The effects of negative reputational contagion on international airlines: The case of the Boeing 737-MAX disasters

David Collings[a], Shaen Corbet[a,b], Yang (Greg) Hou[b], Yang Hu[b], Charles Larkin[c,d,e*], Les Oxley[b]

[a] *DCU Business School, Dublin City University, Dublin 9, Ireland*

[b] *School of Accounting, Finance and Economics, University of Waikato, New Zealand*

[c] *Institute for Policy Research, University of Bath, UK*

[d] *Trinity Business School, Trinity College Dublin, Dublin 2, Ireland*

[e] *Kreiger School of Arts Sciences, Johns Hopkins University, Baltimore, MD, USA*

[*] *Corresponding Author: cjl91@bath.ac.uk*

Abstract

The Boeing 737-MAX was created for the ultra-competitive environment of the aviation industry and advertised as capable of delivering an 8% reduction in fuel and a 14% reduction in CO_2 when compared to the Next-Generation 737, a substantial saving for airlines. This research sets out to establish the interactions of price volatility, information flow and source of price discovery between Boeing and the airlines that were susceptible to reputational contagion due to the Lion Air and Ethiopian Air crashes, both involving the Boeing 737-MAX. Results indicate significant evidence of pricing interactions between Boeing's share price and those airlines with major 737-MAX orders and purchases, particularly those of low-cost carriers and leasing companies. DCC-GARCH estimates are consistent with a significant response to the second crash impacting on airlines, while the information flow and price discovery results present evidence that is consistent with the DCC-GARCH results, that is, that shocks in Boeing presented significant negative effects upon connected airlines. Further, analysts' pricing errors are consistent with an industry caught unawares with regards to the first incident, but which slowly realised the broad sector implications following the second disaster. Financial markets quickly identified the 737-MAX with the disasters and adapted in response. Historical internal practices and decision-making at Boeing cannot be separated as the potential source of error spilling over into connected airlines.

Keywords: Airlines; Contagion; Volatility; Reputation Risk; Financial Markets; Price Discovery.

1. Introduction

It is estimated by the United States National Transportation Safety Board (NTSB) that one fatality due to an aviation disaster takes place every 16.3 million flight hours, presenting evidence of the rarity of such events in a safety-driven sector. The occurrence of two disasters in close proximity of time and involving the same type of aircraft resulted in sharp and negative attention from investors, regulators and policy-makers alike during the Lion Air and Ethiopian Air disasters. Both involved the new Boeing 737-MAX aircraft, which had been partially delivered to several large airlines, with exceptional quantities of further orders placed. This research sets out to establish how these airlines found themselves to be susceptible to the reputational contagion sourced within an aircraft manufacturer such as Boeing. It is important to note that airlines only make money when flying and generate substantial costs when their aircraft are on the ground. At the same time many airlines, especially low-cost carriers, are very sensitive to fuel costs but generally, airlines avoid fuel-inefficient aircraft, to which the Boeing 737-MAX was identified as a future operational game-changer in a highly competitive market. However, the crashes resulted in a safety concern, inducing fear in the flying public for airlines with MAX or large numbers of similar in name and appearance Boeing 737 aircraft. This subsequently hurt the load factors of airlines. Also, the subsequent grounding of the MAX induced airlines that already owned such aircraft, to violate this iron-clad business rule. Boeing did provide support to those airlines with grounded aircraft, but many were located in awkward locations, taking time for relocation (some continue to be located in the jurisdictions where they initially landed after grounding) and beyond that forcing airlines into costly contingency plans. This research specifically focuses on understanding how such reputational contagion influenced a sector, not only resulting in many regional and sectoral changes in aircraft management but also the perceptions of investors and sources and flows within traditional price discovery channels.

Specifically, this paper investigates the specific approach that Boeing has taken to the development, testing, certification, entry into revenue service and crash responses from the point of view of financial risk and volatility spillovers. Airlines, leasing companies and investors unwittingly embraced the idiosyncratic risk of the changing Boeing business model during the 737-MAX project. In a series of analyses using cumulative abnormal returns, DCC-GARCH, information-share, component-share, and the mispricing of analysts' recommendations we are able to demonstrate how Boeing's main customers for the 737-MAX were exposed to these risks, which were taken by the company as it sought to rapidly deliver a new aircraft and avoid costly changes that would endanger rapid FAA certification and require new training. The result is that analysts, evaluating the company from the viewpoint of an older Boeing business model, dedicated to exclusively engineering integrity, made significant errors in judgement about the risk tolerance of Boeing in designing its new aircraft. Fundamentally, the tightly coupled nature of the aircraft and airline industry ensured that Boeing was able to transfer to suppliers, clients, and investors its enhanced risk tolerance while at the same time providing enhanced returns in line with the progress of the 737-MAX.

The evidence presented in the investigations above illustrate a consistent set of relationships between Boeing and the major Boeing purchasers in the aviation sector. The CARs evidence highlights how the crashes of the 737-MAX impacted the airline sector There is evidence to suggest that full-service airlines respond in a very different manner to other tested airlines, most likely due to the possession of mixed fleets, and in the context of the first crash, these airlines, most being legacy flag carriers, possess strong reputations with consumers for safety and reliability when compared with low-cost carriers and charter airlines. Low-cost carriers, with their focus on a single type of aircraft for cost minimisation purposes, absorbed substantial effects following the second crash in particular. Evidence provided from the DCC-GARCH investigation is consistent with the CARs findings. The second crash event results in significant changes in the conditional variances of Boeing and counterpart companies. There are also distinctions within the airline sector. Smaller airlines and airlines not located in advanced economies respond differently. Those airlines are subject to greater concern about safety compliance. The evidence provided by the DCC-GARCH is consistent with the response to the second crash impacting Boeing and on airlines with a large proportion of Boeing aircraft. In the information flow and price discovery results, the evidence is consistent with the DCC-GARCH and with the analysts' recommendations, the second crash increases the information share from Boeing to the airlines, most especially small airlines, which would have smaller fleets and less capacity to manage the grounding of the MAX or indefinite delays in the MAX. The reduced information share after the second crash to the leasing companies may reflect the capacity of those companies to manage their fleets and cancel orders, limiting financial risk. Presenting some evidence of the counterfactual, there is no identified information flow relationship between the low-cost carrier Easy Jet and Boeing, which is theoretically plausible as the company is primarily an Airbus operator and a major customer for the A320neo. Finally, the analysts' errors are also consistent with the evidence presented in the earlier sections of the analysis. Boeing's post-crash equity woes were reflected in the behaviour of airlines that typically have large numbers of Boeing aircraft, such as the low-cost carriers and aviation leasing corporations. The negative relationship, post-crash, between Boeing and the full-service carriers is also consistent with the earlier analysis, as it reflects the capacity of those airlines to engage in fleet management as they have much more diverse fleets in comparison to smaller airlines and those low-cost carriers which gravitate towards single model fleets.

The remainder of this paper is structured as follows: previous literature and theory that guides the development of our selected hypotheses are summarised in Section 2. Section 3 presents a thorough explanation of the wide variety of data used in this analysis, while Section 4 presents a concise overview of the methodologies utilised to analyse the relevant hypotheses. Section 5 specifically investigates the interactions and effects of reputational contagion upon traditional asset-pricing relationships and identified channels of information flow and price discovery. Section 6 presents a concise discussion of the presented results, while Section 7 concludes.

1.1. Understanding the link between Engineering and Finance

The objective of the 737-MAX was for Boeing[1] to build an aircraft that required no simulator training for pilots who were already flying the 737 NG. This necessitated that no more than 16 hours of computer-based instruction on the differences between the 737 NG and 737-MAX for pilots. This objective resulted in Boeing focusing on costs and competitiveness and ultimately undermining safety considerations. The FAA granted an amended type certificate on March 8, 2017, for the 737-8 aircraft, the first of the 737-MAX family. The 737-8 is the successor to the 737 Next Generation (NG) aircraft and the 12th derivative model of the 737 aircraft, which was first certified in 1967. The aircraft entered revenue passenger service with Malindo Air of Malaysian two months after its FAA certification. Seventeen months later the 737-MAX had its first fatal crash.

Boeing's alleged acts, omissions, and errors occurred across multiple stages and areas of the development and certification of the 737-MAX. The first area was in production pressures. Boeing was under financial pressure to compete with the Airbus A320neo aircraft and subsequently increased the pressure on the 737-MAX program to compete. This resulted in an extensive effort to cut costs, maintain the 737-MAX program schedule, and not slow down the 737-MAX production line. Boeing made fundamentally faulty assumptions about critical technologies. Most importantly with respect to MCAS, the Manoeuvring Characteristics Augmentation System. Boeing allowed the MCAS software, which was designed to automatically push the plane's nose down in certain conditions, to rely on a single angle of attack (AOA) sensor for automatic activation. Further, Boeing assumed pilots, who were unaware of the system's existence in most cases, would be able to correct for any malfunctions. In part due to those assumptions, Boeing did not classify MCAS as a safety-critical system. If it was classified as such it would have been subject to much greater scrutiny during FAA certification. Importantly the operation of MCAS violated Boeing's own internal design guidelines.

The violation of the internal design guidelines is in keeping with a culture of concealment that is alleged to have developed at Boeing. Boeing withheld crucial information from the FAA, its customers, and 737-MAX pilots. This included hiding the very existence of MCAS from 737-MAX pilots and failing to disclose that the AOA disagree alert was inoperable on the majority of the 737-MAX fleet. It is important to focus on the AOA disagree alert being inoperable as it was certified as a standard cockpit feature. This alert informed the crew if the aircraft's two AOA sensor readings disagreed. This happens when one sensor is malfunctioning. Boeing also withheld

[1] To be as accurate as possible, significant quotes are taken from the US House of Representatives Committee on Transport and Infrastructure's Preliminary Investigative Findings Report of March 2020. These findings outline verified changes to the Boeing business model and to the process by which the 737-MAX went from initial plans to grounding.

knowledge that a pilot would need to diagnose and respond to a 'stabiliser runaway' condition. This is caused by an erroneous MCAS activation and requires a response in 10 seconds or less to avoid catastrophic consequences. Classic agency problems existed in how Boeing and FAA interacted, created the potential for conflicts of interest that were to the detriment of safety[2].

1.2. The struggle between engineering and balance sheet-based decision-making at Boeing

Boeing's main desire was to bring a new aircraft to market as fast as possible and to make it as similar as possible (for certification purposes) to the existing 737-NG. The only way to achieve that outcome was with software. Boeing's solution to the changes in the overall operation of the aircraft was to include the Manoeuvring Characteristics Augmentation System (MCAS). The shared contributing factor to the fatal crashes was the new software system MCAS, which Boeing designed to address stability issues in certain flight conditions induced by the plane's new, larger engines, and their relative placement on the 737-MAX aircraft compared to the 737-NG. This solution though was not reported in the Flight Crew Operations Manual at the request of Boeing, making pilots unaware of the potential effects of MCAS on the handling of the aircraft. The addition of MCAS created a potential requirement for additional training for thirty-seven MAX pilots. This would have resulted in a negative outcome for customers and Boeing had a strong incentive to ensure that MCAS did not result in further simulator training. Boeing financially was incentivised to ensure that no regulatory determination requiring pilot simulator training for the 737-MAX was made. Part of this included very close relationships with major customers, including the US launch customer, Southwest Airlines. If simulator training was required to transition a pilot from 737-NG to 737-MAX it would have cost Boeing approximately $1m per aircraft delivered. Southwest had ordered 280 aircraft. At the time of the FAA certification of the 737-MAX, the Chief Technical Pilot for the Boeing 737 programme made it clear that simulator training was going to be fought by the company with any regulator that attempts to make it mandatory.

This situation continued even following the initial Lion Air crash. The FAA learned that Boeing had failed to fix an inoperable AOA Disagree alert. This malfunction was present on an estimated 80% of the 737-MAX fleet. Boeing did not inform the FAA or its customers about the non-functioning alert for more than fourteen months. This again raised questions about the agency problems at the core of Boeing management.

[2]There were fundamental cost minimisation and timeline to market pressures brought by management on the engineering teams that resulted in the dismissal of concerns and the elimination of important safety features. The 737-MAX programme was subject to extensive cost-cutting exercises. In 2012, to lower costs, Boeing reduced the work hours involved in avionics regression testing on the 737-MAX by 2,000 hours, flight test support by 3,000 hours, and the engineering flight deck simulator by 8,000 hours. This was equal to 6.5 full-time employees over one year. Further, in 2013, a Boeing engineer raised the issue of installing on the 737-MAX a synthetic airspeed indicator, which allows an estimated indication of speed to be compared to a measured airspeed. This request was rejected due to cost concerns and a new feature on the aircraft could have jeopardised the directive that no new simulator training would be required for the MAX.

Decisions were made at Boeing based on cost and maintaining market share. These decisions relegated the advice of engineers. Boeing, historically, was an engineering-led firm. The exogenous pressures placed on the firm by management resulted in decisions being made for financial purposes as opposed to regulatory purposes, including actively working to ensure that the engineering solutions would be minimised to ensure regulatory compliance. The nature of the aircraft industry ensured that there was a high level of information asymmetry between Boeing and the FAA, with the FAA reliant on proxies in the form of Authorised Representatives. The investment community is subject to an even more important information asymmetry.

The nature of this study is to look at how Boeing's approach to designing, testing, certifying, and entering into revenue service the 737-MAX transferred risk and volatility from Boeing to its suppliers, investors, and its customers. The changing position of the engineer in the Boeing structure is important to note, as the organisation promoted financial requirements ahead of engineering advice. It is possible to argue that the changes in the organisation began from the point of the merger with McDonald-Douglas. Mukunda [2014] links the merger of Boeing and McDonnell Douglas in 1997 to finalisation and the troubles of the 787 Dreamliner. He argues that the culture of McDonnell Douglas came to dominate that of Boeing and that the cost-cutting that ensued ensured that the high-quality engineering that an aircraft requires could not be maintained. Mukunda points to differences in the managerial approaches of Boeing and McDonnell Douglas. The former's approach was that of 'engineering' whereas McDonnell Douglas was 'risk-averse and focused on cost-cutting and financial performance'. Over time the McDonnell Douglas culture came to dominate. It is well understood that organisational culture and motivation are closely related. Learning ceases or becomes sloppy when a workforce is poorly motivated. This is not the first instance where this tension between engineering and management resulted in safety being compromised. Davis [1998] examination of the Challenger disaster distinguishes clearly between the management and engineering cultures in Morton Thiokol which built the rocket, and the role conflict that this caused for the vice president of engineering when his boss asked him to think like a manager rather than an engineer.

2. Hypotheses Development and Previous Literature

Boeing was designing an aircraft with a clear set of customers in mind. The aim was to deliver that aircraft with the required improvements in performance but not to impose any additional training costs on the operators. The cost sensitivity of the low-cost carriers is well known. In our study, we break down the aviation sector into four categories: low-cost carriers, full-service carriers, aviation leasing and charter airlines.

The low-cost carriers are products of the deregulated aviation market and have been noted by their 'no frills' approach (O'Connell and Williams [2011]). Their business model is defined by the use of additional charges for luggage, seats, meals, etc, the use of smaller airports, a single aircraft type and twin priorities of quick turnarounds and high load factors (percentage of seats filled per flight). The pioneers of the sector were Southwest in the USA and Ryanair in Europe, both exclusive users of the 737 series aircraft. Full-service airlines are large 'legacy' operations that were associated with national flag carriers in Europe and pre-1970s carriers in the USA. Defunct examples of legacy full-service carriers are TWA and Pan Am. These airlines tend to have more mixed fleets reflecting a variety of distances, airports cargo and frequency requirements. Aviation leasing firms began as spin-offs from the major operators to provide revenues from aircraft during the down season or where aircraft were underutilised in their existing revenue service. Ireland became a hub of aviation leasing resulting from the initial work by Tony Ryan in Guinness Peat Aviation (GPA), which grew from his work while working for Aer Lingus, the Irish national flag carrier airline, in the leasing part of the Aer Lingus fleet during the off-season. Ireland became an important hub for aviation leasing not only due to experience but also due to Ireland lacking a domestic aircraft manufacturing industry (Aldous [2013]). This allowed GPA, its successors and Ryanair to avail of the US Export-Import Bank (EXIM) credit support for the purchase of Boeing aircraft. Leasing operations offer different levels of lease. The main types are a 'wet-lease' and a 'dry-lease', with the wet-lease type being a lease where the aircraft plus crew, fuel, ground staff, line maintenance and insurance is provided (this can go as far as wearing the uniforms and aircraft livery of the lessor) and the 'dry-lease' being solely the provision of the aircraft with all other aspects being provided by the operator (lessor). The importance of the aviation leasing sector cannot be understated for Boeing, with it being responsible for historically some of the largest customer orders through AerCap and GE Capital Aviation Services. These three groupings of aircraft purchasers dominate in terms of volume purchases of 737s. The final grouping is the charter airlines. These airlines are a product of the pre-deregulation era when there were strict limits on scheduled services between destinations. To circumvent these limits travel agents would 'charter' flights to popular destinations as part of package holidays. These airlines have evolved to support modern business models where the role of travel agents has been nearly eliminated and tend to have a similar approach to fleet management to the low-cost carriers.

Our research builds on several key areas that have been developed in recent times. We must consider that Boeing made internal decisions based on meeting customer demands without the knowledge of the customer of the potential downside implications. Such decisions were made through their agents that were ultimately certified by the FAA based on good faith dealing. Such similar situations have been analysed from a variety of different perspectives. While no specific research has explicitly focused on the internal structural effects of Boeing and potential influences upon corporate relationships, several research areas add value to our selected hypotheses. Much of the specific issues with Boeing appear to have surrounded agency problems and issues surrounding self-certification. Esposito [2004] had previously identified that the aircraft industry is undergoing a global reorganisation featuring an integration process where six groups (two in Europe and four in the United States) had come to the fore. Miller and Clarke [2008] were one of the first to investigate the use of real options analysis to evaluate and guide new aircraft development programs is illustrated through a case study of a real-world aircraft program, presenting evidence that investors can use the numerical results of the real options analysis to determine how much they should spend on an aircraft program, that managers can use the same results to restructure the program to improve the financial feasibility of the project, and that both investors and managers can use the output of derivative analyses to define minimum requirements (in terms of aircraft orders) to ensure program success. Agency problems have received much attention in previous work, with substantial research focusing on venture capital contracting (Cumming [2005]), B2B vertical hubs (Ravichandran et al. [2007]), private equity (Cumming et al. [2007]), information asymmetry (Aitken et al. [2015]), institutional ownership (Rong et al. [2017]) and the interactions between government and private companies (Wainwright and Manville [2017], Yang et al. [2017], Zhang et al. [2019]). Buzacott and Steve Peng [2012] consider the development of appropriate contracts that enable market risks to be shared between the lead manufacturer and the partners, where it is shown to be usually appropriate to have threshold contracts, which are defined to be contracts where a partner only shares in profits if sales exceed a value determined by risk tolerance and target return. Smith [2020] found that companies that receive an Advanced Technology Program (ATP) award have a positive and significant causal impact on a firm's commercialisation and R&D behaviour. Jose et al. [2020] used a nestedness analysis to identify patterns depicting the distribution and evolution of exported products across aerospace and aviation ecosystems, to reveal that developed ecosystems tend to become more analogous, as countries lean towards having a revealed comparative advantage (RCA) in the same group of products. Wu et al. [2020] show that government R&D subsidies can effectively accelerate renewable energy investment (REI). Further research on R&D misallocation (Yang et al. [2020]), productivity effects (Boeing et al. [2016]), subsidies (Boeing [2016]) and gender diversity in R&D teams (Xie et al. [2020]) also add substantial value in the selection process of our research hypotheses.

The ARs were Boeing staff that acted on behalf of the FAA. Boeing, with intimate knowledge of aircraft and the FAA rules, was granted wide-ranging self-certification powers via ARs and an ability to optimise changes to not trigger re-certification processes. This became an abuse of self-certification and self-audit. Similar to internal audit procedures that essentially obstruct external auditors. de Jong et al. [2005] analysed The Netherlands' private sector self-regulation initiative ('The Peters Committee') to improve corporate governance practices, finding evidence of no effects on corporate governance characteristics or their relationship with firm value. The authors concluded that little should be expected from such initiatives that rely on monitoring without enforcement

How do such issues with internal decision-making and the process of self-certification link? Boeing was in the process of developing a plane that met the desires of customers. To achieve this, Boeing took shortcuts but told neither the FAA nor customers. Customers, therefore, absorbed the risk of Boeing in the process, without a clear option to hedge or diversify except by purchasing different aircraft or cancelling orders. In the following hypotheses, we examine through a variety of methods the question of the impact of Boeing's 737-MAX project on airlines. The underlying hypothesis is that Boeing produces negative and positive spillovers into Boeing-dominated carriers and carriers with large 737-MAX orders such that these airlines have unwittingly absorbed the volatility and idiosyncratic risk of Boeing without having oversight or input into important managerial and engineering decisions that resulted in the eventual grounding of the 737-MAX. Therefore, we begin with the first hypothesis stating:

- h_1 Boeing aircraft announcements produce spillovers into the equity prices of Boeing-dominated airlines and airlines with 737-MAX orders. This differs based on the market capitalisation of the airlines and the types of the airline operation.

In this context airlines are categorised into 'low-cost carriers', 'full-service airlines', 'leasing companies' and 'charter carriers'. This can be evidenced by the application of a cumulative abnormal returns modelling framework. Using 181-day windows, we test to see the responses for the four airline categories and airline market capitalisation. The important result is the sensitivity of low-cost carriers to the successes and failures of Boeing following announcements and crashes [Cioroianu et al., 2021a,b, Corbet et al., 2021]. Full-service carriers, with their much more diverse fleets, and in the case of European flag carriers, Airbus dominated fleets, have limited responses.

- h_2 Boeing's equity price variance co-moves with the equity price variance of major Boeing Customers.

Using DCC-GARCH modelling to calculate the time-varying conditional variances between Boeing and major airlines shows that for the listed airlines there is evidence of co-movement. As these airlines and leasing companies make up the most important customers for Boeing it is further evidence of the sensitivity of Boeing customers to Boeing decisions, announcements, and events. Such analysis builds on several previous works that have specifically analysed and investigated the spread of negative reputational contagion throughout a variety of sectors and geographical regions. An et al. [2020] found that higher media coverage is associated with a lower tendency of firms withholding bad news, proxied by stock price crash risk. With regards to aviation companies, Ciliberto and Schenone [2012] found that delays and cancellations are less frequent during bankruptcy filings but return to their pre-bankruptcy levels once the bankrupt firm emerges from bankruptcy[3]. Building

[3] Such research builds upon several areas that have previously focused on the effects of CEO reputation and gender (Jian and Lee [2011], Sila et al. [2016, 2017], Kuang and Lee [2017], Canil and Karpavičius [2020]), financial statement fraud (Firth et al. [2011]), information spillovers (Bradley and Yuan [2013]) and corporate social responsibility (Adhikari [2016], Nofsinger et al. [2019], Cai et al. [2020]).

on such previous research, we, therefore, set out to establish the effects of the reputational transfer due to negative news from Boeing upon aviation companies with significant Boeing 737-MAX orders.

h_3 The crashes of the 737-MAX directly impacted on the equity prices of airlines with fleets dominated by Boeing and with 737-MAX orders. The behaviour of the equity prices of airlines is the product of information spill-overs from the Boeing equity price.

The final tested hypotheses will be analysed using IS-CS-ILS information share models between markets[4]. The Component Share (CS) of information flows is a function of the dynamic responses of the two series to transitory shocks only, whereby transitory shocks are represented by noise due to trading frictions. Meanwhile, Information Share (IS) is a function of the dynamic response of the two series to both transitory and permanent shocks and permanent shocks are denoted by innovations in the fundamental values. In this case, IS and CS may give misleading information regarding price discovery in some situations due to their dependence on the dynamic response to transitory shocks. To circumvent this problem, we use the Information Leadership Share (ILS), presented by Putnins [2013], to generate a cleaner contribution of the series to the price discovery process. This results in the impact from dynamic responses to transitory shocks being cancelled out and a clean measure of relative informational leadership are achieved. The analysis again illustrates consistent evidence for information sharing between Boeing and major Boeing customer airlines and leasing companies.

h_4 The information asymmetries highlighted in the earlier section makes the role of aviation sector analysts important to investor decisions.

Analysts' recommendations are tested for the correlation between recommendations based on airline returns versus Boeing returns before and after crashes. Importantly the large positive post-event correlation for low-cost carriers, leasing companies and charter airlines is consistent with our other hypotheses. Also consistent is the negative correlations for full-service airlines.

3. Data

This paper attempts to establish a thorough analysis as to the behaviours and interactions between Boeing and each company that has ongoing orders for 737-MAX airlines as presented in

[4]Much research has utilised similar techniques to investigate the interactions between the information flows in stock markets (Otsubo [2014], Wang and Yang [2015], Akyildirim et al. [2020]), foreign exchange markets (Wang and Yang [2011], Piccotti and Schreiber [2020]), bond markets (Fricke and Menkhoff [2011]), commodity markets (Jin et al. [2018], Corbet and O'Connor [2020]), cryptocurrency markets (Akyildirim et al. [2020], Corbet et al. [2018, 2019, 2020]), and derivatives markets such as futures markets (Shrestha [Shrestha]) and options markets (Patel et al. [2020]).

Table 1. Within this context, a concise list of companies was readily available with an associated time-series of dates) on which orders were placed, and also for many 737-MAX deliveries before the substantial issues experienced by Boeing. Stock market data relating to the closing prices of publicly traded airlines and the associated exchanges on which each stock trades was obtained from Thomson Reuters Eikon for the period 1 January 2020 through 31 May 2020. While noting that some of the listed companies were not directly publicly traded, the subsequent parent company of each airline was obtained as the adequate share price upon which to run the analysis of cumulative abnormal returns, DCC-GARCH-calculated correlations and the source of information flows and price discovery[5]. A wide variety of corporate characteristics relating to each company were further obtained, through which regression methodologies can be based. Primarily, market capitalisation is deemed to be a significant driver of potential behaviour, with larger companies observed to be best placed to absorb supply chain issues with the Boeing 737-MAX due to diversification ability, while other, smaller companies might not have the same ability to generate liquidity or leverage through which to purchase other planes during the disruption.

Insert Table 1 about here

Another category through which the identified airlines could be separated was by type of aviation company. Four specific types are denoted to best differentiate the companies, listed as charter carriers, full-service carriers, low-cost carriers, and leasing companies. Charter carriers are best described as being in the business of renting an entire aircraft (chartering) rather than the sale of individual aircraft seats as is the standard process with a traditional airline. A 'legacy' or 'full-service carrier' is an airline that focuses on providing a wide range of pre-flight and on-board services, including different service classes, and connecting flights, while low-cost carriers focus on cost reduction to implement a price leadership strategy on the markets they serve. Finally, leasing companies are in the business of providing leases used by airlines and other aircraft operators, primarily to operate aircraft without the financial burden of buying them, and to provide a temporary increase in capacity. There are two main leasing types, namely wet-leasing, which is normally used for short-term leasing, and dry-leasing which is more normal for longer-term leases. The industry also uses combinations of wet and dry. It must be noted that when the aircraft is wet-leased to establish new services, then as the airline's flight or cabin crews become trained, they can be switched to a dry lease.

Insert Tables 2 and 3 about here

[5] In a similar manner to the work presented by Akyildirim et al. [2020], Katsiampa et al. [2019a,b] and Corbet et al. [2020, 2021].

In Table 2, we observe a history of the 737-MAX aircraft from project launch in August 2011 through to both the Lion Air crash in October 2018 and the following Ethiopian Air crash in March 2019. These events were followed by the subsequent grounding by both the FAA and the Civil Aviation Administration of China on 13 March 2019. The final key dates identified in this research with regards to the Boeing 737-MAX were the provision of evidence by the CEO of Boeing in October 2019 and the subsequent dismissal in December 2019 due to the continued onslaught and continued negative media coverage with regards to both the action, and inaction by Boeing throughout this stressful period. In Table 3, we identify the summary statistics of the share prices used in this analysis with regards to each airline that had both active orders for the 737-MAX, or indeed, had taken delivery of the new prototype. The summary statistics are further presented by corporate size, as separated by quintile based on market capitalisation in USD$, and by type of aviation company.

4. Methodology

4.1. Cumulative Abnormal Returns

We calculate the natural logarithm of returns $\left(R_{i,t} = ln\frac{P_{i,t}}{P_{i,t-1}}\right)$ for each traded airline and develop a model of the following form to estimate abnormal returns:

$$AR_{i,t} = R_{i,t} - \alpha_i - \beta_i(R_{m,t}) \tag{1}$$

where on day t, $AR_{i,t}$ is the abnormal return and $R_{i,t}$ is the daily return for airline i, and $R_{m,t}$ is the domestic index upon which each airline trades. β_i is estimated using returns for the pre-event window [-210,-30] for each stock i and each domestic index[6]. We then calculate the abnormal return (arT_0) as the return for stock i on the announcement event day and cumulative abnormal return for each announcement event window [-30,-1], event windows [-1,+1] and for the post-event window [+1,+30]. For each stock i, the CAR for an event interval [T_1, T_2] is computed as:

$$CAR_{i,T_1,T_2} = \sum_{t=T_1}^{T_2} AR_{it} \tag{2}$$

The abnormal and cumulative returns averaged over all airlines (N) are given by:

$$\bar{AR}_t = \frac{\sum_{i=1}^{N} AR_{i,t}}{N} \tag{3}$$

[6] A variety of windows and differential methodological procedures were considered and tested when developing our selected research approach. In line with Corbet et al. [2021, 2022], we select the pre-event window [-210,-30] to best represent medium- to long-term behaviour in the period before that of specific interest. Other variations offer little in terms of significant differential, however, further results of these additional procedures are available from the authors upon request.

$$\bar{CAR}_{T_1,T_2} = \frac{\sum_{i=1}^{N} CAR_{i,T_1,T_2}}{N} \tag{4}$$

For our event study, we calculate corresponding t-statistics to determine the significance for each event window. We compute the t-statistic as:

$$t_{CAR_{T_1,T_2}} = \frac{CAR_{T_1,T_2}}{\frac{1}{\sqrt{N}}\sigma(CAR_{T_1,T_2})} \tag{5}$$

$$\text{where} \quad \sigma(CAR_{T_1,T_2}) = \left(\frac{\sum_{i=1}^{N}(CAR_{i,T_1,T_2} - CAR_{T_1,T_2})^2}{N-1} \right)^{1/2} \tag{6}$$

4.2. The bivariate VEC/VAR-DCC-GARCH model

We first test for the interactions between Boeing share prices and share prices of other airline-related companies that interact with Boeing with respect to the Boeing 737-MAX aircraft. For this testing purpose, we analysed the dynamic correlation between Boeing and the selected airlines in our sample, paying particular attention to specific periods surrounding each aviation disaster involving the Boeing 737-MAX. We carry out this estimation using a bivariate vector error correction (VEC) or Vector Autoregressive (VAR)-Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model. Data relating to each paired sample of Boeing and one counter-party aviation company is employed for each estimation. The conditional correlation between the return series of Boeing and one counterpart airline company is thus derived:

$$\begin{cases} R_{Boe.,t} = \mathrm{c}_1 + ECC_1 ect_{t-1} + \sum_{i=1}^{p} \Gamma_i^{11} R_{Boe.,t-1} + \sum_{i=1}^{p} \Gamma_i^{12} R_{Air.,t-1} + \delta_1 D_{1t} + \delta_2 D_{2t} + e_{1,t} \\ R_{Air.,t} = \mathrm{c}_2 + ECC_2 ect_{t-1} + \sum_{i=1}^{p} \Gamma_i^{21} R_{Boe.,t-1} + \sum_{i=1}^{p} \Gamma_i^{22} R_{Air.,t-1} + \delta_3 D_{1t} + \delta_4 D_{2t} + e_{2,t} \end{cases} \tag{7}$$

where $R_{Boeing,t}$ and $R_{Airline,t}$ are logarithmic returns of Boeing and a counterpart company. ECC_1 and ECC_2 are the error correction coefficients. ect_{t-1} is the error correction term, that is, the cointegrating equation. $D_{1,t}$ is a dummy variable where it takes a value of one when the sample period is from 29 October 2018 to 18 November 2018; and zero otherwise. Henceforth, $D_{1,t}$ labels a sample period of the occurrence of a first crash event of the Boeing 737-MAX aircraft. $D_{2,t}$ is a dummy variable where it takes a value of 1 when the sample period is from 10 March 2019 to 30 March 2019; and zero otherwise. Henceforth, $D_{2,t}$ labels a sample period of the occurrence of a second crash event of the Boeing 737-MAX aircraft. In this paper, we consider the effects of the two crash events on both conditional means and variances of return series. Note that when cointegration does not exist, the terms of $ECC_1 ect_{t-1}$ and $ECC_2 ect_{t-1}$ are removed in the VEC model. Henceforth, the VEC model reduces to a VAR model. Residuals from the VAR model are fitted in the estimation procedure. The lag order p is chosen according to the AIC or SIC. If we let $e_t = [e_{1,t}, e_{2,t}]'$, the model is shown as:

$$e_t \sim \text{SNP}(0, H_t, s_i, k_i)(\text{i=1,2}) \tag{8}$$

$$H_t = D_t R_t D_t \tag{9}$$

$$D_t = \text{diag}(h_{11,t'}^{\frac{1}{2}}, h_{22,t'}^{\frac{1}{2}}) \tag{10}$$

$$R_t = \text{diag}\left\{Q_t\right\}^{-1/2} Q_t \text{diag}\left\{Q_t\right\}^{-1/2} \tag{11}$$

where Q_t is the conditional variance-covariance matrix of standardised innovations $\epsilon_{it} = \frac{e_{it}}{\sqrt{h_{ii,t}}}$ $(i = 1, 2)$. Q_t is defined as $Q_t = (1-a-b)\bar{Q} + a\epsilon_{t-1}\epsilon'_{t-1} + bQ_{t-1}$, where $\epsilon_t = [\epsilon_{1t}, \epsilon_{2t}]'$ and $\bar{Q} = \text{E}\left[\epsilon_t \epsilon_t^T\right]$. H_t is the conditional variance-covariance matrix. s_i and k_i are marginal skewness and kurtosis parameters as defined in a semi non-parametric (SNP) distribution, respectively. $h_{11,t}$ and $h_{22,t}$ are conditional variances of $e_{1,t}$ and $e_{2,t}$, respectively. $h_{11,t}$ and $h_{22,t}$ are specified as:

$$\begin{cases} h_{11,t} = \omega_1 + \alpha_1 e_{1,t-1}^2 + \beta_1 h_{11,t-1} + \theta_1 D_{1t} + \theta_2 D_{2t} \\ h_{22,t} = \omega_2 + \alpha_2 e_{2,t-1}^2 + \beta_2 h_{22,t-1} + \theta_3 D_{1t} + \theta_4 D_{2t} \end{cases} \tag{12}$$

Q_t is the conditional variance-covariance matrix of standardised innovations $\epsilon_{it} = \frac{e_{it}}{\sqrt{h_{ii,t}}}$, where $(i = 1, 2)$. Q_t is defined as $Q_t = (1-a-b)\bar{Q} + a\epsilon_{t-1} + bQ_{t-1}$, where $\epsilon_t = [\epsilon_{1t}, \epsilon_{2t}]'$ and $\bar{Q} = E[\epsilon_t \epsilon_t^T]$. A MLE procedure based on the SNP distribution is employed to obtain estimates of the DCC-GARCH model, aligning with Del Brio et al. [2011], Ñíguez and Perote [2016] and Del Brio et al. [2017].

4.3. Testing for differentials of information flows and price discovery

To investigate information shares between the selected markets, we first let Y_t be a $2\,x\,1$ be the vector of price series of two markets integrated as I(1). If the two-price series are cointegrated at order zero, which means Y_t contains one single common stochastic trend, then Y_t can be specified in the following bivariate vector error correction model (Engle and Granger [1987]):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t \tag{13}$$

where $\Pi = \alpha\beta^t$. Both $\alpha = [\alpha_1, \alpha_2]'$ and $\beta = [1, -\beta]'$ are both $2\,x\,1$ vectors. α_1 and α_2 are the error correction coefficients, measuring responses of two markets to deviations of the past long-run equilibrium. β is the cointegrating coefficient, while Δ is the first-order difference operator. ε_t is a vector of innovations, where the lag order k is chosen by Akaike Information Criteria (AIC). According to Hasbrouck [1995], Eq.13 can be rearranged into the following vector moving average (VMA) model:

$$Y_t = Y_0 + \Psi(1)\sum_{s=1}^{t}\varepsilon_s + \Psi * (L)\varepsilon_t \tag{14}$$

where $\Psi(1)\varepsilon_t$ represents the long run impact of innovations on the price series. If we let $\Psi(1)$ and $\Psi(2)$ be each row of $\Psi(1)$ in Eq.14, following Hasbrouck [1995], $\Psi(1) = \Psi(2)$, which is determined by the cointegrating coefficient β equal to one. $\Psi(1)(\Psi(2))\varepsilon_t$, represents the long-run impacts of innovations on the first (second) price series. If we let Ω be the covariance matrix of ε_t and Ψ denote either $\Psi(1)$ or $\Psi(2)$. Given a general case where Ω is not diagonal, the Information Share (IS) of market j (j = 1,2) is given by Hasbrouck [1995] as:

$$S_j = \frac{([\Psi F]_j)^2}{\Psi\Omega\Psi'} \tag{15}$$

where F is the Cholesky factorisation of Ω such that $\Omega = FF'$. $[\Psi F]_j$ is the jth element of the vector ΨF. Due to the order of price series j in Y_t in the process of Cholesky factorisation, the upper (lower) bound of series j's information share arises if series j is the first (last) variable in Y_t. It has been widely adopted in the literature that IS of market j can be represented by a mid-point of IS upper and lower bounds (see, for example Baillie et al. [2002]; Booth et al. [2002]; Chen and Gau [2010]; Putnins [2013], among others). Following the literature, we calculate two bounds of IS for each market and take the simple average as a result of information share. The IS of market j is the contribution of market j to the total variance of the common efficient price or permanent impact (Baillie et al. [2002]; Lien and Shrestha [2014]). Yan and Zivot [2010] further suggest that IS measures a combination of the relative level of noise and relative leadership in reflecting innovations in the fundamental value (Putnins [2013]). Gonzalo and Granger [1995] propose that the two-price series in Y_t, if cointegrated, can be decomposed into the following form:

$$Y_t = Af_t + \tilde{Y}_t \tag{16}$$

where Y_t is comprised of one permanent component f_t and one transitory component $\tilde{Y}_t$. f_t is a so-called common factor that is a non-stationary series while $\tilde{Y}_t$ is stationary. Two assumptions underlying the validation of Eq.(4) are (i). f_t is a linear function of the series in $\tilde{Y}_t$; (ii). $\tilde{Y}_t$ does not Granger cause f_t in the long run. In other words, the justification of Eq.16 requires:

$$f_t = \theta' Y_t \tag{17}$$

where θ is the $2\,x\,1$ permanent component coefficient vector. It should be noted that the dimension of the permanent component is one since cointegration suggests one common stochastic trend in Y_t. Booth et al. [1999, 2002] and Harris et al. [2002] develop normalised coefficients in θ' that convey information with respect to contributions to the common factor made by the original non-stationary series in Y_t. Such information is interpreted as the contribution of the series to the price discovery process. Let θ =[θ_1,θ_2]' and θ is orthogonal to α in Eq.13 Then we can have component share (CS) as follows

$$\theta_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, \qquad \theta_2 = 1 - \theta_1 \tag{18}$$

where θ_1 is the component share of the first series in Y_t and θ_2 is the component share of the second series in Y_t. Yan and Zivot [2010] interpret CS as the level of noise in one price series relative to the other.

Yan and Zivot [2010] further reveal that, given a case of two price series in Y_t, the resulting CS is a function of the dynamic responses of the two series to transitory shocks only, whereby transitory shocks are represented by noise due to trading frictions. Meanwhile, IS is a function of the dynamic response of the two series to both transitory and permanent shocks and permanent shocks are denoted by innovations in the fundamental values. In this case, IS and CS may give misleading information regarding price discovery in some situations due to their dependence on the dynamic response to transitory shocks (Putnins [2013]). To circumvent this problem, Yan and Zivot [2010] propose the information leadership share (ILS) to generate cleaner contribution of the series to the price discovery process as follows:

$$IL_1 = \left| \frac{IS_1}{IS_2} \frac{CS_2}{CS_1} \right|, \qquad IL_2 = \left| \frac{IS_2}{IS_1} \frac{CS_1}{CS_2} \right| \tag{19}$$

where IS_1 and IS_2 are the mid-points of information share of the two-price series in Y_t while CS_1 and CS_2 are component share of the two-price series in Y_t. Putnins [2013] proposes normalised metrics based on Eq.19 so that the range of ILS can be controlled between 0 and 1. Hence, we have the following:

$$ILS_1 = \frac{IL_1}{IL_1 + IL_2}, \qquad ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{20}$$

As can be seen from the equation above; ILS is a combination of CS and IS so that the impact from dynamic responses to transitory shocks is cancelled out and a clean measure of relative informational leadership is achieved.

In this paper, not only do we offer traditional static CS, IS and ILS measures, we also consider time variations of these metrics. The way to obtain time-varying CS, IS and ILS measures are as follows. First, we obtain time-varying error correction coefficients in the vector α of Eq.13

through applying a rolling window procedure to the full sample of the data[7]. Then the time-varying coefficients are used to calculate time-varying CS, IS and ILS measures. Second, the variance and covariance of innovations in the matrix Ω of Eq.15 is replaced by the conditional time series of the variance and covariance which are obtained from the bivariate VEC/VAR-DCC-GARCH model[8]. In our procedure, the error correction coefficients and the variance-covariance matrix of innovations which carry key information of information share measures, are both modelled to be time-dependent. Moreover, to present a clearer picture of the informational roles of Boeing relative to other counterpart airline companies in each pairwise long-run price discovery process, we calculate logarithmic ratios of the information share measures as follows:

$$CS\,ratio = log\left(\frac{CS_s}{CS_c}\right), \qquad IS\,ratio = log\left(\frac{IS_s}{IS_c}\right), \qquad ILS\,ratio = log\left(\frac{ILS_s}{ILS_c}\right) \tag{21}$$

where $log(.)$ denotes the natural logarithm. CS_s and CS_c are component share of Boeing and one counterpart airline company, respectively. IS_s and IS_c are mid-points of information share of Boeing and a counterpart airline company, respectively. ILS_s and ILS_c are information leadership share of Boeing and a counterpart airline company, respectively. Note that a positive log ratio suggests Boeing dominates in the long-run price discovery process while a negative one suggests a counterpart airline company dominates in the long-run price discovery process. We also calculate time-varying ratios by using time-varying CS, IS and ILS in Eq.21. Moreover, based upon those time-varying CS, IS, and ILS ratios, we examine whether the two crash events of the Boeing 737-MAX aircraft affect the CS, IS and ILS of Boeing relative to other counterpart companies. An extended autoregressive (AR) model is specified for this testing purpose as follows

$$\text{CS Ratio}_t = \text{Constant} + \sum_{i=1}^{p} \lambda_i \text{CS Ratio}_{t-1} + \phi_1 D_{1,t} + \phi_2 D_{2,t} + \varepsilon_t \tag{22}$$

$$\text{IS Ratio}_t = \text{Constant} + \sum_{i=1}^{p} \lambda_i \text{IS Ratio}_{t-1} + \phi_1 D_{1,t} + \phi_2 D_{2,t} + \varepsilon_t \tag{23}$$

$$\text{ILS Ratio}_t = \text{Constant} + \sum_{i=1}^{p} \lambda_i \text{ILS Ratio}_{t-1} + \phi_1 D_{1,t} + \phi_2 D_{2,t} + \varepsilon_t \tag{24}$$

where $CSRatio_t$ is the logarithmic ratio of the time-varying component share of Boeing relative

[7]The window size is normally set to be 100 and the step size is 1. In the case where the lag order k of Eq.13 is large enough, a larger window size might be used.

[8]When calculating the CS, IS and ILS measures, we employ a standard form of the VEC model as specified in Eq.13 where there are no drifts in price series and the cointegration equation has a zero mean. Note that we consider the effects of the two crash events on return series in the conditional mean equations of the DCC-GARCH model in Eq.7.

to a counterpart airline company. $ISRatio_t$ is the logarithmic ratio of time-varying mid-point information share of Boeing relative to a counterpart airline company. And $ILSRatio_t$ is the logarithmic ratio of time-varying information leadership share of Boeing relative to a counterpart airline company. $D_{1,t}$ is a dummy variable where it takes a value of one when the sample period is from October 29, 2018, to November 18, 2018; and zero otherwise. $D_{2,t}$ is a dummy variable where it takes a value of 1 when the sample period is from 10 March 2019 to 30 March 2019; and zero otherwise. The lag order p is chosen according to AIC. ϕ_1 and ϕ_2 examine the effects of the two crash events on the log ratios of time-varying information share measures.

5. Results

5.1. Cumulative Abnormal Returns

We begin our analysis by focusing on the cumulative abnormal returns generated during significant events, whether positive or negative, deviations from each respective market index provides significant information as to the performance of each corporate entity. In Table 4, we present time-varying summary statistics with regards to the returns of both Boeing and the airline average as calculated by the average of the airlines listed in Table 3. Several interesting observations can be made from such analysis. We can identify, that during a period of turmoil in the aftermath of the events of 9/11 in the US and the rapid environmental changes that took place with regards to international travel, Boeing and the broad aviation sector presents evidence of negative mean returns throughout 2001 and 2002. While Boeing returns return to a positive average in 2003 (+0.0011), the negative returns experienced in the aviation industry persist throughout 2006. While the sectoral average and both the maximum and minimum levels of returns for the aviation industry remain relatively stable and close to a range between -3% and +3%, there are many years in which Boeing experiences exceptional volatility in comparison. In 2008, Boeing experienced a daily positive increase in the share price of +15.46%, while in 2016, in one day's trading, the company lost -8.92%. In the period 2018 through 2020, the company experienced minima of -6.59%, -6.79% and -23.5% respectively, presenting evidence of the sharp susceptibility of the company to negative investor sentiment.

Insert Table 4 about here

In the next stage of the analysis, we present the cumulative abnormal returns during key events during the life of the Boeing 737-MAX. Data is separated with regards to Boeing, and the average airline as segregated by low, medium, and large market capitalisation, and then again, by type of airline structure (whether it be denoted as a low-cost airline, a full-service airline, a leasing company, or a charter carrier). In Figure 1, we observe that in response to the maiden 737-MAX flight, Boeing CARs fell to -30% below its share price almost four months period. In the same period, however, when considering airlines with substantial usage of Boeing aircraft, both medium and large companies present negative CARs of -4.7% and -6.2% respectively when compared with three months prior, while small airlines experience share price appreciations of +8.7% in the same period. When estimating CARs by type of airline, low-cost airlines are found to experience CARs of +9.4% for the same period, and while charter companies present evidence of CARs of +1.9%, both full-service airlines and leasing companies present negative CARs (-10.7% and -6.6% respectively). Further, in Figure 1 we observe the granting of the FAA certificate with regards to the 737-MAX, and while presenting little in the way of a significant response by the size of the airline, on the date of the announcement, Boeing CARs were +14.8%, with only charter airlines presenting a similar scale of response (+10.3%) while leasing companies were the only type of airline to present negative CARs during the same period (-2.9%).

Insert Figure 1 about here

In both Figures 2 and 3 we observe the CARs during the period surrounding the Lion Air crash in October 2018 and the Ethiopian Air crash in March 2019. In the first event in Figure 2, we identify the sharp decline in the price of Boeing, as could be expected in the aftermath of such a tragedy. However, while there is limited evidence of size-denoted differentials for airlines with significant Boeing airline holdings, there are substantial differentials when focusing on the estimated CARs by type of airline. In the aftermath of the first Boeing 737-MAX disaster, full-service airlines are found to appreciate by approximately +10% in the three months thereafter. In contrast, all other types of airlines fall more than 5% in the same period, presenting the first evidence of varying behaviour based on the type of analysed airline. However, while the sharp sense of shock from the first 737-MAX disaster was still dissipating, Figure 3 presents evidence of an even more pronounced response in the aftermath of the Ethiopian Air crash, the second 737-MAX disaster in six months. Boeing's share price fell over 20% over the market index in the immediate aftermath. While large and medium-sized airlines present evidence of positive CARs in the aftermath of the second 737-MAX disaster (of 4.1% and 6.2% respectively), smaller airlines with substantial 737-MAX orders present negative CARs of -10.4%. Such a result presents evidence that investors had begun to identify issues with regards to the large financial implications of such smaller airlines possessing such high-risk orders in such a perceived high-risk vehicle. For many larger companies, diversification could be sourced in the use of other types of aircraft such as Airbus, for example, however, some smaller companies had only ever dealt with Boeing before. Many companies had all of their fleet entirely based in the 737-family. Low-cost and charter airlines present evidence of the largest loss-makers during the period after the second 737-MAX disaster (losing -3.8% and -2.8% respectively). However, full-service airlines presented relatively unchanged CARs during the same period, while leasing companies share prices increased by +7.1% over the market index during the same time. These results again present evidence of the susceptibility of low-cost and charter carrier airlines to the reputational damage experienced by Boeing and the 737-MAX, particularly due to both types of airlines relying significantly on the technological and efficiency benefits from ordering such aircraft.

Insert Figures 2 and 3 about here

With regards to the December 2019 decision to change the Boeing CEO, Mr Dennis Muilenburg, we observe that in the one month after the announcement, Boeing CARs increase by approximately +5.0%. Large airlines appear to present similar trends, however, both medium-sized and small-airlines present evidence of declines in CAR by approximately -3.1% and -2.6% respectively. In the same period, both charter companies and low-cost airlines experience elevated CARs of +8.7% and 1.9% respectively, while both full-service airlines and leasing companies experience moderate declines in CAR of -2.4% and -1.6% respectively.

Insert Figure 4 about here

In Figures 5 and 6, we identify the CAR response for 60 days after each airline disaster (Lion Air in 2018 and Ethiopian Air in 2019) as separated by airline size in Figure 5 and type of airline in Figure 6. While each identified event considered is combined into a single analysis, we can identify some interesting observations. While initially experiencing positive CARs of approximately +3.1% in the 3 days after a major event with Boeing, small airlines experience a reduction in share price in the period thereafter, peaking with a negative CAR of -10.7% approximately 7 weeks after the event. However, while initially presenting negative CARs of approximately -2%, both medium and large airlines quickly increase and present no apparent side-effects simultaneously to the calculated sharp fall of Boeing, which is found to be as pronounced as -33.2% within three weeks of the event. When analysing the same data when separated by type of airline, we observe that each type of airline experiences sharp negative CARs in the aftermath of the disasters, however, initially, charter airlines experience a pronounced period of negative CARs with a minimum level of -13.8% four weeks after the event, however, within another 10 days, such CARs turn briefly positive. While the other three types of airline fluctuate between positive and negative returns in the four weeks after each Boeing disaster, both full-service companies and leasing companies CAR turn positive (greater than +5%), presenting evidence that larger full-service companies have diversification ability through the use of airlines other than Boeing and a broader range of other services and ability to generate revenue through alternative sources, while leasing companies experience a potential separation of any perceived responsibility through their third-party role in the airline leasing relationship.

Low-cost airlines experience a very different response. While initially experiencing positive CARs, as the Boeing situation and subsequent allocation of responsibility became clear in the period approximately four weeks after the first event, the CARs of low-cost carriers turned negative, and fell persistently for the following month, experiencing a low of -9.3% approximately eight weeks after the event. It is at this point; the investors appear to have fully considered the substantial ramifications of the 737-MAX crisis and the potential implications for low-cost carriers whose business model was identified to be heavily reliant on the success of this new aircraft with advanced efficiency and capacity.

Insert Figures 5 and 6 about here

In Table 5, we present the results of a regression analysis focusing on the CARs of airlines in the periods surrounding each of the aviation disasters surrounding the Boeing 737-MAX. Boeing is found to be significantly, negatively related to the returns of the airlines throughout the combined periods inclusive of both before and after the event. However, it is interesting to note that in the period exclusively before the event, [-20,-1], Boeing is found not to be significantly related (-0.47%) with each group of airlines, however, in the period after, the result is significant at the 1% level with an estimated coefficient of -21.80%. This presents significant evidence of significant interactions between Boeing and the selected airlines. When focusing on the size of the airline, significant effects are found for most periods analysed, particularly for the two smallest and two largest cohorts analysed by size. In the period before the accident, the smallest group of airlines are found to present CARs of -0.61% before a Boeing 737-MAX event, even though no airline has taken delivery of the new aircraft, however, it is accepted as publicly available information that each has substantial orders in place for future delivery. In the period after each disaster, the smallest two groups are found to present negative CARs of -2.58% and -4.58% respectively. With regards to the largest airlines, no significant interactions are identified in the period before the accidents, however, return coefficients of -2.48% are identified in the period thereafter. Low-cost airlines and leasing companies, similar to the earlier presented results are found to present significant negative effects in the period after each event, of -1.41% and -1.61% respectively. Charter carriers are found to present less significant, and smaller estimates of the interaction of -0.46%. It is interesting to note that the scale of the significant results is more pronounced in both the [-15,+15] and [-10,+10] day periods surrounding the events, suggesting that although the initial response is quite acutely negative, evidence suggests that such effects dissipate in the days following thereafter.

Insert Table 5 about here

In Table 6, we observe the results of a regression analysis that is separated by type of airline investigated. Limited significant results are presented for leasing companies that have 737-MAX orders. However, there is a tentative negative relationship identified between leasing company size and estimated CAR. With regards to low-cost airlines, a substantiative, positive, and significant relationship is identified between market capitalisation and CAR, of +0.0089 for the period [-15,+15] and +0.0078 for the shorter-term period of [-1,+1], indicating that larger low-cost airlines are somewhat sheltered from substantial reputational side-effects from the Boeing 737-MAX disasters. However, this result also indicates that smaller, low-cost carriers are exceptionally vulnerable due to the exceptionally hostile environment experienced in such an exceptionally competitive environment. Similar results are identified with regards to full-service airlines and charter carriers, however, simultaneously, significant negative relationships are obtained between the number of orders and estimated CARs, indicating that those airlines with larger orders tend to exhibit less suppressed estimated CARs. While in Table 7, the results of an analysis inclusive of the entire sample regardless of airline type is presented. Negative interactions are presented with Boeing throughout the sample, irrespective of the type of Boeing event analysed. In the three days surrounding each event, there is a positive coefficient of +0.0005 for the relationship between the variables and market capitalisation, presenting evidence that larger companies exhibit larger positive returns. However, a negative, significant estimate of -0.0072 is identified for the variable relating to 737-MAX orders, indicating that those with larger aircraft orders with Boeing exhibit more significantly negative CARs during the sample analysed.

Insert Tables 6 and 7 about here

In Table 8, we present the estimated change in price correlation between each airline type and Boeing in the period before and after the first 737-MAX aviation disaster in the form of the Lion Air crash in October 2018. While the average correlation between Boeing and the average airline is found to be +0.341 for the entire period throughout 1 January 2000 and 31 May 2020, there are many very significant changes based on three specific groupings. First, we investigate the effects upon each airline by size. Results indicate that smaller airlines have experienced a proportionally larger increase in correlation in the period after the first 737-MAX aviation disaster. The smallest two groups experience a change in the correlation of +0.131 and +0.120 respectively, whereas the largest two quintiles of airlines based on size result in changes of +0.049 and -0.017 respectively.

Insert Table 8 about here

The second group of airlines under observation is that as separated by the number of orders placed by the analysed airlines for the 737-MAX. Results indicate that companies with larger numbers of orders are found to experience a larger increase in correlation with Boeing's share price, with the two largest groups exhibiting significant positive changes in the correlation of +0.363 and +0.401 respectively. This is perhaps the most significant and concise evidence provided that investors had identified the direct influence of reputational contagion and subsequent effects on companies who had decided to order and take delivery of this new aircraft. The final group of airlines analysed are those as separated by type. In line with previous evidence presented, both low-cost airlines and leasing companies provide the largest positive increases in correlation in the period after the 737-MAX disasters with estimates indicating significant increases of +0.317 and +0.180 respectively. Full-service airlines and charter carriers present nominal estimated changes of +0.016 and -0.028 respectively.

5.2. The bivariate VEC/VAR-DCC-GARCH methodology

The result of the bivariate VEC/VAR-DCC-GARCH model is presented in Table A1. The Ljung-Box and ARCH tests suggest that the model is well specified since there are no autocorrelation and heteroscedasticity detected in the standardised innovations. It should be noted that the estimation is respectively conducted for 36 samples of Boeing and one counterpart company's prices. Among the samples, cointegration exists for 12 pairs of price series[9]. Henceforth, the VEC model is specified for these samples. For the rest of the samples, the VAR model is specified. The result of the VEC model suggests that the error correction coefficients for the counterpart companies that transact orders of Boeing 737-MAX aircraft with Boeing are statistically significant for 9 out of 12 samples. And with the same 9 samples, the error correction coefficient for Boeing is not significant. This suggests that Boeing leads the counterpart company in the long run. For the samples of Boeing and 9 Air, error correction coefficients for both series are significant whereas the coefficient for 9 Air has a larger magnitude. It suggests that Boeing leads 9 Air in the long run. In contrast, the error correction coefficients for Boeing and Ryanair are both significant where the coefficient for Boeing is larger. At the same time, the error correction coefficient for Aviation Cap. is not significant whereas that for Boeing is significant. Hence, for the relationships of Boeing with Ryanair and Aviation Cap., Boeing is overshadowed by the two counterpart companies in the long term. [10] Furthermore, there is evidence that the second crash event occurring on 10 March 2019 of Boeing 737-MAX aircraft significantly reduces Boeing returns. In addition, concerning the effects of the two crash events on returns of the counterpart companies, the first event taking place on 29 October 2018 significantly increases returns.

[9] The result of the cointegration test is available upon request.

[10] It is important to note that Aviation Cap is a largely Airbus fleet (nearly 100% until 2019) and currently 5 out 24 aircraft are Boeing 737 NG. They do have significant orders with Boeing for the 737-MAX, illustrating a future transition of the leasing company's stock.

Insert Table A1 (Appendices) about here

As can be seen from Table A1, the GARCH effects are significant for all the companies where the conditional variances of both Boeing and counterpart companies are significantly driven by past shocks and lagged own values. In the meantime, the conditional correlation is affected by past shocks and its own lagged values, pointing to a time-dependent behaviour. We find that the two crash events significantly affect the conditional variances of Boeing and the counterpart companies. The two crash events significantly increase the conditional variance of Boeing. The positive effect of the second crash event is more pronounced. In contrast, the first crash event significantly reduces the conditional variances of a large proportion of the counterpart companies, except for a few companies' variances being positively affected. The impacts of the second crash event on the conditional variances of the counterpart companies are mixed where the effects are negative on the conditional variances of 11 companies while the effects are positive on the conditional variances of 8 companies. Lastly, the kurtosis parameter of the SNP approach is statistically significant for all the samples. It suggests that the kurtosis of the marginal distribution should be considered when estimating the DCC-GARCH model.

Insert Figure 7 about here

Figure 7 visualizes the daily movements of the time-varying error correction coefficients. Note that the time-varying error correction coefficients are obtained via a rolling window procedure on the VEC model. It is observed that the error correction coefficients of Boeing and the counterpart companies vary over time. Some oscillations of the error correction coefficients are observed around the two crash events. For instance, concerning samples of Boeing and 9 Air and Boeing and CALC China, the error correction coefficients of Boeing and counterpart companies move in an opposite direction, where the coefficient of Boeing decreases and that of the 9 Air or CALC China increases during a period between the two crash events. During the same period, the error correction coefficients of Boeing and some other counterpart companies move in a similar direction. Examples include Air Canada and Turkish Airlines where the error correction coefficients of Boeing and both companies drop in tandem.

Insert Figure 8 and 9 about here

The daily movements of conditional variances of Boeing and counterpart airline-related companies are depicted in Figures 8 and 9. Firstly, some variations that align with the result of Table A1 are observed around the two crash events for conditional variances of Boeing and counterpart companies. A second observation is that the conditional variances of Boeing and the counterpart companies increase sharply during the global financial crisis in the years 2007 – 2009 and during the period of late 2019 to early 2020 where the COVID-19 pandemic takes place.

5.3. Information shares and price discovery due to Boeing 737-MAX reputational devastation

The daily movements of logarithmic ratios of time-varying CS, IS and ILS measures of Boeing relative to counterpart companies are depicted in Figure 10. In the aftermath of the first crash event (three weeks after the occurrence of the event), the impact of the event continues as reflected by the oscillations of logarithmic ratios of information share measures. We observe falls of relative information share measures of Boeing to others. It shows that the information contents of Boeing prices are downgraded relative to the counterpart airline-related businesses following the initial impact of the first crash event. Secondly, in the aftermath of the second crash event, the oscillations of ratios are also observed. For most cases, there are increases in ratios of information share measures of Boeing relative to other counterpart companies, following the period of event's occurrence. It is shown that the information contents of Boeing prices are enhanced as the impact of the second crash event progresses three weeks after the advent of the event.

Insert Figure 10 about here

Table 9 presents the estimation result of an extended AR model for the effects of the two crash events on the logarithmic ratios of the ILS measures. The ratios of the ILS measure present strong autoregressive behaviour since they are significantly affected by their own lagged values. As can be seen from the table, the first crash event significantly increases the information leadership share of Boeing relative to 9 out of 12 airline-related companies. Moreover, the second crash event significantly increases the information leadership share of Boeing relative to 8 out of 12 airline-related companies. One exception is that the event significantly reduces the information leadership share of Boeing relative to CALC China. Therefore, after eliminating the noisy dynamic response to transitory shocks inherent in the functions of CS and IS measures, the pure relative leadership of Boeing prices in impounding innovations in fundamental values are elevated by the two crash events. Its informational role is thus enhanced by the two crash events.

Insert Table 9 and 10 about here

We also present the results of the extended AR model for the effects of the two crash events on the logarithmic ratios of both CS and IS measures. The results are shown in Tables 10 and 11, respectively. As can be seen from Table 10, the ratios of CS measure are explained by the own lagged values, showing autoregressive behaviour. There is no significant effect of the first crash event on the component share of Boeing relative to any counterpart company. However, the component share of Boeing relative to some counterpart companies (e.g., Air Canada, United Airlines and ICBC Leasing) significantly declines after the second crash event. In contrast, the component share of Boeing relative to Turkish Airlines significantly increases after the same event. Henceforth, the information contents of Boeing prices, as mirrored only by the level of noise of Boeing relative to other counterpart airline-related companies, are significantly affected by the second event. And most of the effects are negative.

Insert Table 11 about here

Table 11 reports that the logarithmic ratios of IS measure of Boeing over other counterpart companies present autoregressive behaviour, similar to the ratios of CS and ILS measures. More importantly, the first crash event significantly increases the information share of Boeing relative to the counterpart companies (e.g., Air Canada, United Airlines, Turkish Airlines, Jackson Square Aviation and CALC China). Moreover, the second crash event significantly increases the information share of Boeing relative to Nok Air and Turkish Airlines. In contrast, the same event significantly decreases the information share of Boeing relative to Aviation Capital Group and CALC China. Therefore, the first crash event positively affects the informational role, which is reflected by a combination of the relative level of noise and relative leadership in reflecting innovations in the fundamental values, of Boeing prices. In contrast, results for the second crash event are mixed. The second event increases the IS-related informational role of Boeing relative to small airline companies, whereas it reduces the IS-related informational role of Boeing relative to aircraft leasing companies.

5.4. Did aviation analysts underestimate the effects of Boeing's reputational contagion?

The aviation sector suffers from multiple information asymmetries as the operations of airlines, even in an era where travel agents have been largely abandoned by operators. Part of this relates to the extensive engineering knowledge required to understand the aircraft part of the sector, some of the complexities have been outlined above. As airlines operate in a network of international standards and many cases bilateral arrangements going back to the 1947 Chicago Convention on International Aviation, analysts find ways of explaining these to investors. In the case of the 737-MAX, an important International Civil Aviation Organisation regulation was ETOPS (Extended-range Twin-Engine Operational Performance Standards, (sometimes referred to by pilots as 'engines turn or passengers swim') which allows twin-engine aircraft like the MAX to operate non-stop on lucrative transatlantic routes. In addition to these aviation and airport aspects, analysts provide a window into the complex pricing and market structures used by airlines, as well as their approaches to new routes, fleet and manpower planning (Williams [2020]).

As the aviation sector is not very transparent for investors the role of aviation sector analysts is important in investment decisions. We estimate the mispricing correlations from analysts' recommendations to actual equity prices pre and post 737-MAX crashes. The results, presented in Table 12, are consistent with the knowledge that analysts would convey to their investors on the state of the aviation sector and exposure to the impact of the Boeing 737-MAX crash. First looking at the market capitalisation of airlines, those airlines with the lowest market capitalisation were the most exposed, with the 737-MAX crash creating a higher positive correlation between Boeing equity prices and airline prices. This is consistent with smaller airlines, many of which will be in the low-cost carrier segment where consumer safety considerations can become volatile and where fleets are small and leased. A good example of an airline in this area was Norwegian Air, which had a small but exclusively 737-MAX fleet that was instantly grounded. Those airlines with the largest market capitalisation saw their positive correlation fall, reflecting that the largest airlines include many full-service legacy airlines that have much more diverse fleets and are better able to manage their safety reputation image and compensate for any 737-MAX aircraft with alternatives.

Insert Table 12 about here

Orders are again consistent with expectations. While those with a smaller number of orders have had a higher positive correlation between Boeing and the airline equity price before the 737-MAX crash, that is consistent with the market capitalisation evidence. Smaller airlines will have small order books and have seen the MAX as a method of fleet management or fulfilling a niche operation. Those with a large number of orders had a lower positive correlation before the crash but a significant increase post-crash. This is consistent with known large purchasers who will be looking to the 737-MAX as a fleet replacement/renewal product or as an attractive leasing product. These purchasers would be fully aware that it may take many years before they are provided with all the aircraft they have ordered so have put in place management plans for their gradual introduction and the retirement/sale of the existing fleet. Therefore, the day-to-day movements of Boeing will have limited implications but significant, delivery-changing, events will be important. In such conditions, the woes of Boeing and the 737-MAX have a direct and immediate impact on their business models and hence equity prices.

The final analysis looks at different types of airlines. Here the story is consistent with the earlier analysis of analyst error and is consistent with the CARs and IS-CS-ILS analysis. Low-cost carriers have become associated with the 737 series of aircraft, most especially the US and European leaders, Southwest, and Ryanair. Consistent with their connection to Boeing and in the case of Southwest being the key US customer, the positive correlation between Boeing and airline returns dramatically increases post-crash. Low-cost carriers absorb all the risk that Boeing has been quietly adopting in delivering the 737-MAX. As these carriers will find it difficult, to impossible, to diversify away from their existing relationship with Boeing for the 737 series aircraft their fortunes will in part be determined by the success of Boeing at returning the MAX to revenue service. The same holds for aviation leasing companies, who also relied on the MAX as being a global winner in the short to the medium-haul aviation sector. Charter airlines, while still positively correlated, saw a reduction in that correlation. This may reflect their reliance on the aviation leasing sector for aircraft and their ability to manage their fleets, limiting the impact of the MAX crash. The most interesting result is that full-service carriers have a negative correction to Boeing. As full-service carriers have diverse fleets and European legacy carriers operate almost exclusively (and many exclusively) Airbus fleets, it is not surprising that the impact of Boeing returns will be negatively correlated with those full-service airlines. Even larger US airlines, like American, historically a major Boeing customer, having merged with US Air, absorbed a large fleet of Airbus aircraft, enabling it to engage in internal fleet management and to quiet safety concerns.

While analysts may not always be correct, the tightly-coupled and complex system that is the aviation sector, shows an important consistency between their qualitative and quantitative analytical conclusions on the movements of airline equity prices concerning Boeing and the wider empirical investigation undertaken throughout this paper. The consistent evidence is that Boeing's design and manufacturing decisions, its risk tolerance and its approach to regulatory compliance all increased the idiosyncratic risk of Boeing and impacted upon their products and their returns and that airlines with significant orders or operating a large number of Boeing aircraft were unable to hedge that risk and partially absorbed it. While Boeing was attempting to save time and money, and please airlines with a more profitable aircraft, it achieved none of those outcomes. It appears to have achieved the direct opposite for its key customers while incurring tremendous reputational damage.

6. Discussion

The evidence presented in the investigations above illustrate a consistent set of relationships between Boeing and the major Boeing purchasers/operators in the aviation sector. The CARs evidence highlights how the crashes of the 737-MAX impacted the airline sector. It is important to understand the differences between the first and second crashes in terms of responses. According to the National Transportation Safety Board (NTSB), the US regulator responsible for accident investigation highlight that the current rate is one fatality every 16.3m flight hours, making such events extremely rare but not impossible. The occurrence of two in a short period, and involving the same type of aircraft changed the interpretation of the event from one of an unfortunate accident to something more serious. This is evident by the responses of the markets, public and regulators.

The response of the full-service airlines is consistent with their structure and profile. They have more mixed fleets and in the context of the first crash, these airlines, most being legacy flag carriers, possess strong reputations with consumers for safety and reliability when compared with low-cost carriers and charter airlines (even when empirical evidence shows that many established low-cost carriers have exemplary safety records). Low-cost carriers, with their focus on a single type of aircraft for cost minimisation purposes, began to absorb the positive and negative impact of Boeing equity abnormal returns. The impact of the dismissal of the CEO of Boeing, while improving for Boeing, had no positive impact on the airlines themselves. This is not entirely surprising as the dismissal was an admission on the part of Boeing that the 737-MAX's problems were profound and that an airworthiness certification by the FAA was going to more serious effort and time on the part of Boeing. In basic terms, this meant that grounded 737-MAXs was going to remain that way indefinitely.

Our evidence from the DCC-GARCH investigation is consistent with the CARs findings. The second crash event results in significant changes in the conditional variances of Boeing and counterpart companies. There are also distinctions within the airline sector. Smaller airlines and airlines not located in advanced economies respond differently. Those airlines are subject to greater concern about safety compliance and awareness that US and European Union safety requirements have a higher threshold than other jurisdictions (for example, the EU operates a no-fly rule for certain airlines and certain types of aircraft on safety grounds.)

The evidence provided by the DCC-GARCH is consistent with the response to the second crash impacting Boeing and on airlines with a large proportion of Boeing aircraft. This can be seen in the responses of Ryanair and Southwest, before and after the crashes as well as smaller airlines such as NOK Air and Norwegian Air Shuttle and some leasing companies AerCap. The lack of response on IAG, a full-service carrier with a diverse fleet, is consistent with the evidence presented in other methods of analysis. The response of American Airlines is consistent with an airline that is approximately 50% Boeing and one of the longest-standing customers of Boeing. Detailed evidence of proportional ownership of aircraft as primarily separated by Airbus and Boeing is presented in Table 13. At the same time, American Airlines, having merged with Airbus dominated US Airways in 2015, dramatically diversifying its fleet and exposure to Boeing news, but it still has an impact. Some unusual firms are influenced by Boeing, such as the China Development Bank, reflecting its large orders with Boeing for the MAX.

Insert Table 13 about here

In the analysis of information flows and price discovery, the evidence is consistent with the DCC-GARCH and with the analysts' recommendations, that the second crash increases the information share from Boeing to the airlines, most especially small airlines, which would have smaller fleets and less capacity to manage the grounding of the MAX or indefinite delays in the MAX. The reduced information share after the second crash to the leasing companies may reflect the capacity of those companies to manage their fleets and cancel orders, limiting financial risk. The initially higher transfer and subsequently lowed information transfer for Air Canada and United Airlines is consistent with the evidence that larger, full-service airlines can engage in fleet management that while still financially hurt by the MAX grounding will be able to compensate for those aircraft through their diverse fleet.

Looking at the counterfactual, there is no IS-CS-ILS relationship between the low-cost carrier Easy Jet and Boeing. This makes sense at Easy Jet is a 100% Airbus operator and a major customer for the A320neo. So, even as a low-cost carrier, it has no interface with Boeing and the crashes of the 737-MAX would have not generated reputation effects or resulted in the grounding of aircraft.

The analysts' errors are also consistent with the evidence presented in the earlier sections of the analysis. Boeing's post-crash equity woes were reflected in the behaviour of airlines that typically have large numbers of Boeing aircraft, such as the low-cost carriers and aviation leasing corporations. The negative relationship, post-crash, between Boeing and the full-service carriers is also consistent with the earlier analysis, as it reflects the capacity of those airlines to engage in fleet management as they have much more diverse fleets in comparison to smaller airlines and those low-cost carriers which gravitate towards single model fleets.

Why are airlines so sensitive to the performance of an aircraft manufacturer such as Boeing? It is important to note that airlines make money when flying. Airlines generate costs when their aircraft is on the ground. At the same time many airlines, especially low-cost carriers, are very sensitive to fuel costs but generally, airlines avoid fuel-inefficient aircraft. Low-cost carriers also avoid time-consuming airports and attempt to spend a minimum amount of time on the ground between flights. In the case of Ryanair, this is embodied in the famous 22-minute turnaround. All carriers, but especially low-cost carriers prioritise the importance of a high load factor (that is, flying with as many filled seats as possible).

The crashes resulted in a safety concern, inducing fear in the flying public for airlines with MAX or large numbers of similar in name and appearance Boeing 737 aircraft. This hurts the load factors of airlines. Also, the subsequent grounding of the MAX induced airlines to violate this iron-clad business rule. Boeing did provide support to those airlines with grounded aircraft, but many were located in awkward locations, taking time for relocation (some continue to be located in the jurisdictions where they initially landed after grounding) and beyond that forcing airlines into costly contingency plans.

Consistently our hypotheses were confirmed about how the impact of the 737-MAX milestone events and crashes transferred the risk and volatility from the Boeing corporation to the major customers of the Boeing corporation – airlines and leasing companies. Why? The aviation sector is a highly complex sector with many information asymmetries, including sector insiders. Airlines closely align their operations to the capabilities of their aircraft manufacturers and come to rely on new aircraft to maintain market share and profitability. Some airlines become co-dependent with a manufacturer. Others diversify and are large enough to mix economies of scope with economies of scale. Leasing operations seek products that have attractive marketability to a diverse set of operators. As Boeing was aware of this, it tailored its aircraft to suit its customers' demands and to deliver it quickly, resulting in compromises that were ultimately the undoing of the MAX. This is not something the airlines and leasing companies could anticipate but were forced to accept the consequences of grounded and undelivered aircraft. In the unique context of aviation, Boeing's failures not only hurt itself but also its important customers, most especially the low-cost carriers.

7. Conclusions

Boeing's 737-MAX was intended to be the competitive answer to the Airbus A320neo. It was going to keep Boeing in the narrow-body game globally and illustrate all of the learning that had taken place from the difficult birth of the 787 Dreamliner. The customers, airlines, wanted the current 737, but better in every way, competitively priced and that their existing 737 pilots could jump into the cockpit on the first day. This was the intention. To achieve it, Boeing took decisions that exhibited a high degree of risk tolerance.

Part of the process involved Authorised Representatives (ARs) were Boeing staff that acted on behalf of the FAA. Boeing, with intimate knowledge of aircraft and the FAA rules, was granted wide-ranging self-certification powers via ARs and an ability to optimise changes so as not to trigger the re-certification processes. The investigations illustrated how Boeing was in the process of developing an aircraft that met the desires of customers, but, to achieve this took shortcuts. Boeing told neither the FAA nor customers of these shortcuts, including the role of the novel MCAS system on the performance of the aircraft under a particular set of flight conditions. To customers, this was the better in every way 737 they asked for and were delivered.

Following the two fatal crashes of the 737-MAX it was clear that something was profoundly wrong with Boeing's new aircraft and the FAA grounded it indefinitely. U.S. Congressional investigations and the wider evaluation of the engineering community discovered a sequence of decisions that pointed to a company suffering from problematic management practices and an aggressive risk appetite. Airlines and leasing companies with large or exclusive Boeing fleets began to absorb the financial risk and volatility that was originating from Boeing following the second crash. This was especially true for low-cost carrier airlines, many of which exclusively flew the 737 series aircraft. Customers, airlines, and leasing companies did not know the internal decisions that Boeing made in the process of development but internalised the idiosyncratic risk. Customers, airlines, had no option to hedge or diversify except by purchasing different aircraft or cancelling orders once the crashes and grounding had taken place.

Grounded aircraft is ultimately bad for business, not just for Boeing but for the airlines that use them. Going back to the example of the 787 Dreamliner analysed, the outcome was higher costs and more delays. In the case of ANA (All Nippon Airways) and the 787 Dreamliner, the 787 Dreamliner battery fires had negative reputation effects for ANA. Grounding the new aircraft in its fleet resulted in losses for ANA as well as the reputation effects. This mattered as the 787 was to bring about an improved flying experience for their customers, not a source of risk and delays. The aviation sector relies on reputation, not only for timeliness and comfort but most importantly safety. The protracted and ongoing problems at Boeing, and of the MAX, continued to chip away at the reputations of carriers with large Boeing fleets, especially those with the physically similar 737-NG series.

Problems of the 787 Dreamliner in terms of management decisions were reprised in the development of the 737-MAX. Boeing's poor decisions previously brought about an aircraft that was over budget, delayed and briefly grounded. This time the cost financially and in terms of reputation will be difficult to fully quantify but it is clear from our research that part of that cost has already been borne by Boeing customers by sharing in their poor performance.

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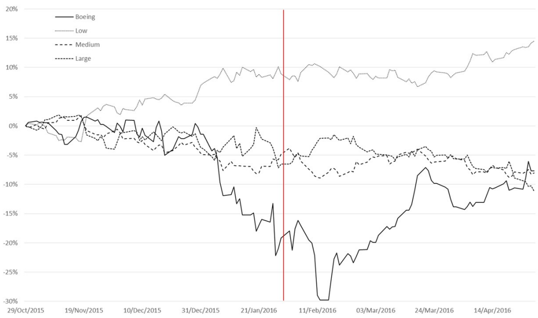
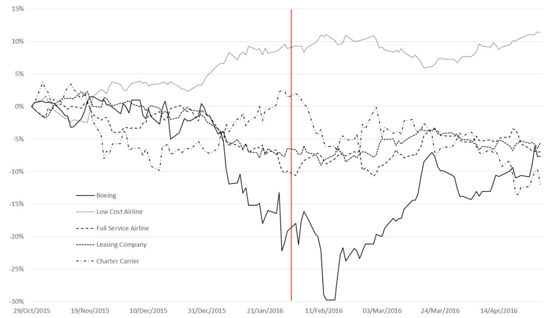
Figure 1: CAR performance due to 737-MAX maiden flight & FAA certificate award

Maiden 737-MAX Flight, 29 January 2016

a) Market Capitalisation

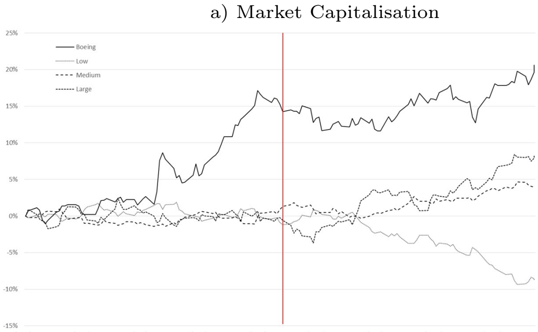


b) Airline Type

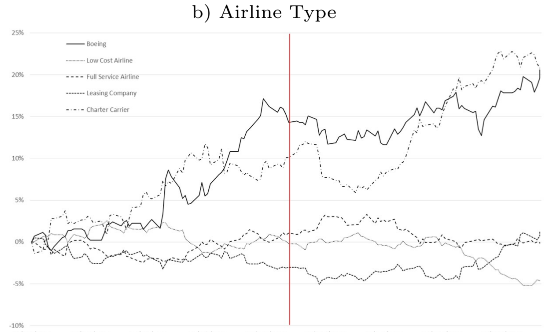


Granting of FAA Certificate, 8 March 2017

a) Market Capitalisation



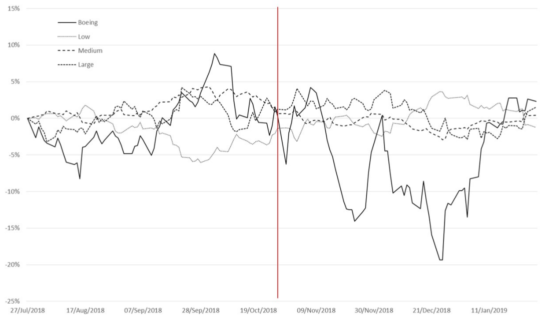
b) Airline Type



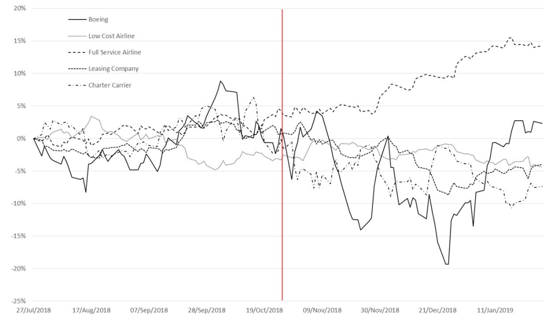
Note: This figure shows the average cumulative abnormal returns by size for a 181 day window [-90,+90]. When considering market capitalisation, the low category firms represent the smallest firm size while the high category represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

Figure 2: CAR performance due to the Lion Air Crash, 29 October 2018

a) Market Capitalisation



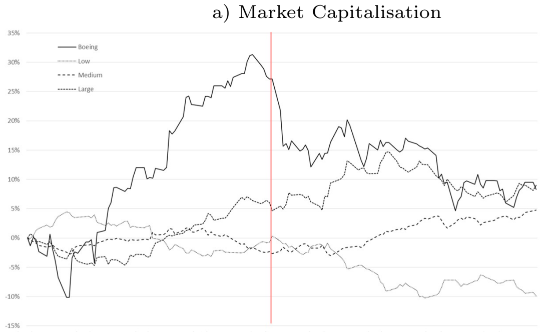
b) Airline Type



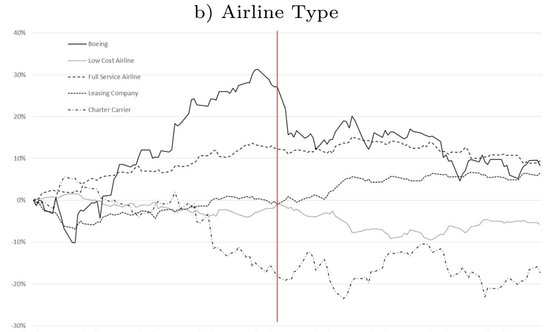
Note: This figure shows the average cumulative abnormal returns by size for a 181 day window [-90,+90]. When considering market capitalisation, the low category firms represent the smallest firm size while the high category represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

Figure 3: CAR performance due to the Ethiopian Air Crash, 10 March 2019

a) Market Capitalisation



b) Airline Type



Note: This figure shows the average cumulative abnormal returns by size for a 181 day window [-90,+90]. When considering market capitalisation, the low category firms represent the smallest firm size while the high category represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

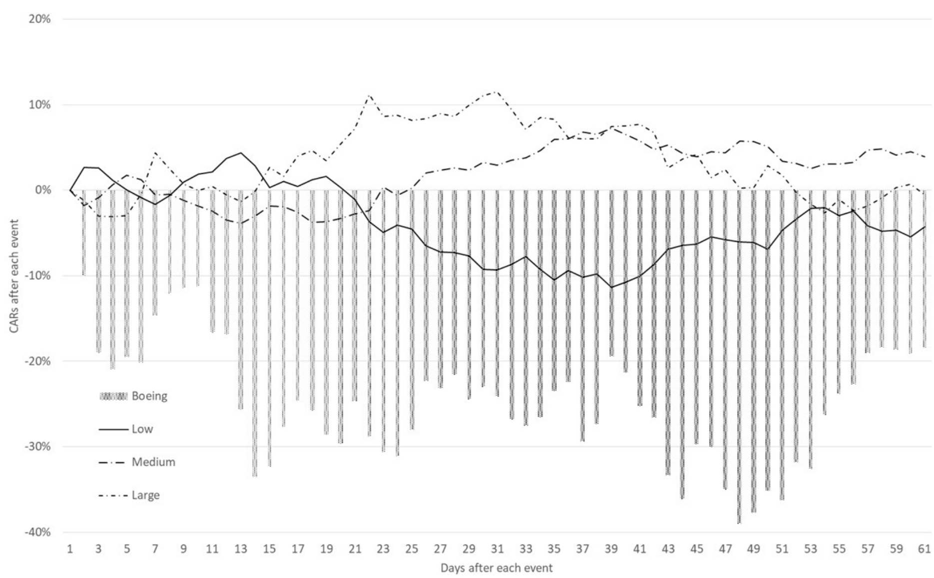
Figure 4: CAR performance due to the Boeing Executive changes, 23 December 2019

a) Market Capitalisation

b) Airline Type

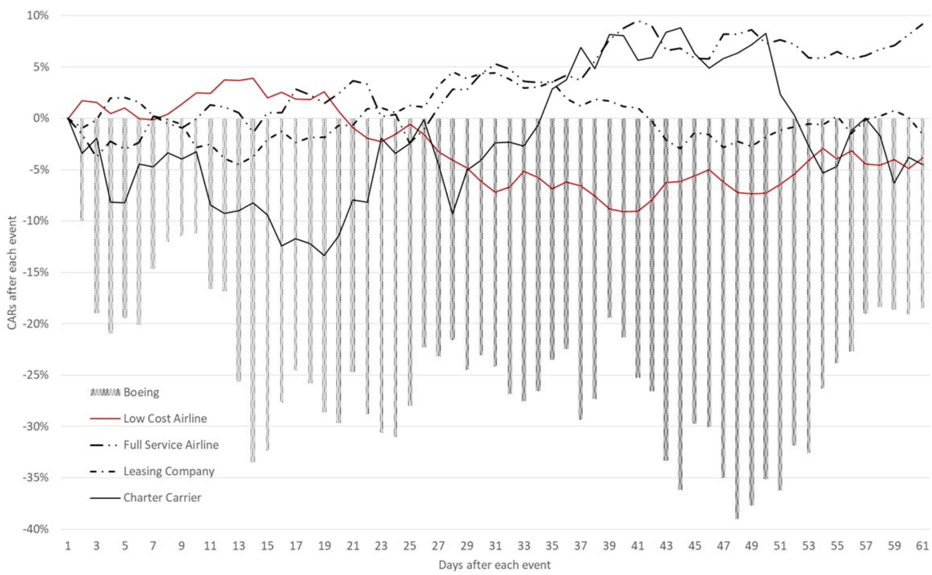
Note: This figure shows the average cumulative abnormal returns by size for a 181 day window [-90,+90]. When considering market capitalisation, the low category firms represent the smallest firm size while the high category represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

Figure 5: CARs by corporate size (during the aftermath of the Lion Air disaster in 2018 and Ethiopian Air disaster in 2019)



Note: This figure shows the average cumulative abnormal returns by size for a 61 day window [0,+60]. When considering market capitalisation, the low category firms represent the smallest firm size while the high category represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

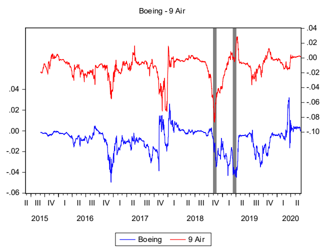
Figure 6: CARs by airline type (during the aftermath of the Lion Air disaster in 2018 and Ethiopian Air disaster in 2019)



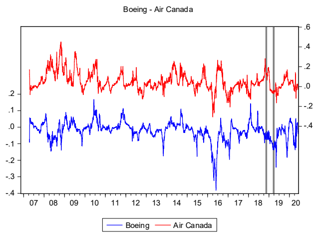
Note: This figure shows the average cumulative abnormal returns by size for a 61 day window [0,+60]. When considering market capitalisation, the low category firms represent the smallest firm size while the high category represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

Figure 7: Time-varying error correction coefficients

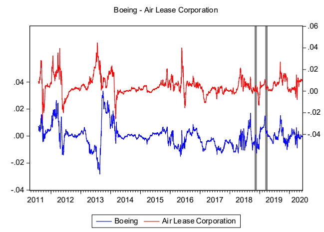
(a) Boeing-9 Air



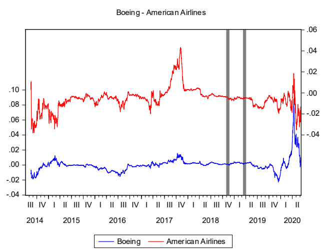
(b) Boeing-Air Canada



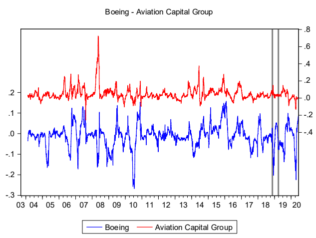
(c) Boeing-Air Lease Corporation



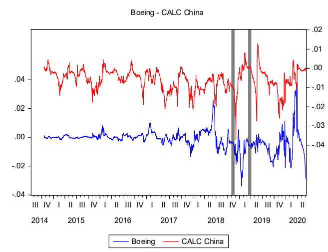
(d) Boeing-American Airlines



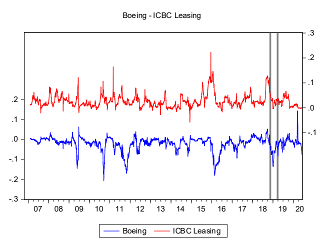
(e) Boeing-Aviation Capital Group



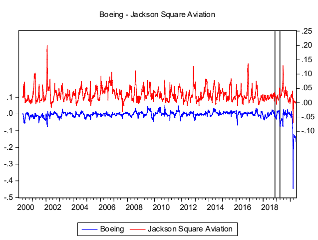
(f) Boeing-CALC China



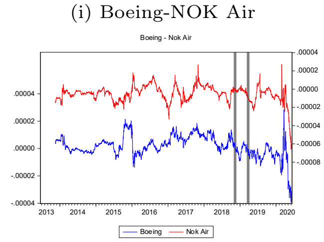
(g) Boeing-ICBC Leasing



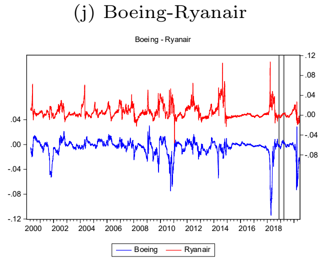
(h) Boeing-Jackson Square Aviation



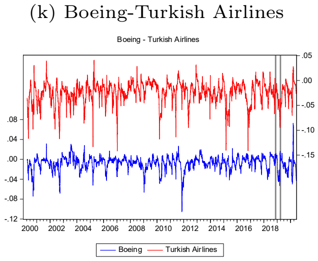
(i) Boeing-NOK Air



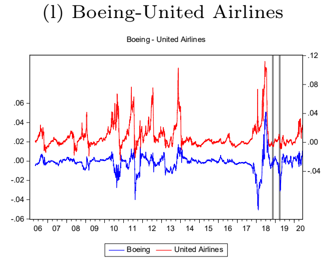
(j) Boeing-Ryanair



(k) Boeing-Turkish Airlines

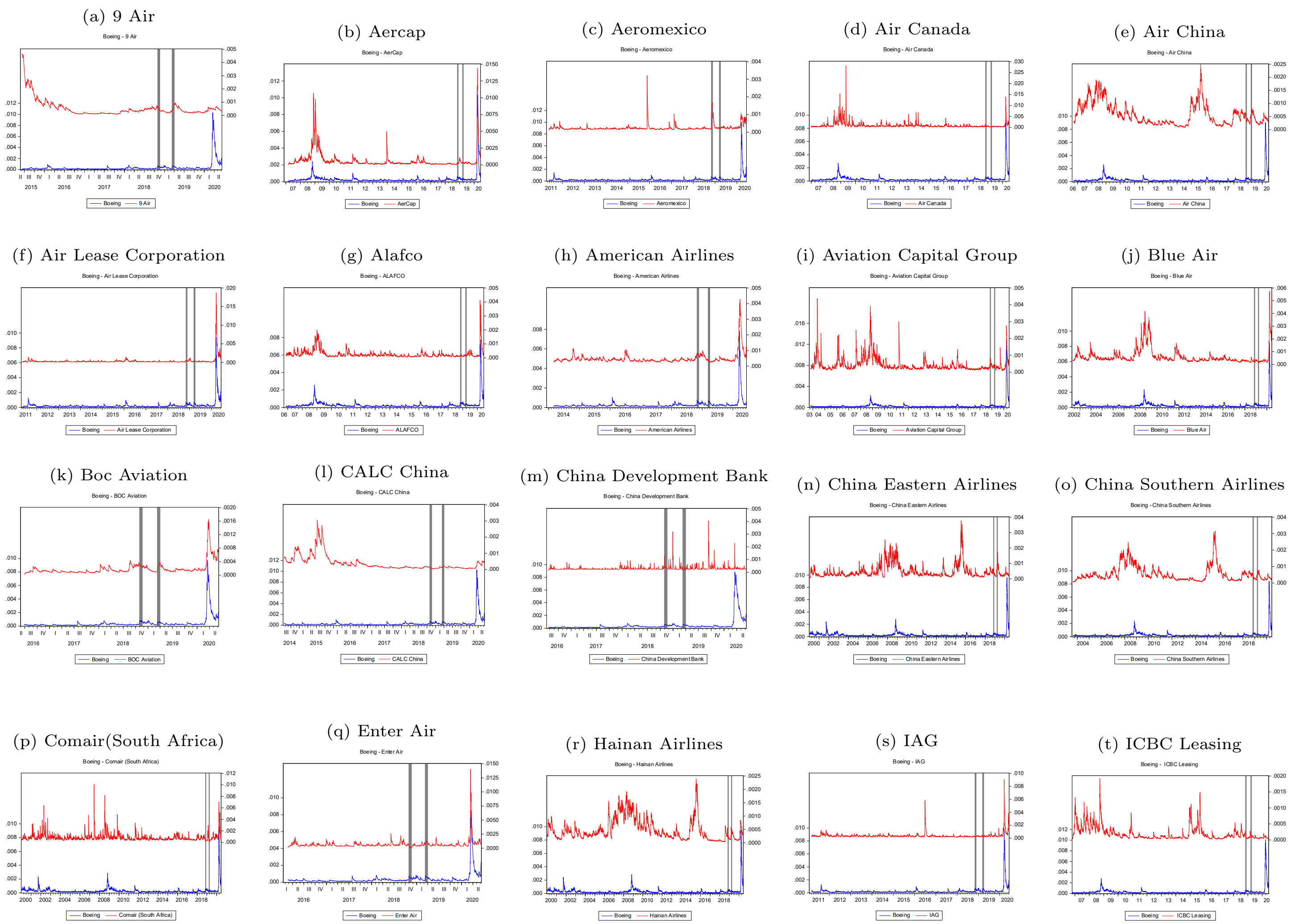


(l) Boeing-United Airlines



Time-varying error correction coefficients are obtained via a rolling window method on estimation of the bivariate VEC model. The first shaded area is the sample period from 29 October 2018 to 18 November 2018. The second shaded area is the sample period from 10 March 2019 to 30 March 2019.

Figure 8: Time-varying conditional variances



(a) 9 Air (b) Aercap (c) Aeromexico (d) Air Canada (e) Air China

(f) Air Lease Corporation (g) Alafco (h) American Airlines (i) Aviation Capital Group (j) Blue Air

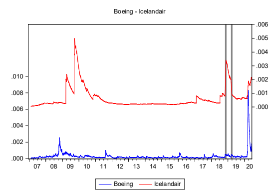
(k) Boc Aviation (l) CALC China (m) China Development Bank (n) China Eastern Airlines (o) China Southern Airlines

(p) Comair(South Africa) (q) Enter Air (r) Hainan Airlines (s) IAG (t) ICBC Leasing

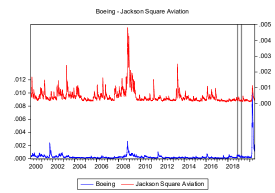
Time-varying conditional variances are obtained via the bivariate DCC GARCH model. The first shaded area is the sample period from 29 October 2018 to 18 November 2018. The second shaded area is the sample period from 10 March 2019 to 30 March 2019.

Figure 9: Time-varying conditional variances

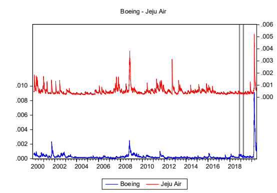
(a) Iceland Air



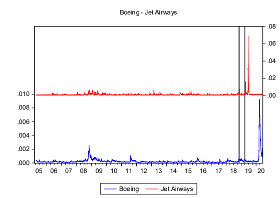
(b) Jackson Square Aviation



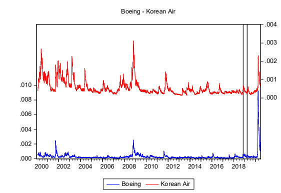
(c) Jeju Air



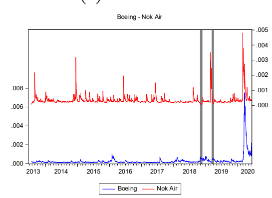
(d) Jet Airways



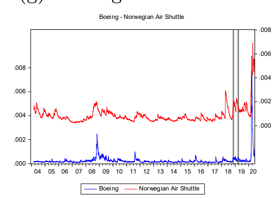
(e) Korean Air



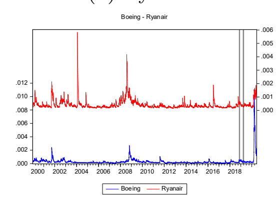
(f) NOK Air



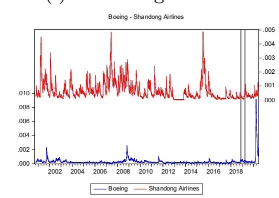
(g) Norwegian Air Shuttle



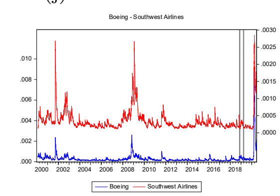
(h) Ryanair



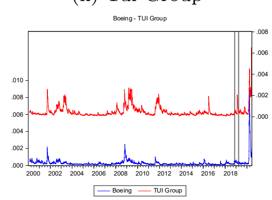
(i) Shandong Airlines



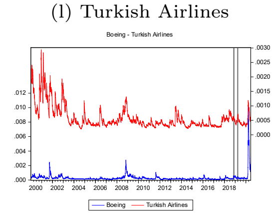
(j) Southwest Airlines



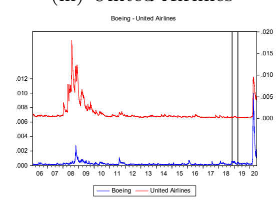
(k) Tui Group



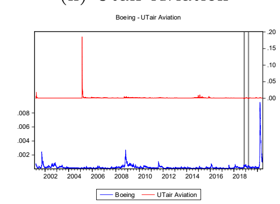
(l) Turkish Airlines



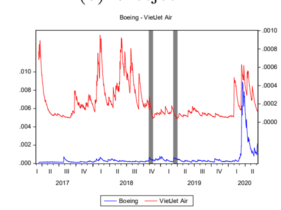
(m) United Airlines



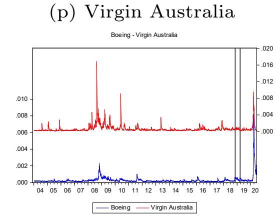
(n) Utair Aviation



(o) Vietjet Air



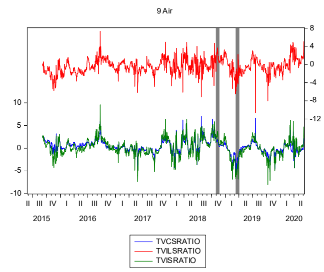
(p) Virgin Australia



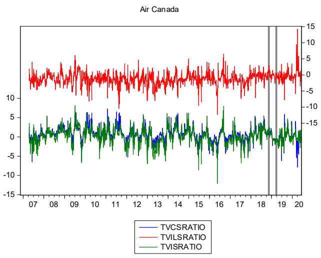
Time-varying conditional variances are obtained via the bivariate DCC GARCH model. The first shaded area is the sample period from 29 October 2018 to 18 November 2018. The second shaded area is the sample period from 10 March 2019 to 30 March 2019.

Figure 10: Daily movements of logarithmic ratios of time-varying information share measures

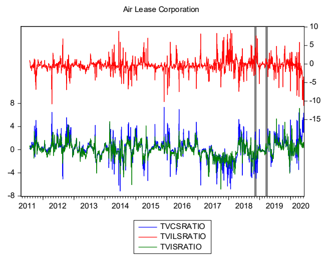
(a) 9 Air



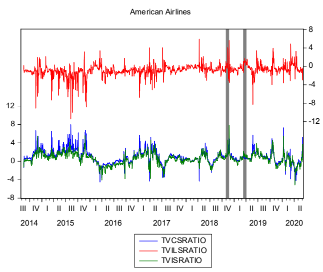
(b) Air Canada



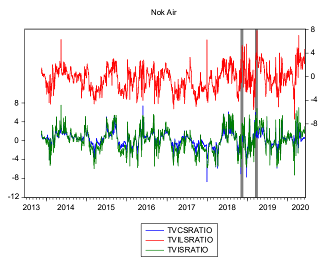
(c) Air Lease Corporation



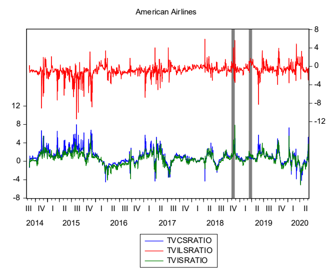
(d) American Airlines



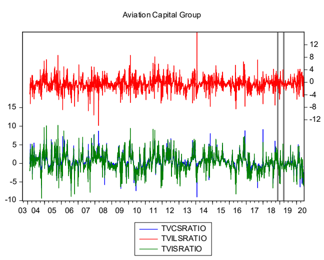
(e) Nok Air



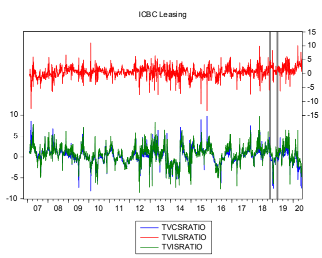
(f) CALC-China



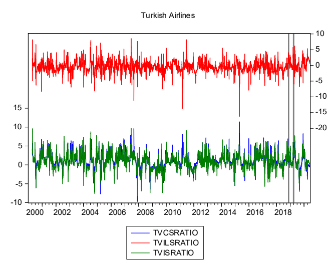
(g) Aviation Capital Group



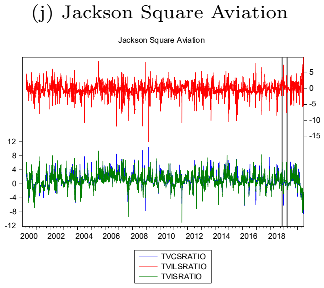
(h) ICBC Leasing



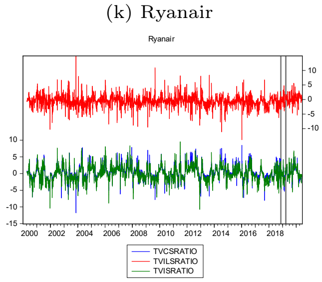
(i) Turkish Airlines



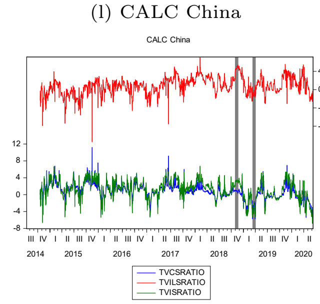
(j) Jackson Square Aviation



(k) Ryanair



(l) CALC China



This figure shows daily movements of logarithmic ratios of time varying information share measures of Boeing over other companies. The first shaded area is the time period from 29 October 2018 to 18 November 2018. The second shaded area is the time period from 10 March 2019 to 30 March 2019. TVCSRATIO is the log ratio of time varying component share; TVISRATIO is the log ratio of time varying information share; TVILSRATIO is the log ratio of time varying information leadership share.

Table 1: Airlines with ongoing Boeing 737-MAX Orders

Model	First Order	Orders	Deliv.	Unfilled	1st Delivery	Ticker	or Parent	Country
9 Air	15-May-14	1	1	-	27-Oct-18	603885.SS	Juneyao Airlines Co.	China
Aeromexico	05-Nov-12	60	6	54	23-Feb-18	AEROMEX	Grupo Aeromexico	Mexico
Air Canada	31-Mar-14	50	24	26	31-Oct-17	AC.T0	-	Canada
Air China	22-Dec-14	16	16	-	02-Nov-17	601111.SS	-	China
Air Lease Corporation	03-Jul-12	141	15	126	01-Dec-17	AL	-	US
ALAFCO	31-Oct-12	40	-	40	-	ALAF.KW	-	Kuwait
American Airlines	01-Feb-13	100	24	76	28-Sep-17	AAL.O	-	US
Aviation Capital Group	20-Dec-12	103	6	97	24-Jan-18	8439.T	Tokyo Century Corp	Japan
Avolon Aerospace Leasing Limit	18-Nov-17	31	-	31	-	JBLU.O	-	Cayman Is.
Blue Air	17-Mar-16	6	-	6	-	2588.HK	-	Singapore
Business Jet / VIP Customer(s)	21-Mar-14	14	2	12	13-Aug-18	-	-	US
CDB Financial Leasing	28-Sep-18	1	1	-	24-Jan-19	1606.HK	-	Hong Kong
China Development Bank Fin.	14-Mar-14	49	1	48	28-Jan-19	1606.HK	-	Hong Kong
China Eastern Airlines	17-Jun-14	14	14	-	27-Nov-17	600115.SS	-	China
China Southern Airlines	17-Dec-15	50	16	34	27-Nov-17	600029.SS	-	China
Comair Limited	03-Dec-13	8	1	7	25-Feb-19	COMJ.J	-	South Africa
Enter Air Sp. z o.o.	29-Oct-14	6	2	4	03-Dec-18	ENTP.WA	-	Poland
Goshawk Aviation Limited	28-Jun-18	20	-	20	-	600221.SS	Hainan Airlines Holding Co.	China
Hainan Airlines Holding	16-Jul-14	7	7	-	17-Nov-17	ICAG.L	Int. Cons. Airlines Group	UK
ICBC Leasing	21-May-13	5	5	-	23-Aug-18	601398.SS	Ind. & Comm. Bank of China	China
Icelandair	12-Feb-13	5	3	2	04-Mar-18	ICEAIR.IC	Icelandair Group HF	Iceland
Jackson Square Aviation	29-Jun-18	30	-	30	-	8593.T	Mitsubishi UFJ Lease & Fin.	Japan
Jeju Air	19-Nov-18	40	-	40	-	006840.KS	AK Holdings INC	South Korea
Jet Airways	23-Apr-13	125	-	125	-	JET.NS	-	India
Jetlines	11-Dec-14	5	-	5	-	003490.KS	-	South Korea
Mauritania Airlines	18-Nov-16	1	1	-	20-Dec-17	NOK.BK	-	Thailand
Nok Air	16-May-14	6	-	6	-	NWC.OL	-	Norway
Ryanair	28-Nov-14	135	-	135	-	RYA.I	-	Ireland
Shandong Airlines	29-Apr-14	7	7	-	01-Jun-18	200152.SZ	-	China
SMBC Aviation Capital	10-Nov-14	91	2	89	24-Sep-18	200152.SZ	Sumitomo Mitsui Fin. & Leas.	Japan
Southwest Airlines	13-Dec-11	280	31	249	26-Aug-17	LUV	-	US
SpiceJet	23-Oct-13	136	7	129	27-Sep-18	SPJT.NS	-	India
SunExpress Airlines	12-Feb-14	42	-	42	-	THYAO.IS	Turk Hava Yollari AO	Turkey
United Airlines	12-Jul-12	185	14	171	23-Apr-18	UAL.O	-	US
UTair Aviation	07-Apr-18	28	-	28	-	UTAR.MM	Aviakompaniya UTair PAO	Russia
VietJet Air	22-May-16	200	-	200	-	VJC.HM	Vietjet Aviation JSC	Vietnam
Virgin Australia Airlines	06-Jul-12	40	-	40	-	VAH.AX	-	Australia

Note: Data was obtained from Boeing in June 2020 (Available here). Orders, Deliv., and Unfilled refer to the number of 737-MAX orders that have been ordered, delivered, and are awaiting delivery at the time of writing. Ticker refers to the stock ticker, which is a unique series of letters assigned to a security for trading purposes.

Table 2: Airlines with ongoing Boeing 737-MAX Orders

Event	Date	Description
Project Launch	30/08/2011	The company's board of directors approved the launch of the new engine variant of the market-leading 737, based on order commitments for 496 airplanes from five airlines and a strong business case. The company stated that 'The new 737 family will be powered by CFM International LEAP-1B engines optimized for the 737. It will have the lowest operating costs in the single-aisle segment with a 7 percent advantage over the competition. Deliveries are scheduled to begin in 2017.'
Prototype	08/12/2015	The first complete assembly of a 737-MAX was announced with the statement 'Today marks another in a long series of milestones that our team has achieved on time, per plan, together,' said Keith Leverkuhn, vice president and general manager, 737-MAX, Boeing Commercial Airplanes. 'With the rollout of the new 737-MAX – the first new airplane of Boeing's second century – our team is upholding an incredible legacy while taking the 737 to the next level of performance.'
Maiden Flight	29/01/2016	The maiden flight took off at 9:48 a.m. piloted by Capt. Ed Wilson, 737 chief pilot. The pilots stayed mostly at 15,000 feet and limited the jet's speed to 250 knots, or 288 miles per hour, during this initial flight test, as they conducted the first basic checks of the airframe. The flight landed at Boeing Field less than three hours later, at 12:32 p.m.
FAA Cert	08/03/2017	Boeing made an announcement stating that the 'U.S. Federal Aviation Administration (FAA) has certified the 737-MAX 8 airplane for commercial service. Boeing is now in the final stages of preparing for the first 737-MAX 8 delivery to customers in the coming months.'
Lion Air Crash	29/10/2018	Lion Air Flight 610 was a scheduled domestic flight operated by the Indonesian airline Lion Air from Soekarno–Hatta International Airport in Jakarta to Depati Amir Airport in Pangkal Pinang. On 29 October 2018, the Boeing 737-MAX operating the route crashed into the Java Sea 13 minutes after takeoff, killing all 189 passengers and crew. It was the first major accident involving the new Boeing 737-MAX series of aircraft. It is the deadliest accident in Lion Air's 18-year history. Preliminary investigations revealed serious flight control problems that traumatized passengers and crew on the aircraft's previous flight, as well as signs of Angle of attack (AoA) sensor and other instrument failures on that and previous flights, tied to a design flaw involving the Maneuvering Characteristics Augmentation System (MCAS) of the 737-MAX series.
Ethiopian Air Crash	10/03/2019	Ethiopian Airlines Flight 302 was a scheduled international passenger flight from Addis Ababa Bole International Airport in Ethiopia to Jomo Kenyatta International Airport in Nairobi, Kenya. On 10 March 2019, the Boeing 737-MAX 8 aircraft which operated the flight crashed near the town of Bishoftu six minutes after takeoff, killing all 157 people aboard. Flight 302 is the deadliest accident involving an Ethiopian Airlines aircraft to date.
FAA Grounding & Civil Av. Adm. of China Grounding	13/03/2019	The grounding of the 737-MAX was followed by a statement by Boeing CEO Dennis Muilenburg on 5 April: 'We now know that the recent Lion Air Flight 610 and Ethiopian Airlines Flight 302 accidents were caused by a chain of events, with a common chain link being erroneous activation of the aircraft's MCAS function. We have the responsibility to eliminate this risk, and we know how to do it. As part of this effort, we're making progress on the 737-MAX software update that will prevent accidents like these from ever happening again. Teams are working tirelessly, advancing and testing the software, conducting non-advocate reviews, and engaging regulators and customers worldwide as we proceed to final certification. I recently had the opportunity to experience the software update performing safely in action during a 737-MAX 7 demo flight. We're also finalising new pilot training courses and supplementary educational material for our global MAX customers. This progress is the result of our comprehensive, disciplined approach and taking the time necessary to get it right.'
Boeing CEO Testimony (US)	30/10/2019	Boeing's chief executive, Dennis Muilenburg, testified before Congress for the first time since the crashes of two 737-MAX jets that killed 346 people. Mr. Muilenburg acknowledged for the first time that he knew before the second crash that a top pilot had voiced concerns about the plane while it was in development.
Boeing CEO Fired	23/12/2019	Boeing CEO Dennis A. Muilenburg was fired approximately one week after the company announced it planned to suspend production of its troubled 737-MAX airplanes, which were grounded after two crashes killed 346 people. 'The Board of Directors decided that a change in leadership was necessary to restore confidence in the Company moving forward as it works to repair relationships with regulators, customers, and all other stakeholders,' the company said in a statement.

Table 3: Summary statistics of abnormal returns of aviation companies with Boeing 737-MAX orders

Company	Mean	Std. Dev	Skew	Kurt	Min	Max
Boeing	0.0004	0.0177	0.1032	26.0017	-0.2384	0.2432
Korean Air	-0.0001	0.0218	0.4818	11.2197	-0.2225	0.2596
Jeju Air	0.0001	0.0206	0.3088	5.96857	-0.1107	0.1058
CDB Financial Leasing	-0.0005	0.0158	2.7525	54.0985	-0.1096	0.3093
China Development Bank	0.0001	0.0287	0.6675	14.7838	-0.2565	0.3631
CALC China	0.0010	0.0266	1.0047	19.7116	-0.2037	0.3104
SMBC Aviation Capital	-0.0005	0.0249	-0.7799	95.0921	-0.4652	0.4800
Shandong Airlines	-0.0005	0.0315	3.7145	113.0198	-0.3986	0.8672
BOC Aviation	-0.0009	0.0199	1.0778	18.2483	-0.1392	0.2020
China Southern Airlines	-0.0002	0.0176	0.8704	14.4459	-0.1191	0.1658
China Eastern Airlines	0.0002	0.0189	1.1878	18.7611	-0.1737	0.2029
Hainan Airlines	0.0001	0.0206	0.3088	5.96857	-0.1107	0.1058
Air China	-0.0002	0.0182	0.4592	8.9398	-0.1801	0.1892
ICBC Leasing	-0.0001	0.0290	0.6217	34.0348	-0.4479	0.4655
9 Air	-0.0025	0.0283	-0.3364	2.7096	-0.1228	0.0776
Aviation Capital Group	0.0001	0.0279	6.3845	223.7805	-0.4793	0.9002
Jackson Square Aviation	-0.0005	0.0247	0.1789	20.8593	-0.2952	0.3065
American Airlines	0.0001	0.0223	0.4137	6.9724	-0.2288	0.1434
Air Canada	-0.0002	0.0176	0.8704	14.4459	-0.1191	0.1658
AerCap	0.0007	0.0217	0.8240	6.3321	-0.1095	0.1121
Aeroméxico	0.0001	0.0227	0.6961	13.1394	-0.1776	0.2919
Air Lease Corporation	0.0002	0.0217	0.4895	7.5488	-0.1659	0.1753
Comair (South Africa)	-0.0004	0.0201	0.6507	15.6127	-0.1781	0.2763
Enter Air	0.0009	0.0159	0.5039	6.6318	-0.0763	0.0753
IAG	0.0004	0.0131	0.3531	11.5432	-0.1173	0.0967
Icelandair	-0.0001	0.0195	0.3408	6.8709	-0.1567	0.1264
Blue Air	0.0002	0.0203	0.7629	9.6465	-0.1458	0.1735
Jet Airways	0.0001	0.0205	0.5532	8.3515	-0.1656	0.1903
Southwest Airlines	0.0002	0.0281	0.9448	32.2266	-0.2939	0.4577
Nok Air	0.0002	0.0245	4.0294	74.5429	-0.2228	0.4679
Norwegian Air Shuttle	0.0001	0.0187	3.9777	121.9883	-0.2616	0.3862
Ryanair	0.0001	0.0170	-0.1170	15.8475	-0.1849	0.1779
SpiceJet	0.0001	0.0202	0.3370	5.0743	-0.1180	0.1141
SunExpress	-0.0001	0.0196	0.5102	5.8638	-0.1056	0.1200
Turkish Airlines	0.0001	0.0208	0.2657	4.7539	-0.1177	0.1150
TUI Group	-0.0001	0.0136	0.5527	10.3478	-0.1118	0.1054
United Airlines	0.0001	0.0219	2.9525	56.1944	-0.2037	0.3788
UTair Aviation	0.0001	0.0169	0.0353	8.7033	-0.1786	0.1592
Virgin Australia	0.0002	0.0188	-0.0756	14.4246	-0.2681	0.1541
VietJet Air	0.0003	0.0320	2.2323	53.6718	-0.3381	0.6502
Market Capitalisation	**Mean**	**Std. Dev**	**Skew**	**Kurt**	**Min**	**Max**
Category 1 (Low)	-0.0002	0.0103	0.1201	7.4107	-0.0823	0.0879
Category 2	-0.0001	0.0106	0.3285	34.0136	-0.1719	0.1946
Category 3	0.0001	0.0105	0.5349	6.3408	-0.0642	0.0900
Category 4	0.0001	0.0104	0.2875	8.2524	-0.0863	0.0868
Category 5 (High)	0.0001	0.0089	0.2332	4.2531	-0.0609	0.0620
Buyer Type	**Mean**	**Std. Dev**	**Skew**	**Kurt**	**Min**	**Max**
Charter Carriers	0.0001	0.0178	0.3583	3.5006	-0.1100	0.1129
Full Service Carriers	0.0002	0.0105	0.1301	2.7073	-0.0722	0.0798
Low Cost Carriers	-0.0001	0.0074	-0.0132	3.1729	-0.0396	0.0557
Leasing Company	0.0002	0.0109	0.1052	5.8055	-0.0863	0.0817

Note: The above table presents the associated descriptive statistics for all airlines included in this sample with outstanding 737-MAX orders from Boeing. Data is used from 1 January 2000 through 31 May 2020. When considering market capitalisation, category 1 firms represent the smallest firm size while category 5 represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located.

Table 4: Time variation of abnormal returns of Boeing and aviation companies with Boeing 737-MAX orders

	Boeing						Airline Average					
Year	Mean	Std. Dev	Skewness	Kurtosis	Min	Max	Mean	Std. Dev	Skewness	Kurtosis	Min	Max
2000	0.0022	0.0261	0.1477	0.7366	-0.0939	0.0797	0.0013	0.0092	0.1014	0.0720	-0.0277	0.0286
2001	-0.0016	0.0263	-1.3956	8.4022	-0.1762	0.0897	-0.0004	0.0084	0.2213	1.6881	-0.0296	0.0334
2002	-0.0003	0.0242	-0.0451	0.3977	-0.0807	0.0653	-0.0001	0.0085	-0.0034	0.3243	-0.0251	0.0263
2003	0.0011	0.0178	0.2542	0.8695	-0.0484	0.0682	-0.0002	0.0073	0.1116	0.2562	-0.0200	0.0252
2004	0.0008	0.0125	0.0893	-0.1764	-0.0335	0.0347	-0.0003	0.0070	-0.2186	2.6321	-0.0347	0.0268
2005	0.0012	0.0134	0.6107	1.8602	-0.0292	0.0702	-0.0008	0.0082	-1.5656	14.1538	-0.0649	0.0274
2006	0.0010	0.0140	0.5497	2.5890	-0.0459	0.0653	-0.0001	0.0087	0.1291	1.8386	-0.0305	0.0320
2007	0.0001	0.0125	-0.2104	1.2607	-0.0430	0.0414	0.0008	0.0101	-0.0004	-0.3538	-0.0254	0.0256
2008	-0.0023	0.0297	0.7111	4.2460	-0.0773	0.1546	0.0005	0.0138	0.0563	-0.2947	-0.0362	0.0346
2009	0.0012	0.0247	0.1317	0.9617	-0.0646	0.0906	-0.0001	0.0110	0.1928	2.0651	-0.0464	0.0445
2010	0.0009	0.0185	0.2327	1.4520	-0.0633	0.0731	-0.0006	0.0079	0.2021	0.1917	-0.0209	0.0222
2011	0.0006	0.0189	-0.4115	2.0361	-0.0790	0.0618	-0.0004	0.0074	0.1998	0.7861	-0.0262	0.0241
2012	0.0002	0.0115	0.4214	2.7128	-0.0362	0.0528	0.0001	0.0062	0.0355	0.1104	-0.0166	0.0160
2013	0.0024	0.0131	0.0557	1.3555	-0.0468	0.0534	-0.0003	0.0075	0.4281	2.7033	-0.0211	0.0380
2014	-0.0001	0.0119	-0.6452	1.8866	-0.0533	0.0354	0.0010	0.0073	0.5129	1.5230	-0.0188	0.0330
2015	0.0005	0.0134	0.2680	2.4583	-0.0432	0.0582	0.0001	0.0107	-0.0268	0.3446	-0.0328	0.0304
2016	0.0004	0.0149	-1.2678	6.7715	-0.0892	0.0469	-0.0001	0.0072	-0.0329	2.0410	-0.0303	0.0249
2017	0.0025	0.0110	2.6601	22.1876	-0.0285	0.0988	0.0004	0.0055	0.0452	0.5492	-0.0177	0.0193
2018	0.0005	0.0194	-0.0648	1.0989	-0.0659	0.0672	-0.0005	0.0077	-0.1388	0.4513	-0.0257	0.0217
2019	0.0002	0.0179	-0.1803	1.9773	-0.0679	0.0625	0.0005	0.0071	0.3538	3.9128	-0.0250	0.0393
2020[#]	-0.0016	0.0699	0.2359	3.2486	-0.2385	0.2432	0.0016	0.0118	0.3718	1.5170	-0.0333	0.0411

Note: The above table presents the associated descriptive statistics per year for both Boeing and for all airlines included in this sample with outstanding 737-MAX orders from Boeing. Data is used from 1 January 2000 through 31 May 2020. When considering market capitalisation, category 1 firms represent the smallest firm size while category 5 represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located. [#]Results are presented for the partial year, 1 January 2020 throughout 31 May 2020.

Table 5: Cumulative abnormal returns by size and type of airline with Boeing 737-MAX orders

	[-60,+60]	[-30,+30]	[-15,+15]	[-10,+10]	[-5,+5]	[-20,-1]	[-1,+1]	[ar,T_0]	[+1,+20]
Boeing	-0.0185	-0.0731*	-0.0620*	-0.0556*	-0.0389**	-0.0047	-0.0338***	-0.0279***	-0.2180***
All	-0.0008***	-0.0014***	-0.0042**	-0.0069***	-0.0118***	0.0218***	-0.0079**	-0.0053***	-0.0161***
Market Cap.									
Category 1	-0.0348**	-0.0611***	-0.0476***	-0.0332**	-0.0092	0.0302***	-0.0045*	-0.0061***	-0.0258***
Category 2	-0.1061***	-0.0536***	-0.0302*	-0.0337**	-0.0055	0.0062	-0.0020***	-0.0025***	-0.0458***
Category 3	0.0077	-0.0125	-0.0067	0.0161*	-0.0152*	0.0151*	-0.0025	-0.0035	-0.0071
Category 4	0.023	-0.0123	-0.0307*	-0.0279*	-0.0141*	0.0092	-0.0106**	-0.0062**	-0.0086
Category 5	-0.0434***	-0.0285***	-0.0159**	-0.0205*	-0.0012	0.0073	-0.0051	-0.0013	-0.0248***
Buyer Type									
Low Cost Airline	-0.0307***	-0.196**	-0.0265**	-0.0070**	-0.0075**	0.0083	-0.0061**	-0.0036***	-0.0141**
Full Service Airline	0.0522***	0.0302**	0.0305**	0.0372**	0.0119	0.0061	0.006	0.0007	0.0031***
Leasing Company	-0.0037	-0.0222	-0.0199*	-0.0310**	-0.0162*	0.0012	-0.0104**	-0.0074***	-0.0161***
Charter Carrier	-0.0305*	-0.0222*	-0.0173*	-0.0065	-0.0139	0.0239	-0.0038	-0.0034	-0.0046*

Note: The above table presents cumulative abnormal returns for a variety of announcement windows surrounding [ar,T_0], inclusive of a 20 trading-day (four-week) period both before and after each event. Data is used from 1 January 2000 through 31 May 2020. When considering market capitalisation, category 1 firms represent the smallest firm size while category 5 represents the largest companies. Abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 6: OLS regression as separated by type of airline

	Low Cost Airlines				Full Service Airlines			
	[-30,+30]	[-15,+15]	[-1,+1]	[ar,T_0]	[-30,+30]	[-15,+15]	[-1,+1]	[ar,T_0]
Year 2017	-0.0478	-0.0629	-0.0067	0.0015	-0.0725	-0.0102	-0.0008	-0.0012
	(0.0663)	(0.0477)	(0.0061)	(0.0012)	(0.0635)	(0.0522)	(0.0023)	(0.0017)
Year 2018	-0.0494	-0.0544	-0.007	0.0015	-0.0136	0.0262	0.0376	0.0008
	(0.0620)	(0.0519)	(0.0103)	(0.0011)	(0.0352)	(0.0219)	(0.0350)	(0.0007)
Year 2019	-0.0521	-0.0649*	-0.0027	0.0030	0.0060	0.0257	0.0086	0.0016
	(0.0541)	(0.0391)	(0.0023)	(0.0028)	(0.0052)	(0.0412)	(0.0184)	(0.0015)
Boeing	-0.0382	-0.0356**	-0.0389**	-0.0015*	-0.0623	-0.0450	-0.0107	-0.0052
	(0.0249)	(0.0179)	(0.0192)	(0.0008)	(0.0429)	(0.0353)	(0.0159)	(0.0047)
Market Cap	0.0182**	0.0089*	0.0078*	0.0062**	0.0107	0.0163**	0.0041	0.0025
	(0.0073)	(0.0052)	(0.0047)	(0.0027)	(0.0095)	(0.0078)	(0.0035)	(0.0017)
Orders	-0.0006*	-0.0021	-0.0006	-0.0012	-0.0010	-0.0005*	-0.0004**	-0.0001*
	(0.0003)	(0.0022)	(0.0007)	(0.0011)	(0.0010)	(0.0003)	(0.0001)	(0.0001)
Constant	0.1049	0.1297***	0.1209***	0.1619***	0.2503*	0.1199	0.1341	0.1976
	(0.0652)	(0.0469)	(0.0245)	(0.0271)	(0.1379)	(0.1133)	(0.1512)	(0.1524)
Adjusted R^2	0.1967	0.1418	0.1376	0.1218	0.1347	0.1107	0.1498	0.1336
	Leasing Company				Charter Carrier			
	[-30,+30]	[-15,+15]	[-1,+1]	[ar,T_0]	[-30,+30]	[-15,+15]	[-1,+1]	[ar,T_0]
Year 2017	-0.0223	-0.0131	-0.0311	-0.0039	0.0305	0.0102	0.0039	-0.0061
	(0.0459)	(0.0285)	(0.0208)	(0.0076)	(0.0381)	(0.0485)	(0.0196)	(0.0049)
Year 2018	-0.0084	-0.0339	-0.027	-0.0048	0.0392	0.0257	0.0229	0.0102
	(0.0056)	(0.0314)	(0.0208)	(0.0052)	(0.0364)	(0.0301)	(0.0204)	(0.0097)
Year 2019	-0.0190	-0.0179	0.0013	-0.0059	0.1050	0.0464	0.0057	0.0026
	(0.0450)	(0.0225)	(0.0016)	(0.0061)	(0.0670)	(0.0384)	(0.0154)	(0.0077)
Boeing	-0.0022	-0.0039	-0.0086	-0.0051	-0.0024	-0.0016	-0.0041	-0.0071
	(0.0019)	(0.0027)	(0.0121)	(0.0048)	(0.0034)	(0.0030)	(0.0038)	(0.0059)
Market Cap	0.0002	0.0003	0.0001	-0.0001*	0.0547***	0.0635***	0.0076***	0.0069***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0209)	(0.0132)	(0.0011)	(0.0034)
Orders	-0.0009	-0.0001	0.0002	0.0001	-0.0015	-0.0055***	-0.0017***	-0.0054***
	(0.0010)	(0.0001)	(0.0002)	(0.0001)	(0.0023)	(0.0013)	(0.0001)	(0.0007)
Constant	0.0317	0.0273	0.0192	0.0199**	0.0853***	0.1312***	0.0499*	0.0199*
	(0.0274)	(0.0374)	(0.0273)	(0.0101)	(0.0231)	(0.0031)	(0.0285)	(0.0942)
Adjusted R^2	0.1336	0.1668	0.1486	0.1795	0.1201	0.1687	0.1277	0.1386

Note: The above table shows regression estimates for 3-, 31-, and 61-day cumulative abnormal returns and abnormal returns on the announcement day ([ar,T_0]) over a sample of blockchain-related listed firms between 2016 and 2019. Year 2017, 2018 and Year 2019 are dummies that take a value of unity if the announcement is made in 2017, 2018 or 2019, respectively, and 0 otherwise. Data is used from 1 January 2000 through 31 May 2020. Cumulative abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 7: OLS regression results for the entire sample

	All			
	[-30,+30]	[-15,+15]	[-1,+1]	[ar,T_0]
Year 2017	0.0064	0.0037*	0.0011	-0.0072***
	(0.0069)	(0.0026)	(0.0007)	(0.0005)
Year 2018	0.0031	-0.0057	-0.0190***	-0.0229***
	(0.0036)	(0.0049)	(0.0047)	(0.0045)
Year 2019	0.0017	0.012**	-0.0249***	-0.0172***
	(0.0029)	(0.0071)	(0.0060)	(0.0036)
Boeing	-0.073**	-0.0616***	-0.0321**	-0.0194***
	(0.0421)	(0.0291)	(0.0131)	(0.0091)
Market Cap	0.0011***	0.0010***	0.0005***	0.0026***
	(0.0002)	(0.0003)	(0.0001)	(0.0003)
Orders	-0.0048***	-0.0015***	-0.0072***	-0.0012***
	(0.0002)	(0.0001)	(0.0009)	(0.0002)
Constant	0.0141***	0.0087***	0.0039***	0.0046***
	(0.0028)	(0.0011)	(0.0008)	(0.0011)
Adjusted R^2	0.1185	0.1291	0.1268	0.1119

Note: The above table shows regression estimates for 3-, 31-, and 61-day cumulative abnormal returns and abnormal returns on the announcement day ([ar,T_0]) over a sample of blockchain-related listed firms between 2016 and 2019. Year 2017, 2018 and Year 2019 are dummies that take a value of unity if the announcement is made in 2017, 2018 or 2019, respectively, and 0 otherwise. Data is used from 1 January 2000 through 31 May 2020. Cumulative abnormal returns are calculated based on the exchanges on which the above airline's (or denoted parent company's) primary listing is located. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 8: Pre- and post-event price correlation

		Mean	Difference
Entire Period		0.3407	
MCap 1	Before	0.1005	0.1305***
	After	0.2310	
MCap 2	Before	0.0620	0.1201***
	After	0.1821	
MCap 3	Before	0.0284	0.0777***
	After	0.1061	
MCap 4	Before	-0.0146	0.0494***
	After	0.0348	
MCap 5	Before	0.2933	-0.0174***
	After	0.2759	
Orders 1	Before	0.1303	0.0125***
	After	0.1428	
Orders 2	Before	0.2919	-0.0678
	After	0.2241	
Orders 3	Before	-0.0018	0.1477***
	After	0.1459	
Orders 4	Before	-0.1020	0.3630***
	After	0.2610	
Orders 5	Before	-0.0177	0.4011***
	After	0.3834	
LowCost Airline	Before	0.2079	0.3165***
	After	0.5244	
Full Service Airline	Before	0.1372	0.0162***
	After	0.1533	
Leasing Company	Before	0.0407	0.1800***
	After	0.2207	
Charter Carrier	Before	0.2271	-0.0279***
	After	0.1992	

Note: The above table shows the change in pre- and post-correlation between company returns and Boeing returns. Pre-correlation is calculated as the correlation between company returns and Boeing returns from the beginning of our sample to the event date. Post-announcement correlation is calculated as the correlation between company returns and Boeing returns after the announcement Data is used from 1 January 2000 through 31 May 2020. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 9: The effects of two crash events on information leadership share

Variables	9 Air	Air Can.	Un. Air.	Air L. Corp.	Nok Air	Am. Air.	ICBC Leas.	Turk. Air.	Av. Capital	Jack. Sq.	Ryanair	CALC
$ILSRatio_{t-1}$	0.455***	0.583***	0.513***	0.506***	0.607***	0.503***	0.523***	0.571***	0.492***	0.586***	0.543***	0.531***
	-10.28	-21.074	-18.128	-14.125	-12.735	-11.968	-17.31	-20.512	-21.229	-25.85	-23.842	-10.417
$ILSRatio_{t-2}$	0.162***	0.156***	0.147***	0.133***	0.152***	0.078*	0.131***	0.135***	0.088***	0.115***	0.115***	0.196***
	-2.871	-5.378	-5.272	-3.671	-4.28	-1.708	-5.014	-5.842	-3.984	-4.474	-6.047	-6.022
$ILSRatio_{t-3}$	0.073**	0.061***	0.044*	0.059**	0.069**	0.027	0.026	0.059***	0.054**	0.011	0.029	0.129***
	-2.338	-2.829	-1.904	-2.228	-2.466	-0.704	-1.142	-3.175	-2.524	-0.427	-1.541	-3.796
$ILSRatio_{t-4}$	0.05	0.014	0.031	0.054*	0.023	0.049	0.040*	0.036	0.041**	0.021	-0.01	0.051**
	-1.318	-0.665	-1.341	-1.724	-0.798	-1.244	-1.885	-1.644	-2.001	-0.925	(-0.559)	-1.985
$ILSRatio_{t-5}$	0.061*	0.032	0.014	-0.017	0.049*	0.026	0.046**	0.025	0.092***	-0.007	0.030*	
	-1.85	-1.64	-0.652	(-0.492)	-1.736	-0.749	-2.363	-1.397	-4.246	(-0.375)	-1.896	
$ILSRatio_{t-6}$	0.089**	0.026	-0.039*	-0.026	0.006	0.049	0.063**	-0.03	-0.008	0.005	0.034**	
	-2.202	-1.222	(-1.892)	(-0.942)	-0.161	-1.453	-2.47	(-1.423)	(-0.438)	-0.261	-2.181	
$ILSRatio_{t-7}$	0.024		0.019	0.032	-0.025	-0.026	0.009	0.008	0.016	0.016	0.01	
	-0.701		-1.11	-1.161	(-0.913)	(-0.967)	-0.352	-0.335	-0.817	-0.746	-0.505	
$ILSRatio_{t-8}$	-0.017		0.056***	0.072**	-0.015	-0.014	-0.013	0.015	0.029	0.011	0.009	
	(-0.523)		-3.019	-2.283	(-0.552)	(-0.491)	(-0.580)	-0.892	-1.607	-0.628	-0.56	
$ILSRatio_{t-9}$	-0.067**			-0.031	0.009	0.054*	-0.014	0.032**	-0.02	0.025	0.01	
	(-2.119)			(-1.379)	-0.303	-1.855	(-0.699)	-2.4	(-1.082)	-1.239	-0.743	
$ILSRatio_{t-10}$	0.065*				0.052**	-0.025	-0.003		0.042***	0.002	-0.001	
	-1.934				-2.134	(-0.806)	(-0.185)		-2.754	-0.127	(-0.063)	
$ILSRatio_{t-11}$						0.018	0.052***			-0.005	-0.003	
						-0.517	-3.146			(-0.314)	(-0.255)	
$ILSRatio_{t-12}$						0.066**				0.035**	0.042***	
						-2.008				-2.182	-3.743	
$D_{1,t}$	0.2	0.595***	0.541***	0.591*	0.658**	0.276	0.633**	0.525***	0.326**	0.630***	-0.02	0.557***
	-0.755	-5.346	-9.233	-1.767	-2.35	-1.182	-2.066	-4.63	-2.017	-4.391	(-0.123)	-5.218
$D_{2,t}$	-0.053	0.287***	0.549***	0.255***	0.822***	0.447***	0.232***	0.529*	0.278	0.064	0.481***	-0.262**
	(-0.215)	-2.342	-9.78	-2.687	-4.89	-4.05	-3.6	-1.869	-0.582	-0.273	-2.717	(-2.537)
Constant	-0.038	-0.156***	-0.284***	-0.087***	-0.034*	-0.169***	0.090***	-0.055***	-0.088***	-0.027*	-0.110***	0.071***
	(-1.466)	(-7.669)	(-10.848)	(-3.852)	(-1.777)	(-6.010)	-4.508	(-4.381)	(-5.180)	(-1.888)	(-6.941)	-2.821
Adj. R2	0.624	0.66	0.471	0.459	0.777	0.432	0.557	0.595	0.473	0.513	0.472	0.753
AIC	2.911	2.834	3.17	3.193	2.684	2.727	3.134	2.845	3.239	3.171	3.19	2.737
Ljung-Box	2.131	6.049	3.761	6.376	0.71	5.651	11.57	3.15	6.248	0.933	4.636	7.467

Note: This table shows the estimation result of an extended auto-regressive (AR) regression model $\text{ILS Ratio}_t = \text{Constant} + \sum_{i=1}^{p} \lambda_i \text{ILS Ratio}_{t-i} + \phi_1 D_{1,t} + \phi_2 D_{2,t} + \varepsilon_t$. where $\text{ILS Ratio}_t = \log\left(\frac{ILS_{Boeing_t}}{ILS_{Airline_t}}\right)$. log(.) is the natural logarithm. ILS_{Boeing_t} denotes the time varying information leadership share (ILS) of Boeing. $ILS_{Airline_t}$ denotes the time varying information leadership share (ILS) of a counterpart company. Note that in our sample, there are twelve companies whose price series are pairwise cointegrated with those of Boeing and thus the ILS measures are calculated for price series of Boeing and one counterpart company based upon a bivariate vector error correction (VEC)-Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC GARCH) model. The time varying ILS measures are computed via the time varying CS measures and mid-point IS measures. The autoregressive lag order p is chosen according to Akaike Information Criterion (AIC). $D_{1,t}$ is a dummy variable where it takes a value of one when the sample period is from 29 October 2018 to 18 November 2018; and zero otherwise. $D_{2,t}$ is a dummy variable where it takes a value of 1 when the sample period is from 10 March 2019 to 30 March 2019; and zero otherwise. ε_t is the error term. Adj. R2 is the adjusted R-square. AIC denotes Akaike Information Criterion (AIC). Ljung-Box Q test denotes the Ljung-Box Q test statistic for the null hypothesis that there are no autocorrelations of residuals up to 12 lags. Figures in the parentheses are t statistic. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 10: The effects of two crash events on component share

Variables	9 Air	Air Can.	Un. Air.	Air L. Corp.	Nok Air	Am. Air.	ICBC Leas.	Turk. Air.	Av. Capital	Jack. Sq.	Ryanair	CALC
$CSRatio_{t-1}$	0.621***	0.664***	0.625***	0.613***	0.538***	0.580***	0.632***	0.619***	0.611***	0.665***	0.645***	0.583***
	-14.851	-31.529	-22.606	-17.434	-14.537	-13.631	-23.75	-27.325	-24.974	-30.928	-31.086	-14.742
$CSRatio_{t-2}$	0.096**	0.159***	0.148***	0.171***	0.192***	0.177***	0.149***	0.143***	0.133***	0.125***	0.192***	0.188***
	-2.134	-6.098	-5.049	-4.603	-4.734	-3.321	-5.762	-6.639	-4.533	-5.388	-9.037	-5.902
$CSRatio_{t-3}$	0.265***	0.009	0.03	0.023	0.068*	0.012	0.024	0.055***	0.051**	0.037	0.005	0.086**
	-5.375	-0.39	-1.225	-0.812	-1.663	-0.275	-0.993	-2.757	-2.272	-1.473	-0.254	-2.028
$CSRatio_{t-4}$	-0.068*	0.033	0.052**	1.85E-04	0.057	0.098**	0.071***	0.026	0.054**	0.018	0.011	-0.019
	(-1.692)	-1.458	-1.968	-0.006	-1.503	-2.212	-2.929	-1.175	-2.438	-0.867	-0.615	(-0.530)
$CSRatio_{t-5}$		0.013	0.033	0.049	0.026	0.014	0.001	0.019	0.040*	0.03	0.019	0.036
		-0.602	-1.469	-1.519	-0.978	-0.418	-0.058	-0.982	-1.776	-1.589	-1.085	-1.265
$CSRatio_{t-6}$		0.032	-0.029	0.017	0.029	0.053**	0.013	0.013	-0.01	0.006	0.011	0.024
		-1.256	-1.324	-0.635	-1.001	-1.962	-0.487	-0.688	(-0.524)	-0.298	-0.642	-0.586
$CSRatio_{t-7}$		-0.026	0.028	-0.034			0.039	-0.021	0.037**	-0.008	-0.002	0.004
		(-1.243)	-1.141	(-1.211)			-1.307	(-0.933)	-2.164	(-0.423)	(-0.091)	-0.13
$CSRatio_{t-8}$		0.009	-0.016	0.055			0.022	0.003		0.005	0.006	-0.032
		-0.421	-0.759	-1.608			-1.003	-0.166		-0.323	-0.363	(-1.274)
$CSRatio_{t-9}$		0.019	0.009	-0.021				0.043**		0.021	0.042***	0.001
		-0.99	-0.457	(-0.767)				-2.318		-0.991	-3.106	-0.018
$CSRatio_{t-10}$		-0.011	0.016	0.029				-0.017		0.026		-4.37E-04
		(-0.517)	-0.865	-1.275				(-1.111)		-1.485		(-0.016)
$CSRatio_{t-11}$		0.036**	0.027*	-0.033				-0.006				0.032
		-2.135	-1.806	(-1.210)				(-0.412)				-1.182
$CSRatio_{t-12}$				0.045*				0.042***				0.04
				-1.958				-2.597				-1.51
$D_{1,t}$	0.014	-0.02	0.17	-0.118	0.006	0.185	-0.111	0.012	-0.037	0.101	-0.153	-0.017
	-0.226	(-0.408)	-1.62	(-0.301)	-0.018	-1.593	(-1.326)	-0.085	(-0.239)	-0.766	(-0.672)	(-0.541)
$D_{2,t}$	-0.194	-0.108***	-0.203*	0.022	0.12	-0.041	-0.128*	0.219***	-0.363	-0.147	0.043	-0.116
	(-1.202)	(-4.197)	(-1.943)	-0.539	-0.758	(-0.804)	(-1.842)	-3.495	(-1.545)	(-0.894)	-0.616	(-0.906)
Constant	0.029*	0.045***	0.061***	0.018	0.024	0.063***	0.012	0.084***	0.040***	0.080***	0.019**	0.045**
	-1.761	-3.91	-5.068	-1.26	-1.459	-3.718	-1.127	-7.429	-3.745	-5.597	-2.131	-2.029
Adj. R2	0.786	0.797	0.75	0.716	0.724	0.785	0.83	0.732	0.743	0.76	0.78	0.781
AIC	1.982	2.11	2.253	2.442	2.339	1.981	2.162	2.263	2.36	2.227	2.351	2.422
Ljung-Box	7.837	0.506	3.891	4.989	3.646	6.229	4.316	6.076	1.172	2.469	1.897	3.511

Note: This table shows the estimation result of an extended auto-regressive (AR) regression model $\text{CSRatio}_t = \text{Constant} + \sum_{t=1}^{p} \lambda_i \text{CSRatio}_{t-i} + \phi_1 d_{1,t} + +\phi_2 d_{2,t} + \varepsilon_t$ where $\text{CSRatio}_t = \log\left(\frac{CS_{Boeing_t}}{CS_{Counterparty_t}}\right)$. log(.) is the natural logarithm. CS_{Boeing_t} denotes the time varying component share (CS) of Boeing. $CS_{Counterparty_t}$ denotes the time varying component share (CS) of a counterpart company. Note that in our sample there are twelve companies whose price series are pairwise cointegrated with those of Boeing and thus the CS measures are calculated for price series of Boeing and one counterpart company based upon a bivariate vector error correction model (VECM). The time varying CS measures are computed via time varying error correction coefficients which are obtained by a rolling window process on the VECM. The autoregressive lag order p is chosen according to Akaike Information Criterion (AIC). $d_{1,t}$ is a dummy variable where it takes a value of one when the sample period is from October 29 2018 to November 18 2018; and zero otherwise. $d_{2,t}$ is a dummy variable where it takes a value of 1 when the sample period is from March 10 2019 to March 30 2019; and zero otherwise. ε_t is the error term. Adj. R^2 is the adjusted R-square. AIC denotes Akaike Information Criterion (AIC). Ljung-Box Q test denotes the Ljung-Box Q test statistic for the null hypothesis that there are no autocorrelations of residuals up to 12 lags. Figures in the parentheses are t statistic. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 11: The effects of two crash events on information share

Variables	9 Air	Air Can.	Un. Air.	Air L. Corp.	Nok Air	Am. Air.	ICBC Leas.	Turk. Air.	Av. Capital	Jack. Sq.	Ryanair	CALC
$ISRatio_{t-1}$	0.623***	0.766***	0.676***	0.756***	0.649***	0.722***	0.738***	0.759***	0.664***	0.739***	0.761***	0.651***
	-16.302	-32.847	-24.454	-20.488	-15.709	-17.98	-30.64	-33.923	-27.288	-38.872	-38.125	-17.135
$ISRatio_{t-2}$	0.145***	0.096***	0.155***	0.075**	0.166***	0.071	0.074***	0.072***	0.105***	0.075***	0.124***	0.220***
	-3.542	-3.252	-5.111	-2.045	-3.614	-1.26	-2.954	-2.822	-4.104	-3.179	-5.71	-5.237
$ISRatio_{t-3}$	0.148***	0.028	-0.012	0.038	-0.003	0.008	-0.023	0.029	0.057***	0.024	-2.14E-04	0.044
	-4.817	-1.031	(-0.552)	-1.072	(-0.077)	-0.187	(-0.811)	-1.311	-2.635	-1.147	(-0.011)	-1.34
$ISRatio_{t-4}$		0.035	0.043**	-0.031	0.061	0.084**	0.110***	0.017	0.025	0.027	-0.007	
		-1.349	-2.109	(-1.165)	-1.523	-2.12	-4.253	-0.807	-1.157	-1.521	(-0.374)	
$ISRatio_{t-5}$		-0.024	0.005	0.044	0.052*	0.003	-0.008	0.033	0.064***	0.005	0.01	
		(-1.102)	-0.223	-1.591	-1.736	-0.091	(-0.318)	-1.522	-3.452	-0.319	-0.46	
$ISRatio_{t-6}$		0.011	0.003	0.032		0.048*	-0.003	-0.017		0.004	0.042*	
		-0.401	-0.105	-1.592		-1.866	(-0.095)	(-0.783)		-0.232	-1.893	
$ISRatio_{t-7}$		-0.01	0.002				0.042	-0.03		-0.005	-0.050**	
		(-0.440)	-0.093				-1.151	(-1.243)		(-0.256)	(-2.389)	
$ISRatio_{t-8}$		0.009	0.002				-0.014	0.021		0.025	0.016	
		-0.407	-0.102				(-0.525)	-0.997		-1.322	-0.865	
$ISRatio_{t-9}$		0.04	0.036**				-0.012	0.012		-0.006	0.040***	
		-1.634	-2.248				(-0.436)	-0.699		(-0.257)	-2.883	
$ISRatio_{t-10}$		-0.037					0.041*	-0.004		0.026		
		(-1.340)					-1.759	(-0.280)		-1.415		
$ISRatio_{t-11}$		0.03						-0.006				
		-1.588						(-0.354)				
$ISRatio_{t-12}$								0.038***				
								-2.721				
$D_{1,t}$	0.079	0.192**	0.294***	0.049	0.312	0.197	0.123	0.196*	0.068	0.298*	-0.166	0.228***
	-0.532	-2.392	-3.031	-0.199	-0.879	-1.476	-1.569	-1.684	-0.357	-1.877	(-0.666)	-3.962
$D_{2,t}$	-0.224	0.017	-0.062	0.084	0.458**	0.058	-0.062	0.371**	-0.259*	-0.113	0.179	-0.308**
	(-1.362)	-0.251	(-0.577)	-1.323	-2.297	-0.924	(-0.846)	-2.159	(-1.740)	(-1.279)	-1.235	(-2.223)
Constant	0.014	0.005	0.011	-0.001	0.003	0.033**	0.033**	0.063***	0.02	0.085***	-0.001	0.102***
	-0.64	-0.431	-1.031	(-0.071)	-0.148	-2.572	-2.458	-5.682	-1.515	-6.565	(-0.109)	-3.522
Adj. R2	0.788	0.847	0.749	0.782	0.791	0.818	0.821	0.791	0.758	0.765	0.823	0.799
AIC	2.581	2.251	2.205	1.72	2.903	1.535	2.476	2.493	2.848	2.433	2.487	2.809
Ljung-Box	9.735	0.197	11.596	8.052	10.372	8.13	0.429	0.592	2.484	3.1	4.672	7.089

Note: This table shows the estimation result of an extended auto-regressive (AR) regression model $\text{IS Ratio}_t = \text{Constant} + \sum_{i=1}^{p} \lambda_i \text{IS Ratio}_{t-i} + \phi_1 D_{1,t} + \phi_2 D_{2,t} + \varepsilon_t$. where $\text{IS Ratio} = \log\left(\frac{IS_{Boeing_t}}{IS_{Airline_t}}\right)$. log(.) is the natural logarithm. IS_{Boeing_t} denotes the time varying mid-point of information share (IS) upper and lower bounds of Boeing. $IS_{Airline_t}$ denotes the time varying mid-point of information share (IS) upper and lower bounds of a counterpart company. Note that in our sample, there are twelve companies whose price series are pairwise cointegrated with those of Boeing and thus the IS upper and lower bounds are calculated for price series of Boeing and one counterpart company based upon a bivariate vector error correction (VEC)-Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC GARCH) model. The mid-point of IS is calculated as an average of the upper and lower bounds. The time varying IS measures are computed via the time varying error correction coefficients which are obtained by a rolling window process on the VECM as well as a conditional variance-covariance matrix of innovations via the DCC GARCH model. The autoregressive lag order p is chosen according to Akaike Information Criterion (AIC). $D_{1,t}$ is a dummy variable where it takes a value of one when the sample period is from 29 October 2018 to 18 November 2018; and zero otherwise. $D_{2,t}$ is a dummy variable where it takes a value of 1 when the sample period is from 10 March 2019 to 30 March 2019; and zero otherwise. ε_t is the error term. Adj. R2 is the adjusted R-square. AIC denotes Akaike Information Criterion (AIC). Ljung-Box Q test denotes the Ljung-Box Q test statistic for the null hypothesis that there are no autocorrelations of residuals up to 12 lags. Figures in the parentheses are t statistic. ***, **, and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 12: Pre- and post-event analyst' mis-pricing correlation

		Mean	Difference
Entire Period		0.3625	
MCap 1	Before	0.3639	0.3251***
	After	0.6891	
MCap 2	Before	0.7071	0.1731***
	After	0.8802	
MCap 3	Before	0.7607	-0.0581***
	After	0.7026	
MCap 4	Before	0.7175	0.0502***
	After	0.7677	
MCap 5	Before	0.8563	-0.1299***
	After	0.7264	
Orders 1	Before	0.6178	0.1033***
	After	0.7211	
Orders 2	Before	0.7083	-0.0276***
	After	0.6807	
Orders 3	Before	0.5166	0.2078***
	After	0.7244	
Orders 4	Before	0.1629	0.2503***
	After	0.4131	
Orders 5	Before	0.4481	0.2411***
	After	0.6892	
Low Cost Airline	Before	0.0918	0.5949***
	After	0.6867	
Full Service Airline	Before	-0.7038	0.0946***
	After	-0.6092	
Leasing Company	Before	0.0388	0.6851***
	After	0.7239	
Charter Carrier	Before	0.7211	-0.1554***
	After	0.5657	

Note: The above table shows the change in pre- and post-correlation between company returns and Boeing returns. Pre-correlation is calculated as the correlation between company returns and Boeing returns from the beginning of our sample to the event date. Post-announcement correlation is calculated as the correlation between company returns and Boeing returns after the announcement Data is used from 1 January 2000 through 31 May 2020. ***, ** and * denote significant at the 1%, 5% and 10% level respectively.

Table 13: Proportion of aircraft fleet as separated by Airbus, Boeing 737-MAX and all other types

	Airbus fleet		*Boeing fleet*		*Boeing 737-NG/MAX*		*Other*			**Boeing fleet % of total**
Airline	Active	Parked	Active	Parked	Active	Parked	Active	Parked	Total	
9 Air	0	0	19	1	0	1	0	0	20	100.0%
Aeroméxico	0	0	48	14	0	6	0	0	62	100.0%
Air Canada	62	18	42	34	0	24	0	0	156	48.7%
Air China	235	7	180	20	0	16	1	0	443	45.1%
American Airlines	657	155	344	95	0	24	0	0	874	50.2%
Blue Air	0	0	13	2	0	0	0	0	15	100.0%
China Eastern Airlines	411	2	150	3	0	2	0	0	543	28.2%
China Southern Airlines	332	6	239	30	0	24	3	6	617	43.6%
Comair (South Africa)	0	0	6	11	0	1	0	0	17	100.0%
Enter Air	0	0	17	6	0	2	0	0	23	100.0%
Hainan Airlines	25	9	156	29	0	11	0	0	219	84.5%
Icelandair	0	0	17	12	0	2	0	0	31	93.5%
Jeju Air	0	0	22	22	0	0	0	0	44	100.0%
Korean Air	29	20	86	31	0	0	0	0	166	70.5%
Lion Air	4	6	90	38	0	10	0	0	138	92.8%
Nok Air	0	0	12	2	0	0	8	0	22	63.6%
Norwegian Air Shuttle	0	0	7	11	0	3	0	0	18	100.0%
Ryanair	0	0	273	0	0	0	0	0	273	100.0%
Shandong Airlines	0	0	119	7	0	7	0	0	126	100.0%
Southwest Airlines	0	0	641	94	0	34	0	0	735	100.0%
SpiceJet	0	0	45	34	0	13	30	2	112	70.5%
TUI Group	0	0	45	10	0	5	0	0	55	100.0%
Turkish Airlines	122	46	117	24	0	12	0	0	309	45.6%
United Airlines	105	67	354	0	2	12	0	0	797	44.4%
UTair Aviation	13	1	40	3	0	0	0	0	57	75.4%
Virgin Australia	0	6	43	41	0	0	0	0	90	93.3%

Note: Data obtained from AIRFLEETS.NET and correct as of June 2020