air	2	35	Swiftair	2	116
Afriqiyah Airways	1	103	Cubana	1	112	Necon Air	3	20	Swiss	1	229
Air Algerie	2	102	Dana Air	1	163	Nepal Airlines	2	18	Taesa	1	18
Air Anguilla	1	11	Dirgantara Air Services	1	18	Nigeria Airways	1	11	Taiwan Airlines	1	13
Air Asia	1	162	EAS Airlines	1	149	Nusantara Buana Air	1	18	TAM	1	199
Air Caraibes	1	20	Egyptair	5	297	Ocean Airways	1	20	Tame	3	147
Air China	1	129	Ethiopian Airlines	3	215	One Two Go	1	90	TANS	1	40
Air Fiji	1	17	Faucett	1	123	Overtec	1	13	Tara Air	2	45
Air France	3	228	First Air	3	12	Pakistan Int. Airlines	1	47	Tatarstan Airlines	1	50
Air Guilin	1	17	Fly Corporate	1	13	Parsa	1	10	Thai Airways	2	102
Air India Express	1	158	Fly Dubai	1	62	Paukn Air	1	38	Tracep	1	17
Air Moorea	1	20	Gabon Express	1	19	PenAir	2	10	TransAsia	3	91
Air Philippines	1	131	Garuda Indonesia	4	259	Petrovlosvk-Kham. Air	1	10	Transportes AÃfreos P.G.	1	14
Airblue	1	152	Germanwings	1	150	Proteus Airlines	1	14	Trigana Air	4	60
Aires	2	10	GOL Transportes	1	154	Rico	3	56	Tuninter	1	16
Airline of PNG	1	28	Gulf Air	2	143	Royal Nepal Airlines	2	25	Turkish Airlines	6	84
Airlink	4	32	Gum Air	1	10	RusAir	1	47	TWA	1	230
Alaska Airlines	1	88	Hageland Aviation Services	6	13	S7 Airlines	1	125	United Airlines	7	122
Alliance Air	1	60	HaÃfti Air Express	1	10	SAL Express	1	16	US Airways	2	21
American Airlines	8	588	Henan Airlines	1	44	SAS	3	114	US-Bangla Airlines	1	51
Armavia	1	113	Hewa Bora	3	117	SASCA	2	15	UTA	1	141
atlasjet	1	57	Iran Air	2	77	SATA Air	1	35	Utair	4	40
Austral	1	74	Iran Aseman Airlines	1	66	Satena es Colombia	2	22	ValuJet	1	110
Aviastar	2	10	Itek Air	1	65	Saudi Arabian Airlines	4	312	Vostok Av. East Air	1	16
Aviateca	1	65	Kam Air	1	104	SAX	1	10	Yemenia Yemen Airways	2	152
Bellview Airlines	1	117	Kenya Airways	2	283	SBA Airlines	1	46	Yeti Airlines	3	27
Bhoja Air	1	127	Korean Air	3	228	SCAT Airlines	2	21			
Blue Wing Airlines	3	27	LAM	2	33	Selva Taxi Aereo	1	12			

Note: We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords relating to aviation disasters. For added robustness of our developed dataset, we leverage upon that of the National Transportation Safety Board (available at: <https://www.ntsb.gov>), the International Civil Aviation Organization, ICAO (available at: <https://www.icao.int>) and the Aviation Safety Reporting System (available at: <https://asrs.arc.nasa.gov>). To obtain a viable observation, a single observation must be present across each of the selected search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. All incidents that resulted in less than ten fatalities are omitted for presentation purposes. All companies used in the final dataset must have been publicly traded at the time of the aviation disaster.

Table 4: List of airlines that are no longer in operation after a major airline incident

Company	No. of Events	Fatalities	Company	No. of Events	Fatalities	Company	No. of Events	Fatalities	Company	No. of Events	Fatalities
ACES Colombia	1	14	Binter Mediterraneo	1	4	Nigeria Airways	1	11	Sowind Air	1	4
Adamair	3	102	Blackwak Int. Air	1	9	Nusantara Buana Air	1	18	Swiss Air*	1	229
ADC Airlines	4	242	Cameroon Airlines	1	71	Ocean Airways	1	20	Taesa	1	18
Aerodat	1	4	CrossAir	2	34	Olson Air Service	1	2	TANS	1	40
AeroPeru	1	70	Dirg. Air Service	1	7	One Two Go Airlines	1	90	Tatarstan Airlines	1	50
AeroTaca	1	5	Dirgantara Air	1	18	Overtec	1	13	Tracep	1	17
Air Fiji	1	17	EAS Airlines	1	149	Pacific Air	1	1	TransAsia	2	91
Air Littoral	1	1	Evolga AVV	1	8	Paradise Air	1	9	Transniugini Airways	1	2
Air Moorea	1	20	Gabon Express	1	19	Proteus Airlines	1	14	TACSA	1	8
Air Satellite	1	7	Guicango	1	7	Regionn Air	1	1	T.A.P. Guatemalteca	1	14
Air Services Guyana	1	3	HaAfti Air Express	1	10	Rico	3	56	Tula Air Enterprise	1	4
Airlink	4	32	Henan Air	1	44	RusAir	1	47	TWA (merged with Am. Airways)	1	230
Armavia	1	113	Hewa Bora Air	3	117	SAL Express	1	16	ValuJet	1	110
ATESA	1	5	Itek Air	1	65	SASCA	2	15	Vanair	1	7
Atlantic Southeast Air	1	8	Jetlink Express	1	1	Selva Taxi Aereo	1	12	VARIG	2	1
Avia Air	1	8	Joy General Av.	1	5	Shangri-La Air	1	18	Victoria Air - Equatorial Guinea	2	7
BAL Bremerhaven Air	1	7	Linearea Bolivariana	1	4	Sky Power Express Airlines	1	2	Vincent Aviation	1	5
Bellview Airlines	1	117	Lumbini Air	1	18	Skyline Airways	2	14	Western Straits Air	1	8
Bhoja Air	1	127	Manunggal Air	1	1	Sonic Blue Airways	1	3	Wings of Alaska	1	1
Bigfoot Air	1	4	Necon Air	2	20	Sosoliso Airlines	1	108			

Note: We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords relating to aviation disasters. For brevity, the following companies were removed from the above list as the sole incidents associated with each did not result in fatalities: Aero Continente; Aerobol - Aerovias Bolivar; Aerolineas Nacionales - ANSA Panama; Aerotaxi; Air Afrique; Air Gabon; Air Hi-O; Air Quarius; Air Saint Barth; Airlink Papua New Guinea; Allegro; America West (merged with US Airways); LMT; Mauritania Airways; Pacific Island Air; PacificAir; Regionnair; TransGuyana Airways; Vanua Air Charter; VASP; Viarco; VoronezAvia; Weasua Air Transport; West Coast Air; West Star Aviation and Wind Jet. For added robustness of our developed dataset, we leverage upon that of the National Transportation Safety Board (available at: <https://www.ntsb.gov>), the International Civil Aviation Organization, ICAO (available at: <https://www.icao.int>) and the Aviation Safety Reporting System (available at: <https://asrs.arc.nasa.gov>). To obtain a viable observation, a single observation must be present across each of the selected search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. All companies used in the final dataset must have been publicly traded at the time of the aviation disaster. *Swiss Air has subsequently been re-branded to Swiss and is now part of the Lufthansa group.

Table 5: Summary statistics as separated by publicly traded airline-type involved in major incident

Airline Type	Occurrences	Fatalities	Airline Type	Occurrences	Fatalities	Airline Type	Occurrences	Fatalities
Airbus A300	5	0	Boeing 737-400	12	124	De Havilland DHC-3 Otter	4	9
Airbus A300-600	3	699	Boeing 737-500	5	152	De Havilland DHC-6 Twin Otter	45	361
Airbus A310	6	577	Boeing 737-700	2	2	Douglas C-47 Skytrain (DC-3)	1	0
Airbus A319	1	0	Boeing 737-800	16	588	Douglas DC-10	2	3
Airbus A320	17	841	Boeing 747-100	3	542	Douglas DC-3	3	14
Airbus A321	2	152	Boeing 747-200	3	225	Douglas DC-9	20	458
Airbus A330	3	331	Boeing 747-300	3	228	Embraer EMB-110 Bandeirante	15	102
Airbus A340-300	1	0	Boeing 747-400	2	83	Embraer EMB-120 Braslia	10	100
Airbus A340-600	1	0	Boeing 747SP	1	0	Embraer EMB-820 Navajo	1	4
ATR42-300	11	119	Boeing 757-200	5	339	Embraer ERJ-135	1	0
ATR42-500	3	48	Boeing 767-200	5	411	Embraer ERJ-145	5	0
ATR72-200	14	184	Boeing 767-300	3	217	Embraer ERJ-190	5	77
ATR72-500	3	48	Boeing 777-200	6	540	GAF Nomad N22	1	0
ATR72-600	2	92	Boeing 777-300	1	0	GAF Nomad N24	4	20
Avro 748	8	34	Britten-Norman Islander	25	67	Grumman G-159 Gulfstream I	1	0
Avro RJ100	4	99	Britten-Norman Trislander	1	0	Grumman G-21A Goose	2	2
Avro RJ70	1	0	Canadair RegionalJet CRJ-100	5	2	Grumman G-73 Mallard	1	20
BAc 111	5	150	Canadair RegionalJet CRJ-200	4	126	IAI 1124 Westwind	1	0
BAe 146	4	38	Casa 212 Aviocar	8	59	Lockheed L-1011 TriStar	1	0
BAe ATP	2	50	Casa-Nurtanio CN235 (IPTN)	1	4	McDonnell Douglas MD-11	2	232
BAe Jetstream 31	15	50	Cessna 207 Skywagon/Stationair	7	19	McDonnell Douglas MD-81	1	0
Bae Jetstream 41	2	0	Cessna 208 Caravan	29	81	McDonnell Douglas MD-82	10	392
Beechcraft 100 King Air	2	2	Cessna 208B Grand Caravan	14	43	McDonnell Douglas MD-83	8	424
Beechcraft 1900C	6	28	Cessna 402	9	43	McDonnell Douglas MD-87	1	114
Beechcraft 1900D	4	36	Cessna 404 Titan	2	4	McDonnell Douglas MD-88	1	0
Beechcraft 200 Super King Air	4	1	Cessna 406 Caravan	1	2	McDonnell Douglas MD-90	2	0
Beechcraft 300 Super King Air	1	4	Cessna 414 Chancellor	1	3	Mitsubishi MU-2 Marquise	1	0
Beechcraft 99 Airliner	5	12	Cessna 421 Golden Eagle	1	8	PZL-Mielec AN-2	19	15
Beechcraft G18	1	1	Cessna 425 Conquest	1	0	PZL-Mielec AN-28	11	96
Beechcraft H18	1	0	Convair CV-580	1	0	Saab 340	8	45
Boeing 707	3	3	De Havilland Dash-7	2	0	Short 330	1	0
Boeing 727-100	2	171	De Havilland Dash-8-100	4	28	Short 360	2	0
Boeing 727-200	13	415	De Havilland Dash-8-200	2	0	Transall C-160	1	1
Boeing 737 MAX 8	2	346	De Havilland Dash-8-300	2	0	Tupolev TU-134	1	47
Boeing 737-200	40	1573	De Havilland Dash-8-400	7	101	Tupolev TU-154	2	3
Boeing 737-300	16	140	De Havilland DHC-2 Beaver	5	18	Yakovlev Yak-40	5	7

Note: We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords relating to aviation disasters. For added robustness of our developed dataset, we leverage upon that of the National Transportation Safety Board (available at: <https://www.nts.gov>), the International Civil Aviation Organization, ICAO (available at: <https://www.icao.int>) and the Aviation Safety Reporting System (available at: <https://asrs.arc.nasa.gov>). To obtain a viable observation, a single observation must be present across each of the selected search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. All companies used in the final dataset must have been publicly traded at the time of the aviation disaster.

Table 6: Summary statistics as separated by publicly traded engine supplier to airlines involved in major incident

Company	Count	Fatalities
BAE Systems*	71	1,603
General Electric	30	1,269
Leonardo SpA*	33	491
Lockheed Martin #	31	125
MTU Aero Systems	19	116
Rolls Royce	157	3,938
Safran	19	1,187
Textron	90	290
United Technologies Corp	160	3,926
Total	610	14,400

Note: * indicates a corporation denoted as a component supplier, while # indicates a company that is primarily operational in military engine supply. We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords relating to aviation disasters. For added robustness of our developed dataset, we leverage upon that of the National Transportation Safety Board (available at: <https://www.ntsb.gov>), the International Civil Aviation Organization, ICAO (available at: <https://www.icao.int>) and the Aviation Safety Reporting System (available at: <https://asrs.arc.nasa.gov>). To obtain a viable observation, a single observation must be present across each of the selected search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. All companies used in the final dataset must have been publicly traded at the time of the aviation disaster.

Table 7: Modelling the impact of aviation disasters on firms' profitability and financing structure (Regression analysis, levels)

Dep. Var:	Income				Leverage			
	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Model Specification								
Market Cap	-0.8242 (1.4670)			-0.2325 (0.1590)	-0.0179 (0.0231)			-0.0236 (0.0252)
Book to Market Ratio	1.0903 (0.7680)			0.1139 (0.8102)	-0.0014 (0.0121)			0.0030 (0.0128)
Returns (Q_{t-1})	-0.0110 (0.0140)			-0.0114 (0.0141)	0.0000 (0.0002)			0.0000 (0.0002)
Returns ($Q_{t-4} - Q_{t-2}$)	0.0021 (0.0025)			0.0019*** (0.0025)	0.0000*** (0.0000)			0.0000*** (0.0000)
β	0.9928 (2.4382)			0.1126* (0.2584)	-0.0375 (0.0384)			-0.0193 (0.0410)
Stock Price		0.7991*** (0.2398)		1.0612*** (0.2656)		0.0309 (0.0380)		0.0152 (0.0421)
Turnover Ratio		0.0000*** (0.0000)		0.0000*** (0.0000)		0.0000*** (0.0000)		0.0000*** (0.0000)
Amihud Ratio		0.0000*** (0.0000)		0.0000*** (0.0000)		0.0000*** (0.0000)		0.0000*** (0.0000)
Age			0.1255* (0.0736)	0.1788*** (0.0811)			-0.2390** (0.1155)	-0.1979 (0.1285)
Dividend Yield			-0.3210 (0.4252)	-0.4413 (0.4891)			0.9612 (0.6670)	1.4661* (0.7754)
Benchmark Index			0.0000*** (0.0000)	0.0000*** (0.0000)			0.0000*** (0.0000)	0.0000*** (0.0000)
Volatility			-0.4071 (0.7091)	-0.2412 (0.7245)			-0.1286 (0.1112)	-0.1378 (0.1148)
γ	-0.6687*** (0.1312)	-0.6792*** (0.1288)	-0.7419*** (0.1320)	-0.7112*** (0.1391)	-0.6152*** (0.0207)	-0.3837*** (0.0038)	-0.9915*** (0.2070)	-0.4552*** (0.0220)

Note: Table displays the results of the regression $Y_{t+1} = \alpha + \beta X_t + \gamma Name_t + \epsilon_t$ where Y is either net income or financial leverage, and X_t are the control set. The values in the parentheses are standard errors. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 8: Modelling the impact of aviation disasters on firms' profitability and financing structure (Robustness test, first-difference)

Dep. Var:	Income				Leverage			
	M1	M2	M3	M_{All}	M1	M2	M3	M_{All}
Market Cap	-0.80324* (0.44077)			-0.69049 (0.57971)	0.035198 (0.10658)			0.021489 (0.14128)
Book to Market Ratio	1.242657*** (0.68703)			5.780171*** (1.89721)	0 (0.00012)			-0.00025 (0.00049)
Returns (Q_{t-1})	1.255625 (0.93539)			0.62701 (0.94021)	-0.00099 (0.00222)			-0.00099 (0.00235)
Returns ($Q_{t-4} - Q_{t-2}$)	0.280716 (1.6386)			0.048783 (1.64823)	-0.00012 (0.00037)			-0.00012 (0.00037)
β	0.491407*** (0.13375)			0.928103*** (0.13881)	-0.24762 (0.3232)			-0.21761 (0.33827)
Stock Price	2.186444 (1.73456)			0.92835 (1.02209)		0.045201 (0.16549)		0.110039 (0.2491)
Turnover Ratio		0*** (0)		0*** (0)		0*** (0)		0*** (0)
Amihud Ratio		0*** (0.00012)		0*** (0.00012)		0*** (0)		0*** (0)
Age		-0.17179 (0.1892)		0.336167 (0.29949)			0.17006 (0.67913)	0.123994 (0.72989)
Dividend Yield			1.307371*** (0.62948)	0.832143*** (0.17994)			0.001853 (0.02137)	0.017908 (0.04384)
Benchmark Index			-0.4869 (0.54735)	-0.84268 (0.67023)			-0.56849 (1.33084)	-1.40447 (1.63316)
Volatility			1.1015*** (0.29578)	0.368366*** (0.31641)			-0.00049 (0.00716)	0.000491 (0.00766)
γ	-0.48285*** (0.080855)	-0.48105*** (0.027565)	-0.44194*** (0.013412)	-0.47541*** (0.013795)	-0.35806*** (0.032975)	-0.35778*** (0.033012)	-0.33357*** (0.032604)	-0.28603*** (0.033629)

Note: Table displays the results of the regression $\Delta Y_{t+1} = Y_{t+1} - Y_t = \alpha + \beta X_t + \gamma Incident_t + \epsilon_t$ where Y is either net income or financial leverage, and X_t are the control set. The values in the parentheses are standard errors. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 9: Cumulative Abnormal Returns (CARs) per engine manufacturer in the aftermath of an aviation disaster

<i>Day after event</i>	0	1	2	3	4	5	10	15	20	30	40	50	60	90	180
BAE Systems*	-9.16%	-9.56%	-9.44%	-9.75%	-9.68%	-10.22%	-8.80%	-7.12%	-2.78%	-3.49%	-5.91%	-5.99%	-9.45%	-7.73%	-9.13%
General Electric	-0.32%	-0.59%	-0.56%	-0.58%	-0.50%	-0.34%	-1.47%	-2.11%	-2.15%	-2.64%	-2.71%	-3.29%	-3.31%	-3.42%	-12.04%
Honeywell International	-2.84%	-2.89%	-2.55%	-3.84%	-5.98%	-6.70%	-6.58%	-6.97%	-5.64%	-9.11%	-10.45%	-8.95%	-10.82%	-16.75%	-16.13%
Leonardo SpA*	-2.38%	-2.08%	-2.32%	-2.92%	-3.10%	-3.19%	-2.81%	-1.84%	-1.73%	-4.06%	-6.58%	-8.15%	-12.05%	-9.76%	-15.99%
Lockheed Martin #	0.04%	-0.18%	-0.62%	-0.87%	-0.70%	-0.83%	-2.26%	-1.95%	-3.00%	-0.52%	-1.11%	-1.68%	0.83%	2.15%	5.76%
Northrop Grumman #	-0.83%	-1.02%	-0.80%	-0.47%	-0.49%	-0.48%	0.24%	-0.23%	-0.61%	-1.09%	-1.59%	-1.54%	-1.62%	-3.13%	-1.00%
Rockwell Automation*	0.20%	0.20%	0.22%	0.40%	0.71%	0.85%	0.26%	0.13%	-0.02%	-1.24%	-1.33%	-2.10%	-2.51%	-1.31%	-1.23%
Rolls Royce	-1.52%	-1.13%	-1.28%	-1.10%	-0.83%	-0.90%	-1.18%	-1.57%	-2.37%	-3.09%	-3.69%	-4.47%	-4.39%	-4.29%	-6.82%
Safran	-0.75%	-0.85%	-0.96%	-1.00%	-0.71%	-0.55%	-0.88%	-0.84%	-1.05%	-1.11%	-1.57%	-2.09%	-4.21%	-4.17%	-5.72%
Textron	-0.18%	-0.23%	0.10%	0.11%	0.25%	0.38%	0.09%	-1.31%	-0.27%	0.42%	-0.92%	-1.37%	-1.78%	-1.92%	-3.36%
United Tech. Corp	-0.24%	-0.26%	0.00%	0.00%	-0.22%	-0.30%	0.07%	-0.72%	-0.75%	-1.60%	-2.40%	-3.66%	-4.76%	-3.95%	-8.18%
<i>Average</i>	-1.64%	-1.69%	-1.66%	-1.82%	-1.93%	-2.03%	-2.12%	-2.23%	-1.85%	-2.50%	-3.48%	-3.94%	-4.92%	-4.93%	-6.71%

Note: The above table presents the Cumulative Abnormal Returns (CARs) in the 180 days after each aviation incidents. * indicates a corporation denoted as a component supplier, while # indicates a company that is primarily operational in military engine supply.

Table 10: Number of companies experiencing an increase in their stock returns' conditional variances in the denoted period after an aviation incidents

Significant positive dummy coefficient							
Company	D^{1d}	D^{5d}	D^{10d}	D^{20d}	D^{40d}	D^{60d}	D^{Alld}
BAE Systems*	2	2	2	0	1	0	4
General Electric	14	14	14	14	10	7	3
Leonardo SpA*	2	1	1	1	1	1	1
Lockheed Martin [#]	4	4	3	3	2	3	2
Rockwell Automation*	0	0	0	1	1	1	2
Rolls Royce	18	17	16	12	19	14	14
Safran	3	2	2	0	1	0	2
Textron	11	12	9	6	7	7	18
United Technology Corp	23	18	21	17	20	12	20

Note: * indicates a corporation denoted as a component supplier, while [#] indicates a company that is primarily operational in military engine supply. Individual results are available from the authors on request. This table presents the statistical results on the positive dummy coefficients estimated in the following EGARCH model

$\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$. Before estimating the EGARCH model, returns are filtrated through the process provided in equation (5).

Values in this table show the number of companies that experience an increase in their stock returns' conditional volatility after aviation incidents. The column headers show the number of days that we analyse the volatility increase after the aviation incidents. The values in the parentheses are the percentage of companies within the sub-groups experiencing an increase in their stock returns' conditional volatility. The above table reports the number of companies that experience a significantly higher conditional volatility in their stock returns.

Table 11: Number of events initiating an increase in their stock returns' dynamic correlation with aviation index by company

Significant positive dummy coefficient							
company	D^{1d}	D_i^{5d}	D_t^{10d}	D_t^{20d}	D_t^{40d}	D_t^{60d}	D_t^{All}
BAE Systems*	0	0	1	1	1	1	2
General Electric	23	24	30	36	32	32	40
Leonardo SpA*	0	0	0	0	0	0	2
Lockheed Martin [#]	0	0	0	0	0	0	0
Rockwell Automation*	0	0	0	0	0	0	0
Rolls Royce	5	14	22	22	22	20	23
Safran	0	1	1	1	1	1	1
Textron	0	1	1	1	1	1	1
United Technology Corp	2	3	4	10	12	12	24

Note: * indicates a corporation denoted as a component supplier, while [#] indicates a company that is primarily operational in military engine supply. Individual results are available from the authors on request. The above panel presents the statistical results on the significant positive dummy coefficients estimated in the following regression $\rho_{i,avi}^t = \alpha + D_t + \varepsilon_t$. ρ^t denotes the dynamic conditional correlations, i stands for the selected company's returns, avi is the returns of the benchmark index where D_t is a dummy variable that takes the value one for a certain period of time after aviation incidents. Values in this table show the number of companies that experience a change in their stock returns' correlation between the above mentioned indices after aviation incidents. The column headers show the number of days that we analyse the correlation change after the announcements. The values in the parentheses are the percentage of companies within the sub-groups experiencing a change in correlations.