Guilt through association:
Reputational contagion and the Boeing 737-MAX disasters

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Abstract

The unfortunate set of circumstances surrounding the loss of both Lion Air Flight 610 and Ethiopian Airlines Flight 302 led to the immediate grounding of the advertised 'incredibly fuel-efficient' Boeing 737-MAX. The side-effects of the decision to ground such flights led to delays and cancellation of orders. Companies with entire Boeing fleets and a heavy reliance on the proposed cost-savings in an ultra-competitive industry thereby made their shareholders aware that identified future revenue generation was now on hold indefinitely. Results indicate that investors identified this reliance, but also, the subsequent negative polarity and subjectivity of social media response is found to have significantly influenced the share price of airlines with no fleet diversification, and subsequently, no reputational diversification.

Keywords: Sentiment; Boeing; 737-MAX; Aviation Disaster; Financial Crisis.

Preprint submitted to Economics Letters *January 12, 2021*

1. Introduction

The United States National Transportation Safety Board (NTSB) have estimated that one fatality due to an aviation disaster takes place every 16.3 million flight hours. When considering such rarity, the occurrence of two disasters in close proximity, not to mention, involving the same type of aircraft resulted in exceptionally negative public response. This occurred during the 2018 Lion Air and 2019 Ethiopian Air disasters, both unfortunately involving the new Boeing 737-MAX aircraft, which had been partially delivered to a number of large airlines. A broad range of issues and errors relating to internal Boeing processes are described in detail in the work of Corbet et al. [2020b], where it has been broadly identified that both accidents were attributed to the Manoeuvring Characteristics Augmentation System (MCAS) software. Boeing was under financial pressure to compete with the Airbus A320neo aircraft and this generated a heavy reliance on the completion of the 737-MAX program, albeit with extensive cost-savings and elevated production capacity. Such ambitions appear to have been mutually exclusive in the circumstances, while Boeing made fundamentally faulty assumptions about critical technologies. Most importantly, with respect to the included MCAS software, which was designed to automatically push the plane's nose down in certain conditions, relaying on a single angle of attack (AOA) sensor for automatic activation, whereas multiple sensors had been advised. Further, Boeing assumed that pilots would be able to correct for any malfunctions, which in tragic circumstance proved not to be the case. In part due to those assumptions, Boeing did not classify MCAS as a safety-critical system, thereby reducing scrutiny during FAA certification. Importantly, the operation of MCAS violated Boeing's own internal design guidelines, whereby the rush for project completion and simultaneous cost-reduction led to the dismissal of concerns and the elimination of important safety features.

Insert Tables 1 and 2 about here

Airlines who had ordered the plane appear to have been fundamentally unaware of such issue, particularly to the extent that the 737-MAX programme was subject to extensive regulatory engineering and cost-cutting exercises. Instead, in an ultra-competitive industry, the Boeing 737-MAX was advertised as capable of delivering an 8% reduction in fuel-usage and a 14% reduction in CO_2 production when compared to the 'Next-Generation 737'. Ongoing orders of the 737-MAX for publicly traded airlines are presented in Table 1. Further, in Table 2, we identify the proportion of these airlines' fleets that are calculated to be either Boeing, or its main competitor in operation, Airbus. We can clearly identify that a number of airlines are found to possess 100% Boeing fleets, presenting a substantial lack of fleet diversification. This research attempts to establish as to whether the sharp negative public response presented significant effects upon the share prices of these airlines, in comparison to those airlines with diversified fleets, namely a mixture of Airbus, Boeing and other types of aircraft.

2. Data

We collected stock data for our selected companies from Thomson Reuters Eikon for the period 1 January 2016 through 28 February 2020 where returns are presented in Table 1. As per Corbet et al. [2018], we define returns as the daily log changes and volatility as the five-day standard deviation.

Insert Figures 1 and 2 about here

The next stage of data collection surrounded the identification of investor sentiment. To complete this task, Twitter data was collected with regards to Boeing. All tweets mentioning the terms 'Boeing' or '737-MAX' with a robust lexicon of further inclusive search terms were computationally collected through the search Twitter function using the Python 'twitterscraper' package, observing platform rate limiting policies. A total number of 255,035 unique tweets were collected[1]. The data was then aggregated by company and by day as presented in Figure 2, taking sums of the quantitative variables and aggregating the text.

Insert Figure 3 about here

We then computationally code tweets relating to Boeing and the 737-MAX based on sentiment[2]. This research focuses specifically on the subjectivity and polarity of the social media posts, indicative of the scale of real-time understanding of the market as to the severity of the Boeing 737-MAX disasters. Subjectivity analysis of the text is a part of sentiment analysis, where using Natural Language Processing (NLP) researchers classify a text as opinionated or not opinionated. We next determine the sentiment of a tweet through polarity analysis, to ascertain whether it expresses a positive or negative opinion. The purpose of polarity analysis is to determine the emotional attitude of the text writer with respect to the topic under discussion. Each type of sentiment analysed is presented in Figure 3. Evidence of a substantial decline in all measures are presented throughout late 2018 and the period thereafter, appearing to coincide with the Lion Air Flight 610 disaster of 29 October 2018 and the Ethiopian Airlines Flight 302 disaster on 10 March 2019.

3. Empirical Approach and Results

To specifically analyse the effects of the reputational damage associated with the Boeing 737-MAX sentiment on the returns of airlines with aircraft orders placed, we employ a GARCH (1,1)

[1] For brevity, additional summary statistics based on these tweets are available from the authors upon request.

[2] The sentiment variables are based on the Harvard General Inquirer IV-4 dictionary and the Loughran and McDonald Financial Sentiment dictionary.

methodology as developed by Bollerslev [1986] and previously used by Corbet et al. [2020a, 2021], plus other examples including Akyildirim et al. [2020], Kiss and Österholm [2020], Corbet et al. [2020], Carnero et al. [2012], Arin et al. [2008] and Vilasuso [2002], of the following form:

$$R_t = a_0 + \sum_{j=1}^{5} b_j R_{t-j} + b_2 dj_t + b_3 av_t + b_4 d_1 + b_5 d_2 + b_6 \lambda_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t | \Omega_t \sim i.i.d. \quad N(0, h_t) \tag{2}$$

$$h_t = \omega + \alpha_1 h_{t-1} + \beta_1 u_{t-1}^2 \tag{3}$$

R_{t-j} represents the lagged value of the selected cryptocurrency returns, j number of periods before R_t is observed. $b_2 dj_t$ represents the effects of the Dow Jones Industrial Average as a measure of international effects, while $b_3 av_t$ represents the value of the of the MSCI Aviation Index as a representative measure of effects sourced within the broad aviation sector. $b_4 d_1$ and $b_5 d_2$ represent the twenty days after each Boeing 737-MAX-related aviation disaster, with d_1 relating to the Lion Air Flight 610 disaster of 29 October 2018 and d_2 measuring the effects of the Ethiopian Airlines Flight 302 disaster on 10 March 2019. Finally $b_6 \lambda_t$ measures the influence of both the polarity and subjectivity of COVID-19 sentiment respectively. As per Corbet et al. [2020a], we present Bonferroni-adjusted results in this analysis. To cater the multiple hypothesis problem, we adjust the significance level using the Bonferroni correction, which leads to a significance level of 0.1%. The selection of this methodological structure enables robust analysis with regards the influence of negative sentiment relating to the Boeing 737-MAX disasters, where results are presented in Table 3 for both HI and LM measures of polarity and subjectivity respectively.

Insert Table 3 about here

Both clear and significant results are identified through the multiple responses for both dummy variables relating to the 737-MAX disasters, but in particular, D_2, where financial markets clearly identified that issues relating to MCAS as a potential contributory factor could not be eliminated. Companies with no diversification with regards to their fleet were influenced significantly with regards to the negative sentiment surrounding the 737-MAX. The ultra-competitive nature of the low-cost carrier industry has been well-documented (Oum and Yu [1998], Corbet et al. [2019], Good et al. [1995]); the sharp responses for Ryanair, Shandong Airlines, Southwest Airlines and TUI Group with regards to the second Boeing 737-MAX disaster present clear evidence that investors had identified forthcoming fleet and structural issues. This is particularly true when comparing the second response to that of the first disaster. The significant effects of the polarity and subjectivity measures present evidence that social media-driven negativity possessed significant explanatory power with regards to the negative returns experienced by airlines, therefore, indicative that negative news relating to Boeing possessed substantial and significant influence on these companies. Diversified fleets present no similar evidence (with the exception of Icelandair and China Eastern Airlines) either in scale of response to the disasters, or indeed, such effects from the polarity and subjectivity of online public response to the Boeing 737-MAX disasters. The stability of outcomes across both HI and LM structures presents evidence of methodological robustness.

4. Conclusions

Results suggest that airlines with homogeneous fleets, and low-cost carriers heavily reliant on their use of Boeing aircraft, present particular susceptibility to the negative reputational effects sourced within the recent Boeing 737-MAX disasters. A lack of fleet diversification manifested in a subsequent lack of reputational diversification in the aftermath of each disasters. Companies with diversified fleets do not present the same evidence of reputational exposure. In an attempt to obtain cost-savings through the improved fuel-efficiency of the 737-MAX, such low-cost carriers inadvertently exposed themselves to the side-effects of the mutually exclusive production cost-cutting and development limitations imposed by Boeing management in an attempt to neutralise the threat posed by the Airbus A320neo. Such evidence furthers our understanding of the effects of third-party reputational contagion from internal corporate decision-making.

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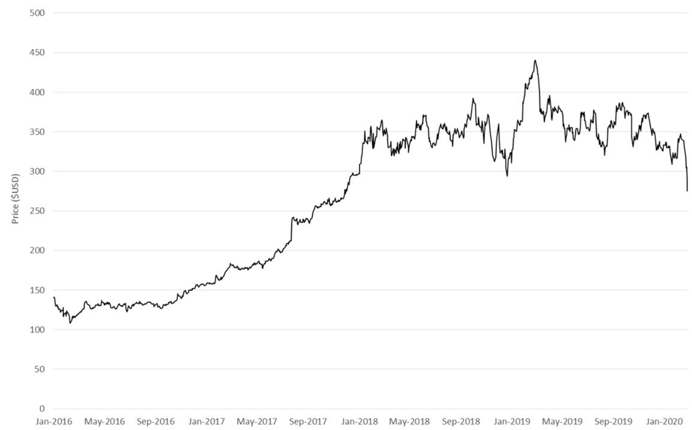
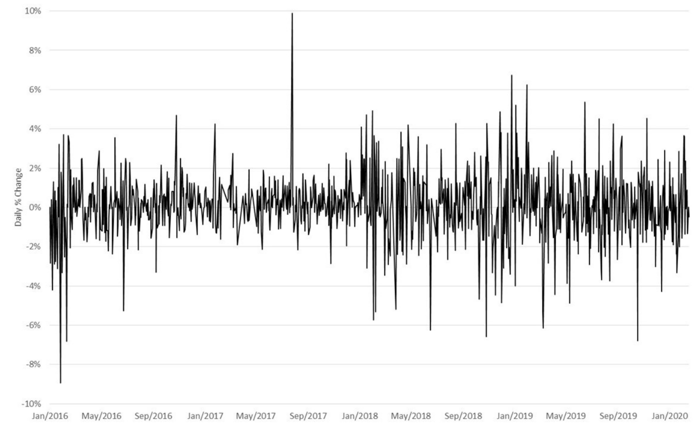
Figure 1: Boeing and broad aviation returns and return volatility, 2016 through 2020

a) Boeing

i) Price



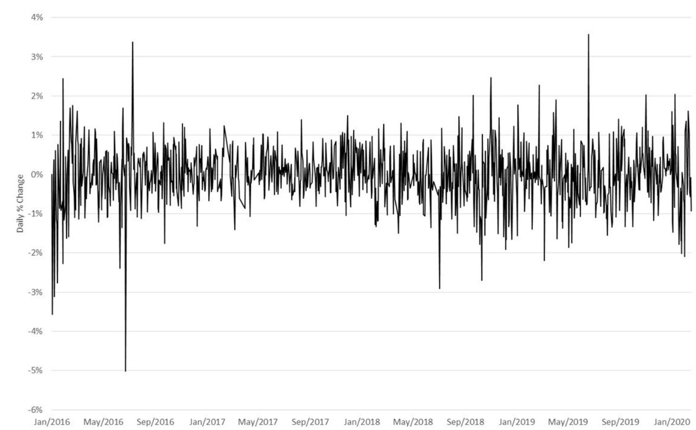
ii) Volatility



b) MSCI World Airlines Aviation Index

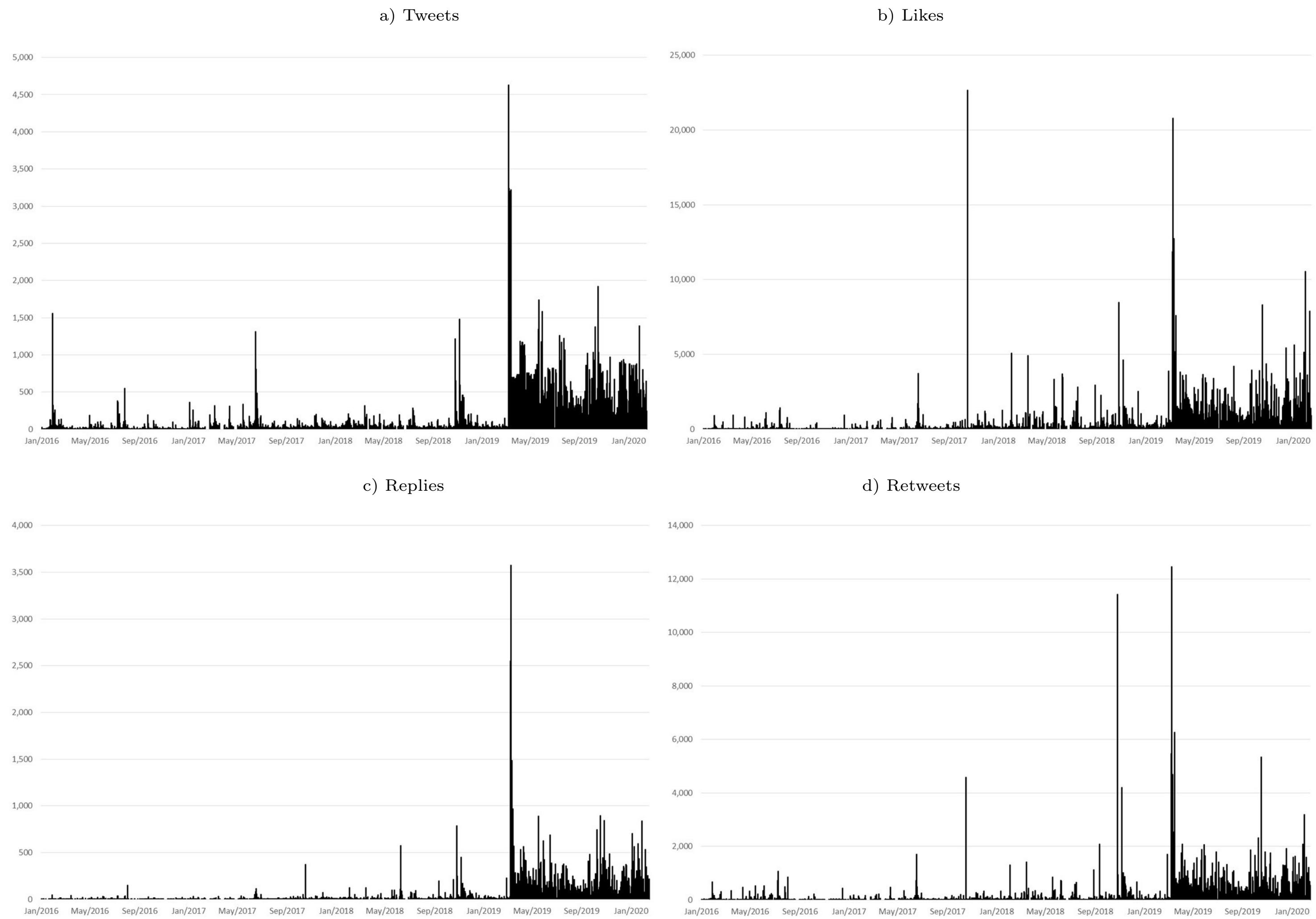
i) Price

ii) Volatility



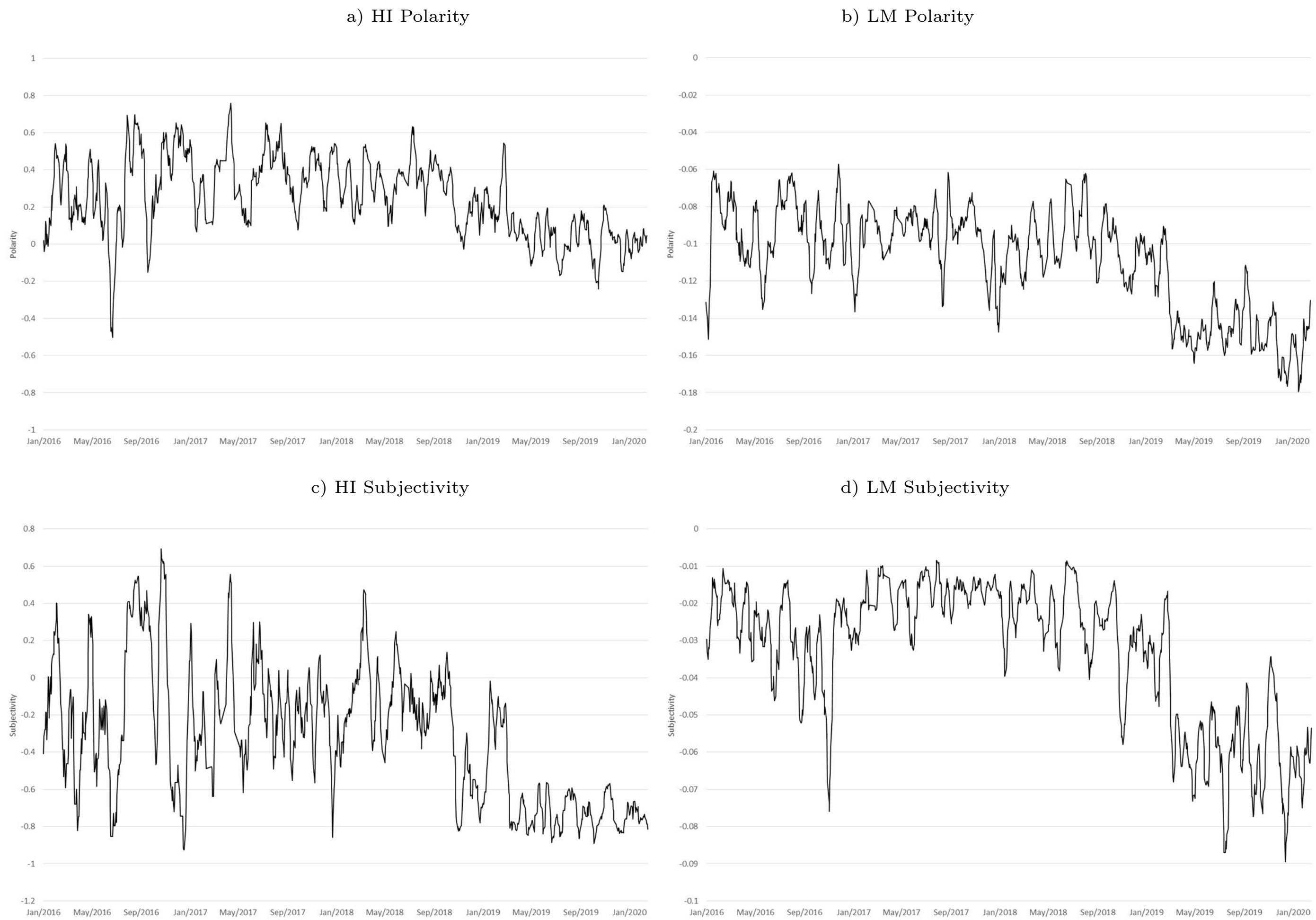
Note: We collect stock data for our selected companies from Thomson Reuters Eikon for the period 1 January 2016 and 28 February 2020.

Figure 2: Boeing-related social media data statistics



Note: Twitter data was collected for a period between 1 January 2016 and 28 February 2020 with regards to Boeing. All tweets mentioning the terms ‘Boeing’ or ‘737-MAX’ with further inclusive search terms were computationally collected through the search Twitter function on https://twitter.com/explore using the Python ‘twitterscraper’ package, observing platform rate limiting policies. A total number of 255,035 unique tweets were collected.

Figure 3: Boeing-related social media polarity and subjectivity



Note: The sentiment variables are based on the Harvard General Inquirer IV-4 dictionary and the Loughran and McDonald Financial Sentiment dictionary. This research focuses specifically on the subjectivity and polarity of the social media analysis, indicative of the scale of real-time understanding of the market as to the severity of the Boeing 737-MAX disasters.

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
American Airlines	01-Feb-13	100	24	76	28-Sep-17	AAL.O	-	US
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
Hainan Airlines Holding	16-Jul-14	7	7	-	17-Nov-17	ICAG.L	Int. Cons. Airlines Group	UK
Icelandair	12-Feb-13	5	3	2	04-Mar-18	ICEAIR.IC	Icelandair Group HF	Iceland
Jeju Air	19-Nov-18	40	-	40	-	006840.KS	AK Holdings INC	South Korea
Ryanair	28-Nov-14	135	-	135	-	RYA.I	-	Ireland
Shandong Airlines	29-Apr-14	7	7	-	01-Jun-18	200152.SZ	-	China
Southwest Airlines	13-Dec-11	280	31	249	26-Aug-17	LUV	-	US
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
Virgin Australia Airlines	06-Jul-12	40	-	40	-	VAH.AX	-	Australia

Note: Data was obtained from Boeing in June 2020 (Available here).

Table 2: 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%
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	0	0	6	11	0	1	0	0	17	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%
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%
TUI Group	0	0	45	10	0	5	0	0	55	100.0%
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

Table 3: GARCH-calculated polarity and subjectivity influence based on the Boeing disasters

	Boeing	MSCI Av	D_1	D_2	ARCH	GARCH	HI Pol.	LM Pol.	HI Sub.	LM Sub.	Wald Chi^2	Prob
100% Boeing fleet												
9 Air	-0.0766***	1.3958***	-0.0020	-0.0051***	0.0549***	0.9228***	0.0014	0.0057***	-0.0022	-0.0011	1,139.42	0.000***
	(0.0236)	(0.0427)	(0.0045)	(0.0022)	(0.0081)	(0.0107)	(0.0017)	(0.0077)	(0.0007)	(0.0038)		
AeroMexico	0.0470*	0.3835***	-0.0086***	-0.0021	0.0946***	0.6974***	0.0008	0.0075***	-0.0021***	-0.0040***	176.98	0.000***
	(0.0244)	(0.0487)	(0.0016)	(0.0020)	(0.0157)	(0.0437)	(0.0017)	(0.0093)	(0.0001)	(0.0003)		
Comair	-0.0232	0.5869***	0.0009	-0.0049	0.1056***	0.0791***	0.0008	0.0150	-0.0046***	-0.0088*	54.58	0.000***
	(0.0399)	(0.0894)	(0.0046)	(0.0058)	(0.0102)	(0.0173)	(0.0031)	(0.0142)	(0.0001)	(0.0052)		
Jeju Air	0.0056	0.7598***	-0.0061**	-0.0031	0.2317***	0.7017***	0.0033*	0.0058	-0.0061**	-0.0054	261.22	0.000***
	(0.0246)	(0.0539)	(0.0030)	(0.0035)	(0.0251)	(0.0302)	(0.0018)	(0.0097)	(0.0030)	(0.0039)		
Ryanair	0.0269	1.1628***	-0.0041	-0.0054*	0.0385**	0.4385*	0.0025	0.0010	-0.0080***	-0.0046	990.36	0.000***
	(0.0286)	(0.0453)	(0.0027)	(0.0030)	(0.0164)	(0.2318)	(0.0020)	(0.0093)	(0.0031)	(0.0036)		
Shandong Air.	-0.1707***	1.1497***	-0.0019	-0.0047***	0.0582***	0.8730***	0.0012	0.0044	-0.0063***	-0.0043***	1,294.83	0.000***
	(0.0199)	(0.0337)	(0.0021)	(0.0018)	(0.0076)	(0.0136)	(0.0013)	(0.0070)	(0.0024)	(0.0003)		
Southwest Air.	0.3167***	0.7796***	0.0019	-0.0199***	0.1510***	0.8254***	0.0010***	0.0085*	-0.0025***	-0.0033***	2,078.88	0.000***
	(0.0141)	(0.0293)	(0.0022)	(0.0011)	(0.0323)	(0.0089)	(0.0012)	(0.0051)	(0.0004)	(0.0003)		
TUI Group	0.1166***	1.0036***	-0.0062***	-0.0051**	0.3692***	0.5440***	0.0026*	0.0185**	-0.0044*	-0.0045***	1,387.21	0.000***
	(0.0223)	(0.0349)	(0.0017)	(0.0023)	(0.0297)	(0.0218)	(0.0014)	(0.0075)	(0.0025)	(0.0002)		
>50% Boeing fleet												
	Boeing	MSCI Av	D_1	D_2	ARCH	GARCH	HI Pol.	LM Pol.	HI Sub.	LM Sub.	Wald Chi^2	Prob
American Air.	0.2593***	1.3529***	0.0043**	-0.0035	0.2400***	0.6439	0.0024	0.0055	0.0001	-0.0032	1,862.37	0.000***
	(0.0199)	(0.0403)	(0.0019)	(0.0029)	(0.0289)	(0.0273)	(0.0016)	(0.0068)	(0.0027)	(0.0034)		
Hainan Air.	-0.0175	0.7466***	0.0007	-0.0028	0.2117***	0.7219***	0.0025***	0.0084*	-0.0014	-0.0020	1,857.66	0.000***
	(0.0158)	(0.0224)	(0.0016)	(0.0027)	(0.0233)	(0.0157)	(0.0007)	(0.0045)	(0.0017)	(0.0021)		
Icelandair	-0.0705	0.8647***	0.0074	-0.0092***	0.0166***	0.9639***	0.0049	-0.0029	-0.0065	-0.0080	114.07	0.000***
	(0.0449)	(0.0910)	(0.0046)	(0.0043)	(0.0023)	(0.0050)	(0.0032)	(0.0160)	(0.0057)	(0.0076)		
Korean Air	0.0111	0.7552***	0.0040***	0.0008	0.0185	0.9123	0.0014	0.0024	-0.0035	-0.0024	270.21	0.000***
	(0.0225)	(0.0518)	(0.0021)	(0.0026)	(0.0133)	(0.3417)	(0.0021)	(0.0104)	(0.0035)	(0.0043)		
Utair Av.	-0.0008	0.1801***	-0.0005	-0.0014	0.0515***	0.6891***	0.0001	0.0007	-0.0016	-0.0017	17.43	0.096*
	(0.0237)	(0.0469)	(0.0046)	(0.0051)	(0.0151)	(0.0895)	(0.0017)	(0.0083)	(0.0034)	(0.0040)		
Virgin Aus.	-0.1040***	0.5930***	-0.0017	-0.0029	0.2468***	0.6881***	0.0014	0.0040	-0.0011	-0.0011	84.08	0.000***
	(0.0351)	(0.0675)	(0.0041)	(0.0057)	(0.0342)	(0.0334)	(0.0025)	(0.0098)	(0.0045)	(0.0057)		
<50% Boeing fleet												
	Boeing	MSCI Av	D_1	D_2	ARCH	GARCH	HI Pol.	LM Pol.	HI Sub.	LM Sub.	Wald Chi^2	Prob
Air Canada	0.1079***	1.0879***	0.0022	-0.0009	0.2321***	0.4086***	-0.0004	0.0044	0.0001	-0.0020	867.25	0.000***
	(0.0285)	(0.0503)	(0.0031)	(0.0033)	(0.0228)	(0.0403)	(0.0018)	(0.0110)	(0.0035)	(0.0047)		
Air China	-0.1766***	1.7517***	-0.0002	-0.0026	0.1898***	0.7572***	0.0014	0.0093	-0.0009	-0.0007	2,323.09	0.000***
	(0.0256)	(0.0399)	(0.0030)	(0.0027)	(0.0233)	(0.0338)	(0.0017)	(0.0075)	(0.0028)	(0.0036)		
China East.	-0.1588***	1.5662***	-0.0004	0.0082***	0.1747***	0.7478***	0.0004	0.0123	-0.0008	-0.0020	2,248.32	0.000***
	(0.0199)	(0.0357)	(0.0025)	(0.0019)	(0.0295)	(0.0640)	(0.0016)	(0.0063)	(0.0028)	(0.0034)		
China South.	-0.1992***	1.7704***	0.0008	0.0033	0.1477***	0.7733*	0.0002	0.0172*	-0.0005	-0.0006	2,486.45	0.000***
	(0.0218)	(0.0389)	(0.0032)	(0.0022)	(0.0277)	(0.0401)	(0.0017)	(0.0066)	(0.0028)	(0.0036)		
United Air.	0.1486***	1.1360***	0.0007	-0.0005	0.2448***	0.7050***	0.0016	0.0038	-0.0037	-0.0035	2,112.73	0.000***
	(0.0214)	(0.0361)	(0.0025)	(0.0032)	(0.0323)	(0.0119)	(0.0012)	(0.0070)	(0.0030)	(0.0037)		

Note: ***, ** and * denote significance at the 1%, 5% and 10% levels. For brevity, some additional results have been omitted from the above table and are available from the authors on request.