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Impact of Airplane Crashes on Firm's Credit Risk Under the CreditGrades Model

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Abstract

The paper examines the impact of airplane accidents with 40 or more fatalities, on airline's firm credit risk. The sample contains 20 airplane crashes for the period 2000-2017. The analysis proposes the CreditGrades model introduced by Finger et al. (2002) , which is an extension of the first passage time model of Black and Cox (1976). The study concludes that airplane accidents lead to a statistically significant increase in airline's Probability of Default. The results are both significant and robust under the t-Test and the non-parametric Wilcoxon Signed-rank test.

Keywords

Aviation accidents, Airlines, Credit risk, Probability of Default, CreditGrades model

Cover Page Footnote

I am grateful to all of those introducing me into the world of Financial Mathematics. Any error remains author's responsibility.

1. Introduction

Aviation industry is constantly changing due to it's particular dynamics in legal, institutional, technological and safety domain. According to Cento (2009), the last half-century was marked by market deregulation in terms of pricing capacity, route determination, entrance of low-cost carriers in the market as well as mergers among major airlines. Until the Airline Deregulation Act of 1978 in United States, ticket pricing was under the authority of the International Air Transport Association (IATA). The same applies to Europe (Butcher 2010), where the deregulation process consisted of three air transport liberalization packages. The first package in 1987 eliminated capacity limitations and enabled a number of smaller airlines to enter important routes or to provide the capacity they wished. The second package in 1990 permitted airlines to set the fares considered appropriate unless both States of departure and arrival disapprove it. The third package in 1992 established full access to all routes within Member States,free pricing and defined the financial standards that air carrier should fulfill in order to grant or maintain license.

Apart from the institutional framework, commercial aviation faced various technological improvements. The average fuel consumption fell by about 45% from 1968 to 2014 in contrast with volatility of fuel prices which increased sharply the last decade (Kharina and Rutherford 2015). The rise of aviation engineering lead to manufacture of supersonic turbojet-powered aircrafts, two of which operated commercial flights, the Concorde and the Tupolev Tu-144. Moreover, innovation in Avionics such as ACARS [1], ILS [2] and FMS [3] improved flight functionality and reduced the workload on the flight crew. The aforementioned imply, that aviation industry has become more efficient through time.

Although, this efficiency is often being replaced by uncertainty and fear, with reference to safety issues. The main reason is occurrence of a potential airplane accident. Poor aircraft maintenance, pilot and traffic control error, severe weather conditions or even terrorism may result in a fatal accident and therefore reverse public perception towards civil aviation. The most representative example is the case of 9/11 attack, where 4 aircrafts were hijacked, resulting in thousands of fatalities and a great hit in safety systems and procedures. As reported by IATA (2011), the aftermath was a decline of 2.7 % in global passenger traffic and 13 $ billion loss for airline firms in 2001. Drakos (2011) finds that

[1] Aircraft Communications Addressing and Reporting System (ACARS) is a digital system which enables communication between aircraft and ground stations

[2] Instrument Landing System (ILS) is a navigation system which provides aircraft with horizontal and vertical guidance during landing

[3] Flight Management System (FMS) is a computer system that automates a variety of in-flight tasks

9/11 attacks increased significantly both systematic and idiosyncratic risk for a sample of airline firms.

In corporate level, a significant number of airlines ceased operations or restructured months after a fatal airplane accident [4], being unable to sustain increased costs.[5] As stated by Cavka and Čokorilo (2012) and National Aerospace Laboratory (2001), direct accident related costs consist of hull loss due to catastrophic or disastrous aircraft physical damage and loss of use associated with leasing costs until aircraft replacement or repair. Other direct costs are these related to airport closure in case of a severe accident during takeoff or landing near the runway as well as site contamination and clearance. Occurrence of fatalities or injuries add onto financial burden since compensation per death is the Value of a Statistical Life (VOSL) and compensation per injury accounts as 13 % of the VOSL. Indirect costs are the "second-round effects", evolved from search and rescue services,the investigation carried out by the relevant safety board and finally the loss of reputation.

Many studies focus on the impact of airplane accidents on airline's stock price. Indicatively, following Homar (2015), cumulative abnormal average return is negative and statistical significant the first 13 days after the airplane crash, for a sample of U.S airlines. Kaplanski and Levy (2010) find that aviation accidents lead to negative returns which are accompanied by a reversal effect two days later. Although, the literature with reference to airline's credit risk is limited. Grétarsson and Göransson (2008) apply different structural models for several airline firms, calculating their probability of default [6]. However, there is no conclusion about the impact of airplane crashes on the PD. We are going to examine this using the CreditGrades model proposed by Finger et al. (2002). The model is an extension of the first passage time model introduced by Black and Cox (1976). The sample consists of 20 airplane accidents for the period 2000-2017. Our sample seems relative small compared to the total number of airplane crashes in the selected period, since many airline firms are private without stock listed in the stock exchange. Table 1 provides details with regards to date of accident occurrence, the operator, number of fatalities and the source of the accident report. We define an event window of 90 days before the crash and 360 days after. Our hypothesis is that airplane accidents increase significantly airline's PD. We conduct a parametric two-tailed t-test and a non parametric Wilcoxon signed-rank test to check whether our hypothesis holds.

[4]We do not distinguish whether the crash was an incident or accident. For brevity, we denote the crash as accident

[5]For instance, Helios Airways, ValuJet Airlines, Air Florida and Pan American World Airways

[6]For convenience, we will often refer to Probability of Default as PD.

2. Data

The sample consists of 20 airplane accidents for the period 2000-2017. All historical information from the Balance Sheet, the Income Statement as well as stock prices were collected from the Thomson Reuters Eikon database, except of a few particular cases. Due to absence of data, the stock prices of Air France were retrieved from the official web page of Air France-KLM Group[7]. The stock price series of American Airlines Group was gathered from Morningstar. From the 20 airplane crashes, 17 were used for testing our hypothesis.

3. Methodology

3.1. The Model

Following the Technical Document by Finger et al. (2002), the CreditGrades model assumes that firm's asset value V follows a Geometric Brownian Motion

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t \tag{1}$$

Where W_t is a Standard Brownian Motion under the physical measure P, μ the asset's drift [8] and σ asset's volatility. We define the default barrier as the value of firm's assets after a potential default. Since, debt is modelled as short put option and equity as a long call option, debt holders will receive the remaining amount of firm's assets, denoted as LD. Dept-per-share is expressed as D and L is the average recovery rate on debt.

In contrast with other structural models where the default barrier is fixed, the CreditGrades model introduces randomness through the recovery rate L, since the exact level of leverage is unknown until the time of default. Hence, the recovery rate is L is assumed to follow a lognormal distribution with mean $\bar{L}$ and percentage variance λ^2 . The random default barrier is given by:

$$LD = \bar{L}De^{\lambda Z - \frac{\lambda^2}{2}} \tag{2}$$

$$\mathbb{E}(L) = \bar{L} \tag{3}$$

$$Var[log(L)] = \lambda^2 \tag{4}$$

Where, Z $\sim N(0,1)$ independent of the Brownian motion W_t. Recovery rate is a

[7]http://www.airfranceklm.com

[8]μ is assumed to be zero, since firm is expected to maintain a steady level of leverage

random variable and therefore the default barrier can bit hit unexpectedly. The firms does not default as long as

$$V_0 e^{\sigma W_t - \sigma^2 t/2} > \bar{L} D e^{\lambda Z - \lambda^2/2} \tag{5}$$

The survival probability of the firm at time t is approximated in a closed-form as:

$$P(t) = \Phi\Big(-\frac{A_t}{2} + \frac{ln(d)}{A_t}\Big) - d\,\Phi\Big(-\frac{A_t}{2} - \frac{ln(d)}{A_t}\Big) \tag{6}$$

Where

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L} D} \tag{7}$$

$$A_t^2 = \sigma^2 t + \lambda^2 \tag{8}$$

Φ denotes the cumulative normal distribution function. For a rigorous description of the CreditGrades model and it's theoretical derivation, see Finger et al. (2002).

3.2. Parameter Specification and Calibration

In order to apply the model in the sample of the airline firms, we have to specify the parameters used as inputs. Let S denote firm's equity price, S_0 the stock price at time t=0 and σ_s the equity volatility. The asset and equity volatility is connected through

$$\sigma_s = \sigma \frac{V}{S} \frac{\partial S}{\partial V} \tag{9}$$

By examining the boundary conditions, Finger et al. (2002) conclude that asset volatility is given by

$$\sigma = \sigma_s \frac{S}{S + LD} \tag{10}$$

and the initial asset value V_0 at time t=0

$$V_0 = S_0 + \bar{L} D \tag{11}$$

For the estimator of the equity volatility $\hat{\sigma}_s$, we use the 252-day historical volatility, annualized from the daily stock price returns. As equity price we use the current stock price S_t. Hence, asset volatility is estimated as

$$\sigma = \hat{\sigma}_s \frac{S_t}{S_t + \bar{L} D} \tag{12}$$

Asset's value drift μ is assumed to be zero. The mean recovery rate $\bar{L}$ and the percentage standard deviation λ are estimated to be 0.5 and 0.3 respectively (Hu and Lawrence (2000), as stated by Finger et al. (2002)). Moreover, we specify the debt-per-share D using the data from firm's financial statements. The debt consists of the Liabilities that add onto firm's financial leverage. Specifically,

$$\begin{aligned} Financial\_Debt = {} & ST\_Borrow + LT\_Borrow \\ & + 0.5(Other\_ST\_Liabilities + Other\_LT\_Liabilities) \\ & + 0(Acct\_Payable) \end{aligned} \tag{13}$$

Financial debt contains the principal value of both short-term and long-term borrowings and half the sum of other liabilities. Accounts payable are excluded since they are non-financial liabilities. The technical document assumes usage of the Bloomberg Database. The matching between the Bloomberg Variable and the respective Balance Sheet accounts follows Martins (2014). From the financial debt we have to subtract the Minority Interest, which is the portion of the subsidiary that parent company does not own.

$$Debt = Financial\_Debt - Minority\_Interest \tag{14}$$

Finally, we need to divide the debt with firm's number of shares. The technical document uses the Common Shares Outstanding and the equivalent number of preferred shares. Preferred shares are estimated as the Preferred Equity divided by the current stock price. We deviate from Finger et al. (2002) and instead of the Common Shares Outstanding we use the Basic Weighted Average Shares as reported in firm's Income Statement. An airplane accident increases firm's costs and therefore the probability of a share capital increase is higher. Basic Weighted Average Shares "smooth" changes in outstanding shares, taking into consideration the period that new shares were outstanding. Hence,

$$Number\_of\_Shares = BWAS + PFD\_Equity/Stock\_Price \tag{15}$$

Using (14) and (15), we calculate the debt-per-share as

$$D = Debt/Number\_of\_Shares \tag{16}$$

We use the accounts from quarterly or annual financial statements, which depends on the availability provided by each airline. We prefer the most frequent data as they adjust earlier to the change in firm's debt-per-share. For a detailed description, Table 2 contains the accounts used as input in order to calculate the debt-per-share.

3.3. Cross-sectional PD and log changes

To examine the impact of airplane crashes, firstly we have to calculate the log changes in PD around the accident. We define an interval 90 calendar days before the accident until 360 after. For each accident, we isolate the 5 year implied PD, 90,60 and 30 calendar days before the crash as well as 30,60,90,180,270 and 360 after. Moreover, we calculate the log changes for each pair (i, j), where i denotes the days before and j the days after the crash. $ln(PD_j/PD_i)$ is the log change of PD from day i to j, and not the cumulative log change from i to j. We create the cross-sectional samples which contain the log changes

$$ln(PD_j/PD_i), \ \ \forall i \in \{-90, -60, -30\} \text{ and } j \in \{30, 60, 90, 180, 270, 360\} \quad (17)$$

The accident day (day "0"), the days before i and the days after the crash j, might not correspond to a trading day. We choose the closest trading day measured by the distance in calendar days.

4. Results

We estimate the PD for each airline for the window (-90,360). Figure 2 provides the sub-figures of each case, which display the progression of PD around the accident. Table 3 provides the descriptive statistics of the log changes. Moreover, we estimate the average and median log changes of PD in weekly frequency, the cumulative average log changes and the mean normalized PD for each accident. We scale all PDs in the time interval (-90,360) to [0,1] using the min-max normalization. The normalized PD is given by

$$PD_{norm} = \frac{PD - PD_{min}}{PD_{max} - PD_{min}} \quad (18)$$

By linearly scaling the PDs to [0,1], we reduce the variance cross-sectionally. We use the normalized PDs only in Figure 1-a. All other calculations implement the raw data . Figure 1-b provides the weekly average and median log changes. As can be seen, a week after the accident the average PD increases around 22 % (median PD increases around 5%). This is consistent with Walker et al.(2009), who find that cumulative abnormal returns reach the smallest value a week after the crash, since in the short-run, PD is mainly affected by changes in the stock price. On the other hand, the cumulative log changes generally increase until a year after the accident. Intuitively, accidents seem to increase airline's PD.

To test whether this hypothesis holds, we conduct a two-tailed t-Test and the non-parametric Wilcoxon signed-rank test for the log changes in PD. Table

4 provides the t-Statistics and in parentheses the respective p-values. Sample sizes differ since Panel 4-A contain all accidents except of American Airlines flight 11,77 and 587. Panel 4-B excludes all accidents affected by 9/11, ensuring that changes in PD are primarily caused by firm specific factors. As aforementioned, 9/11 attack increased significantly both systematic and idiosyncratic risk for airline firms (Drakos, 2011). For the whole sample, all t-Statistics are positive and large, indicating that PD changed significantly in 5% level. For the sample excluding accidents during 9/11 , the t-Statistics remain positive but, as expected, are smaller relative to the t-Statistics of the whole sample. The most log changes remain significant at 5% level.

However, by conducting the Shapiro-Wilk normality test for the log changes in PD, we reject the null hypothesis in significance level 1%, as displayed in Table 3. Hence, we apply the Wilcoxon signed-ranked test. Table 5 contains the test statistics and in parentheses the corresponding p-values. For the whole sample in Panel 5-A, all statistics are significant and less than 34, which is the cutoff value for the 5% level. Panel 5-B contains the same samples as Panel 4-B. The majority of cases presents significance at 5% level. In total, changes are significant 1,3,6,9 and 12 months after the crash. For the log changes 2 months after, the t-statistics in Panel 4-B are non-significant. This could partially be explained by a reversal in stock price , as well as by the calculation of debt-per-share, since potential increase in liabilities might not be absorbed fully in airline's accounts as displayed in Figure 3.

5. Conclusion

In the present study, we investigate the impact of airplane disasters on firm's credit risk. Implementing a structural model, we find that accidents with 40 or more fatalities increase significantly airline's PD. A week after the crash, mean PD increases about 22% and median PD about 5%, indicating that agents absorb partially the economic consequences of the crash. On average, the effect persists and PD keeps rising even 12 months after the disaster.

Our sample is relative small and does not take into account firm's size or market trends that might affect airline's stock price reaction. Even though, for the whole sample and the sample excluding 9/11 period, results are robust and significant under the parametric t-Test and the non-parametric Wilcoxon signed ranked test. Findings can have practical implications, since the increase in PD directly affects portfolio's credit risk with exposure to an airline involved in a fatal disaster.

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6. Tables

Table 1: Information about the sample of airplane accidents

Table 1 reports the essential data of the airplane crashes used in the calculations, such as the aircraft operator and flight code,date of occurrence and number of fatalities as well as the source of the accident report (in the majority of cases the Investigation and Safety Board in charge). Spanair was a subsidiary of SAS Group, but 80.1 % of the holding was sold in January 2009 (SAS Group, 2009). Germanwings is a subsidiary wholly owned by Lufthansa Group.

#	Airline	Date	Flight	Fatalities	Source
1	Aeroflot-Nord	14 Sep 2008	AFL 821	88	Interstate Aviation Committee (2008)
2	Air France	25 Jul 2000	AFR 4590	113	Bureau Enquêtes-Accidents (2002a)
3	Air France	1 Jun 2009	AF 447	228	Bureau Enquêtes-Accidents (2012)
4	American Airlines	11 Sep 2001	AAL 11	92	National Transportation Safety Board (2006a)
5	American Airlines	11 Sep 2001	AAL 77	64	National Transportation Safety Board (2006b)
6	American Airlines	12 Nov 2001	AA 587	265	National Transportation Safety Board (2001)
7	China Airlines	25 May 2002	CI 611	225	Aviation Safety Council (2005)
8	China Eastern Airlines	21 Nov 2004	CES 5210	55	National Transportation Safety Board (2005)
9	GOL Lihnas	29 Sep 2006	GLO 1907	154	CENIPA (2008)
10	Indonesia AirAsia	28 Dec 2014	QZ 8501	162	KNKT (2015)
11	Kenya Airways	30 Jan 2000	KQ 431	169	Bureau Enquêtes-Accidents (2002b)
12	Kenya Airways	5 May 2007	KQA 507	114	Cameroon Civil Aviation Authority (2010)
13	Pakistan Airlines	10 Jul 2006	PK 688	45	Pakistan Civil Aviation Authority (2006)
14	Pakistan Airlines	7 Dec 2016	PK 661	47	ICAO (2017)
15	SAS	8 Oct 2001	SK 686	114	ANSV (2004)
16	Spanair	20 Aug 2008	JKK 5022	154	CIAIAC (2011)
17	Turkish Airlines	8 Jan 2003	TK 634	75	National Transportation Safety Board (n.d.)
18	Germanwings	24 Mar 2015	4U9525	150	Bureau Enquêtes-Accidents (2016)
19	Alaska Airlines	31 Jan 2000	Flight 261	88	National Transportation Safety Board (2003)
20	Singapore Airlines	31 Oct 2000	SQ 006	83	Aviation Safety Council (2002)

Table 2: Accounts used in the calculation of debt-per-share

Category	**Account**
ST_BORROW	Current Port. of LT Debt/Capital Lease
	Note Payable/Short Term Debt
LT_BORROW	Total Long Term Debt
OTHER_ST_LIABILITIES	Payable/Accrued
	Accrued Expenses
	Other Current Liabilities,Total
OTHER_LT_LIABILITIES	Deferred Income Tax
	Other Liabilities,Total
ACCT_PAYABLE	Accounts Payable
MINORITY_INTEREST	Minority Interest
PFD_EQUITY	Redeemable Preferred Stock, Total
	Preferred Stock - Non Redeemable, Net
BWAS	Basic Weighted Average Shares

Table 3: Descriptive statistics for the log changes in PD

Table 3 provides the descriptive statistics for the log changes in PD. Shapiro-Wilk contains the test statistic of the Shapiro-Wilk normality test. ">0" denotes the positive changes and "<0" the negative changes. N displays the sample size. For brevity, we do not provide all the 18 possible combinations. *,** and *** indicate significance at 10% , 5% and 1% level, respectively.

	Mean	**Median**	**Std. Dev.**	**Shapiro-Wilk**	**>0**	**<0**	**N**
$ln(\frac{PD_{+90}}{PD_{-90}})$	0.90	0.12	1.54	0.69***	12	5	17
$ln(\frac{PD_{+60}}{PD_{-60}})$	0.62	0.13	1.16	0.76***	13	4	17
$ln(\frac{PD_{+30}}{PD_{-30}})$	0.46	0.17	0.82	0.64***	13	4	17
$ln(\frac{PD_{+60}}{PD_{-30}})$	0.48	0.10	0.92	0.74***	13	4	17
$ln(\frac{PD_{+90}}{PD_{-30}})$	0.53	0.24	0.93	0.73***	13	4	17
$ln(\frac{PD_{+180}}{PD_{-30}})$	0.74	0.28	1.13	0.76***	13	4	17
$ln(\frac{PD_{+270}}{PD_{-30}})$	0.69	0.41	1.20	0.84***	11	6	17
$ln(\frac{PD_{+360}}{PD_{-30}})$	0.85	0.44	1.33	0.83***	11	6	17

Table 4: One sample-two tailed t-Test for the log changes in PD

Table 4 contains the t-Statistics for the log changes in PD and in parentheses the respective p-values. Panel A contains all the accidents except of the American Airlines flights 11,77 and 587. At 9/11 flights 11 and 77 were hijacked and isolating the effect of each accident would require an arbitrary assumption. Also, flight 587 is excluded since the corresponding accident occurred a few days after 9/11. Panel B contains only the accidents whose PD is not affected by 9/11 . All accidents happened 90 calendar days after 11 September are removed. If an accident took place before 11 September, all calculation of PD after that date would be excluded. N denotes the sample size. *,** and *** indicate significance at 10% , 5% and 1% level, respectively.

Panel A: Including accidents during 9/11 period												
	N	30	N	60	N	90	N	180	N	270	N	360
-90	17	2.36**	17	2.25**	17	2.41**	17	2.71**	17	2.55**	17	2.90**
		(0.031)		(0.039)		(0.028)		(0.015)		(0.021)		(0.010)
-60	17	2.44**	17	2.22**	17	2.40**	17	2.85**	17	2.46**	17	3.15***
		(0.027)		(0.041)		(0.029)		(0.012)		(0.026)		(0.006)
-30	17	2.33**	17	2.13**	17	2.36**	17	2.70**	17	2.38**	17	2.63**
		(0.033)		(0.049)		(0.031)		(0.016)		(0.030)		(0.018)
Panel B: Excluding accidents during 9/11 period												
	N	30	N	60	N	90	N	180	N	270	N	360
-90	16	2.21**	16	2.11*	16	2.26**	16	2.57**	16	2.38**	15	2.36**
		(0.043)		(0.052)		(0.039)		(0.021)		(0.031)		(0.033)
-60	16	2.31**	16	2.11*	16	2.27**	16	2.73**	16	2.31**	15	2.64**
		(0.035)		(0.052)		(0.039)		(0.016)		(0.036)		(0.019)
-30	16	2.16**	16	1.98*	16	2.19**	16	2.55**	16	2.20**	15	2.11*
		(0.048)		(0.066)		(0.045)		(0.022)		(0.044)		(0.053)

Table 5: Wilcoxon Signed-rank test for the log change in PD

Table 5 provides the two tailed Wilcoxon signed-rank test statistics for the log changes in PD and in parentheses the respective p-values. Panel A contains all accidents except of American Airlines flights 11,77 and 587. Panel B contains only the accidents whose PD is not affected by 9/11. N denotes the sample size. *,** and *** indicate significance at 10% , 5% and 1% level, respectively.

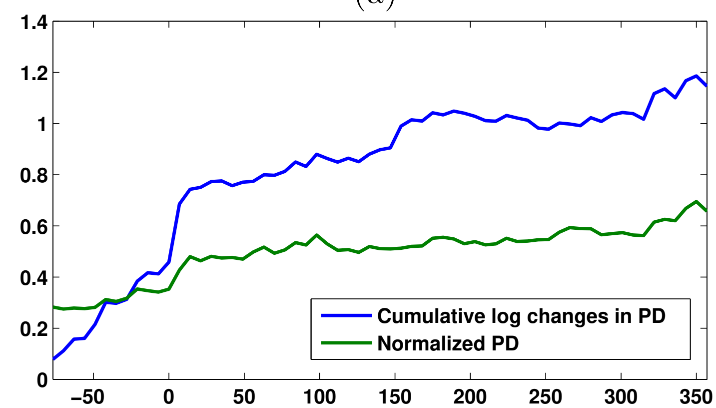
Panel A: Including accidents during 9/11 period												
	N	30	N	60	N	90	N	180	N	270	N	360
-90	17	22***	17	31**	17	27**	17	22***	17	27**	17	20***
		(0.010)		(0.031)		(0.019)		(0.010)		(0.019)		(0.007)
-60	17	10***	17	24**	17	20***	17	15***	17	27**	17	15***
		(0.002)		(0.013)		(0.007)		(0.004)		(0.019)		(0.004)
-30	17	14***	17	23**	17	24**	17	17***	17	26**	17	26**
		(0.003)		(0.011)		(0.013)		(0.005)		(0.017)		(0.017)
Panel B: Excluding accidents during 9/11 period												
	N	30	N	60	N	90	N	180	N	270	N	360
-90	16	22**	16	31*	16	27**	16	22**	16	26**	15	20**
		(0.017)		(0.056)		(0.034)		(0.017)		(0.030)		(0.022)
-60	16	10***	16	23**	16	20**	16	15***	16	26**	15	15***
		(0.003)		(0.020)		(0.013)		(0.006)		(0.030)		(0.008)
-30	16	14***	16	22**	16	24**	16	17***	16	26**	15	26*
		(0.005)		(0.017)		(0.023)		(0.008)		(0.030)		(0.055)

7. Figures

Figure 1: Normalized PD and log changes in raw data around the accident

Figure 1-a contains the cumulative average log changes in PD and the normalized PD according to min-max normalization. Figure 1-b displays the median and average log changes in PD. All calculations are done in weekly frequency. American Airlines flights 11,77 and 587 have been excluded.

(a)



(b)

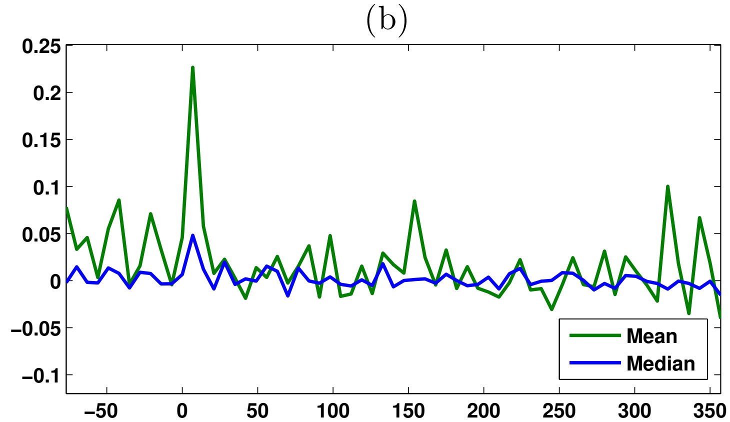


Figure 2: 5 year implied Probability of Default for each airline around the accident

Figure 2 provides the 5 year PD 90 calendar days before the accident until 360 after. Each sub-figure's title contains the airline's name and the respective flight code number. For integrity reasons, we provide the sub-figure of American Airlines flight 11,77 and 587 without incorporating the results in the hypothesis testing.

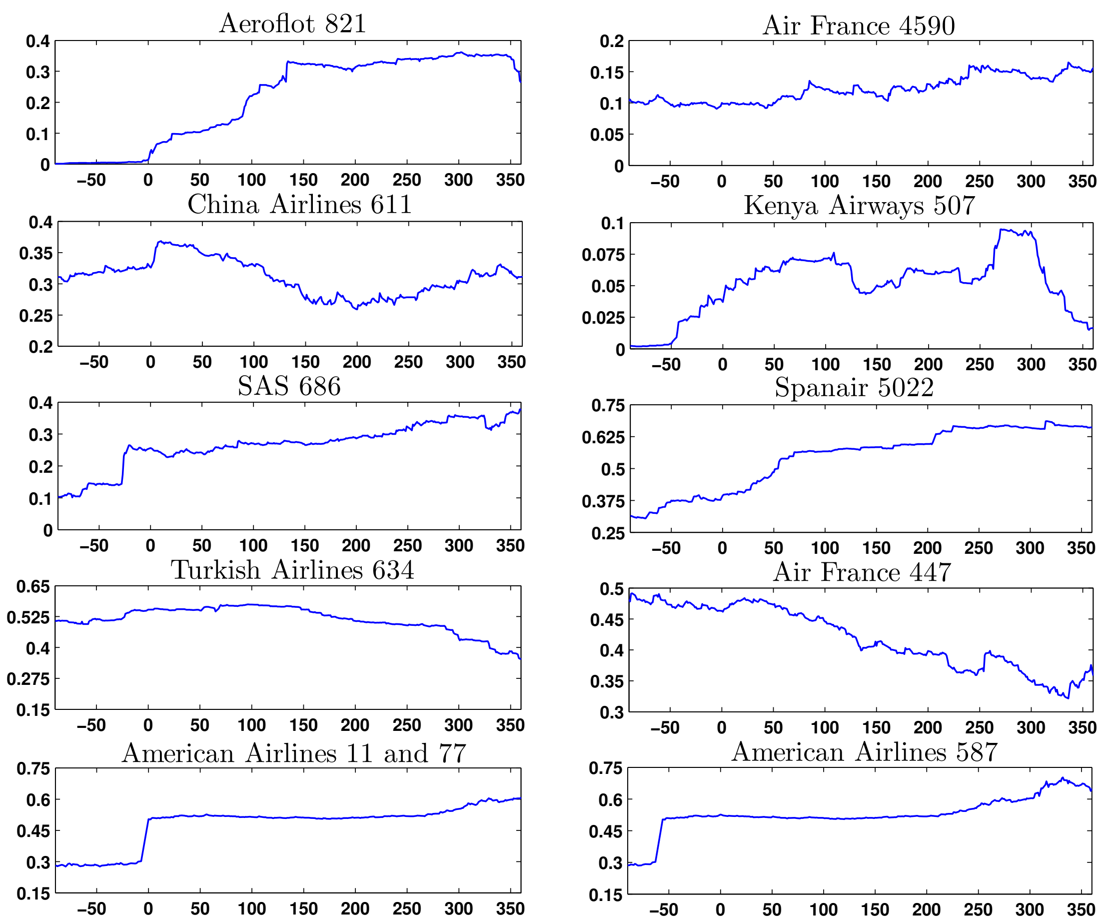


Figure 2: Continued from previous page

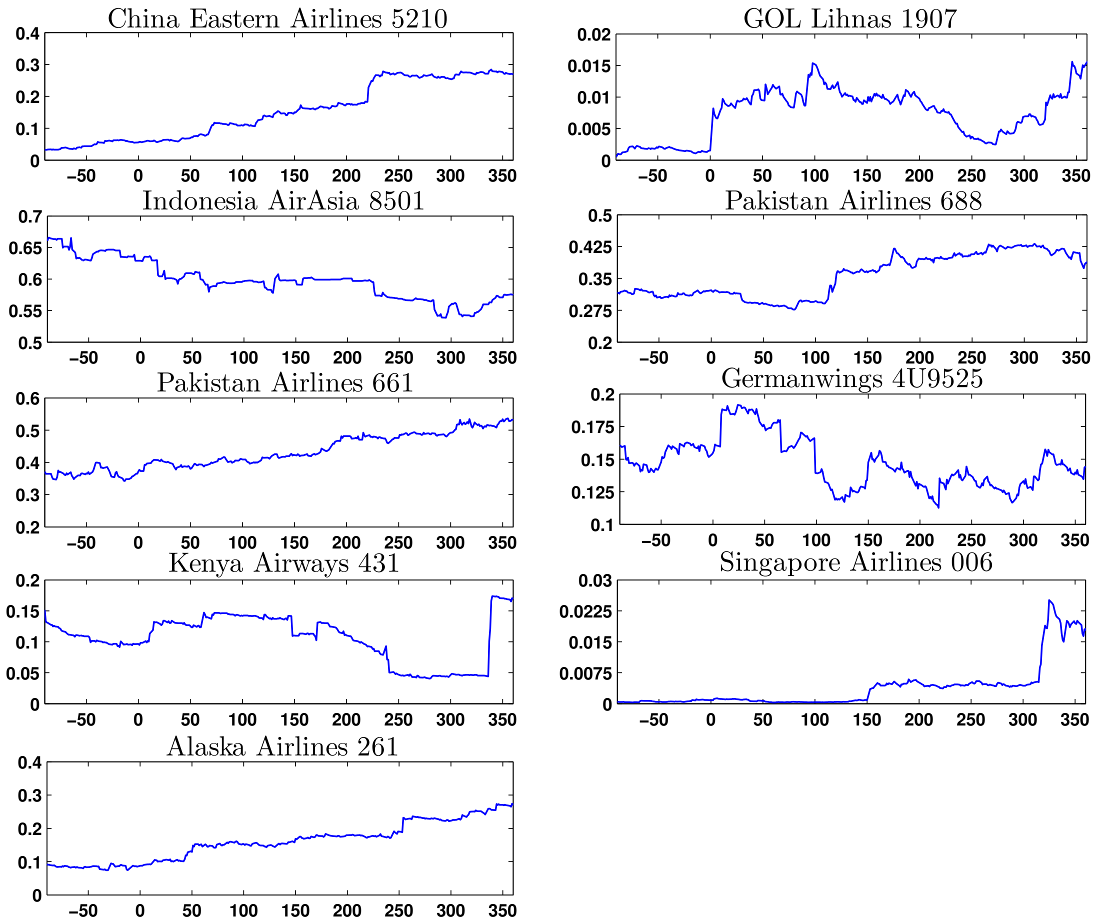


Figure 3: Average and Median indexed debt-per-share around the accident

Figure 3 contains the median and average debt-per-share for all accidents except of American Airlines flights 11,77 and 587. For each case, debt-per-share is indexed 90 days prior the crash to 100. Debt data are available annually or quarterly, depending on each airline. Hence, if for a certain time point debt data are not renewed, calculations implement the latest values. The frequency of debt-per-share calculation is marked in the figure.