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Financial Health and Airline Safety

Gregory Noronha[a,†] and Vijay Singal[b,*]

[a] *School of Management, Arizona State University West, Phoenix, AZ 85069-7100, USA*
[b] *Department of Finance, Pamplin College of Business, Virginia Tech, Blacksburg, VA 24061-0221, USA*

Agency-cost models suggest that firms may pursue riskier strategies in times of financial distress. For example, stockholders of financially weak firms in industries where quality cannot be observed *ex-ante* have an incentive to compromise safety and quality to maximize current period profit. However, there exists only a modest amount of empirical evidence that relates financial health to the risk-taking behavior of firms.

We explore this relationship for the airline industry. Using bond ratings to proxy for financial health and airline mishaps to measure safety, we find a significant correlation: airlines with higher quality bond ratings are less likely to experience mishaps than airlines with lower quality ratings. On average, a whole letter grade better bond rating is associated with a 10% lower probability of a mishap.

INTRODUCTION

This paper examines whether the safety record of airlines is related to their financial health. The issue is of importance to airline passengers as well as to financial economists and federal regulators.

Assuming that investments in product quality are positive value projects, all firms should accept such projects because their acceptance will enhance firm value. However, financial economists have long realized that, under certain conditions, maximization of firm value for levered firms may be inconsistent with maximization of equity value.[1] Under these conditions, stockholders of firms in financial trouble have an incentive to select the riskiest of equivalent net present value projects. They also have incentives to under-invest in positive net present value projects. Myers (1977) shows that as the probability of default increases, firms are more likely to reject positive NPV projects. Similarly, Jensen and Meckling (1976) illustrate the agency costs of debt by relying on such rational, yet perverse, incentives of stockholders of levered firms. Some examples of wealth transfers are discussed in Daigle and Maloney (1994): firms near distress paying dividends or repurchasing stock, engaging in project switching, participating in deals with insiders, or committing outright fraud as a means of transferring wealth from bondholders.

Two potential forces can mitigate the value-reducing incentives of the stockholders. If firms access the capital markets frequently, then monitoring by financial intermediaries and by bondholders will limit the problem of under-investment (see Jensen, 1986). Second, since managers have a disproportionate fraction of their wealth (including human capital) invested in the firm, they try to reduce the risk of the firm by accepting safe projects.[2]

The effect of capital structure on product-market behavior has been modeled by Brander and Lewis (1986) and Maksimovic (1988). They obtain maximum amounts of debt that firms in an oligopolistic framework can assume without jeopardizing tacit collusion. On the other hand, Dasgupta and Titman (1998) model less aggressive firm behavior when firms take on large amounts of debt.[3]

The basic idea that a firm's capital structure may affect its product-market operations can be

*Correspondence to: Vijay Singal, Department of Finance, Pamplin College of Business, Virginia Tech, Blacksburg, VA 24061-0221, USA. E-mail: singal@vt.edu
†gnoronha@asu.edu

extended to quality. Models of reputation, such as Klein and Leffler (1981) and Allen (1984), show that to maximize firm value, firms invest in reputation by producing more expensive higher quality goods when the quality of goods is unobservable *ex-ante*. This behavior characterizes firms that are solvent and not under threat of imminent bankruptcy. Maksimovic and Titman (1991) model stockholder behavior of levered and unlevered firms. They show that levered firms not close to financial distress mimic unlevered firms by producing high quality goods. However, when the levered firms are close to financial distress, equity holders have an incentive to produce inexpensive low quality goods, earn high profits in the current period, and relinquish control of the firm to debt holders. These papers suggest that there is a trade-off between quality and current period profits and circumstances exist under which firms will compromise quality. Though the relation between financial condition of a firm and the quality of its products seems intuitively plausible, there are relatively few empirical papers that have documented this relationship.[4]

In this paper, we empirically examine this relationship for the airline industry.[5] We choose the airline industry due to its several positive features. First, the airline industry fits the structural assumptions in these models. Product safety is not observable *ex-ante*, though the past may provide some information about the airline's safety record. The level of debt of airlines is usually high because of large capital requirements. Therefore, the probability of bankruptcy is non-trivial. Second, due to the cyclical nature of the industry, large changes in financial performance and health can take place even when the firm has not voluntarily changed its level of debt.[6] Finally, the FAA and the National Transportation Safety Board (NTSB) maintain extensive records with regard to safe operation of airlines.

Besides financial economists, federal regulators are interested in how the financial health of an airline affects safety. One major concern at the time of deregulation in 1978 related to airline safety was whether, in their attempt to maximize profits, airlines would underinvest in safe operations. While the issue remains unresolved, interest has not waned. In October 1996, the General Accounting Office yet again recommended that the FAA reexamine the feasibility of relating airline safety to pilot competence, maintenance quality, financial stability, and management attitude (GRA Inc., 1997).

One broad strand of literature has turned to the stock market's role in ensuring product safety. Jarrell and Peltzman (1985) examine the effect of product recalls of defective drugs and Mitchell (1989) investigates the impact of the 1982 Tylenol poisoning. Within the airline industry, air accidents have been studied by Chance and Ferris (1987), Borenstein and Zimmerman (1988), Mitchell and Maloney (1989), and Chalk (1987). Nearly all the studies analyzing the market reaction to announcement of accidents have found that stockholders of the firm in question suffer significant value deterioration. However, no airline has actually gone bankrupt because of accidents or a disregard for safety. Further, Borenstein and Zimmerman (1988), find that the cost imposed by the stock market on the errant or unfortunate firm is less than the social cost of the accident. Using intra-industry airline data to identify close rivals and distant rivals of the crash airline, Bosch *et al*. (1998) find that the close rivals gain from a consumer switching effect while the distant rivals lose from a general fear-of-flying effect. The negative externality that unsafe operation exerts on the entire industry indicates that external regulation by an agency like the FAA may be necessary to protect the industry from being hurt by the poor safety record of a few airlines.[7]

Given the possible need for the FAA's supervision, the allocation of its oversight resources should be governed by the potential benefits; i.e. more resources should be allocated for supervision of airlines most at risk of having accidents. However, unless determinants of airline safety are identified, the allocation will be arbitrary. To that end, many papers have investigated whether the popular wisdom of a relationship between financial health and airline safety does exist. Golbe (1986) uses 1963–1970 data for the domestic operations of large airlines to relate profits with safety after controlling for departures, flight time, load factor, and broad indicators of economic activity. She relies on many statistical formulations but finds no relationship between safety and profits. In some instances the relationship is of the 'wrong' sign, that is, profitable firms have more accidents. Rose (1990) conducts a similar analysis with a longer period and more control variables. She finds an insignificant correlation for large carriers between accidents and profitability but finds a weakly significant correlation for small and medium carriers. Dionne *et al.* (1997) study Canadian airlines and find that airlines experiencing financial difficulties are more likely to suffer from the moral hazard problem.

Instead of relying on profits or operating margins as a proxy for financial distress, we use bond ratings in this paper. Neither operating margins nor profitability are forward-looking, a condition necessary to forecast whether the firm will remain financially strong or not. Operating margins or profits may vary with cyclical changes in market conditions. These variations may not necessarily affect the long-term probability of financial distress as assumed by the model specifications employed in prior work. Further, profitability or operating margins can vary cross-sectionally due to differences in competition, labor costs, maintenance expenditure, capital expenditure, etc. All else equal, operating margins will be higher for companies with less experienced pilots and older aircraft. This implies that more profitable airlines would have more accidents, a result found by Golbe (1986), but contrary to the hypothesized outcome. Another shortcoming of the profitability–safety relationship is that an airline may be profitable in the short run precisely because it underinvests in safety. This too may help explain earlier results that show a positive correlation between profitability and safety.

Bond ratings are not perfect either. For one thing, bond ratings tend to be sticky—rating agencies change them infrequently. And, not all airlines are rated. However, we prefer bond ratings because they are assigned with the primary objective of determining the 'likelihood of default'.[8] The likelihood of default fits our requirement well: the greater the likelihood of default the greater will be the incentive to compromise safety. Research has also found that bond ratings are good indicators of the financial health of a company. Hand *et al.* (1992), and Griffin and Sanvicente (1982), find that stock and bond prices react negatively whenever bonds are downgraded.[9]

NTSB's database of airline accidents and incidents is used to measure airline safety. Modeling airline mishaps as a Poisson process, we relate prior month's bond rating with the current month's accident activity. We find a correlation between bond rating and airline mishaps. Airlines whose bonds are rated a whole letter grade higher have a 10% lower chance of a mishap. The results are similar when the experiment is repeated with annual data and for mishaps with aircraft damage. These results suggest that the FAA should allocate a greater fraction of resources to airlines with lower bond ratings than to airlines with higher bond ratings.

The next section discusses the methodology, the data, and their selection. The following section presents the results. The penultimate section reports some robustness checks including alternative definitions of accidents and other variations of bond ratings. The last section concludes.

METHODOLOGY AND DATA

When the probability of an accident (or incident) during a given period is low and there is a finite count of mishaps in a given population, a Poisson process usually best describes the dependent variable. The Poisson probability distribution has been used extensively to model infrequent events with count data such as McCullagh and Nelder (1983) for ship accidents, Hausman *et al.* (1984) for patents, Rose (1990) and Dionne *et al.* (1997) for air crashes, Michener and Tighe (1992) for highway fatalities, and Keeler (1994) for the effect of regulation on highway fatalities, and in numerous studies relating to disease frequencies in the biomedical sciences.

We use the Hausman *et al.*'s (1984) implementation of the Poisson process. It assumes that the expected rate of accidents, λ_{it} for firm i at time t, is given by

$$\lambda_{it} = \exp(X_{it}'\beta),$$

where X is the vector of explanatory variables. The rate of accidents is defined as the number of accidents, n_{it}, per unit of the population. The population, N_{it}, is a measure of scale for the number of accidents. The log likelihood function can be written as given in Equation (1). Estimates of the log likelihood function will indicate the relevance of different factors in determination of the probability of a mishap.

$$LL = \sum_i \sum_t n_{it}\ln(N_{it}) + n_{it}X_{it}'\beta - N_{it}\exp(X_{it}'\beta) - \ln(n_{it}!). \quad (1)$$

The dependent variable, n_{it}, is a measure of airline safety—a count variable of the number of mishaps at time t for airline i. Several alternative definitions of airline safety are possible: fatal accidents only, accidents only, accidents and incidents, etc. The National Transportation Safety Board (NTSB) that monitors airline safety defines an accident as one in which 'any person suffers death or serious injury, or in which the aircraft receives substantial damage'. An incident is an occurrence other than an accident that 'affects or could affect the safety of operations'. In contrast to the popular notion of an incident, many occurrences where an aircraft sustains damage may be categorized as an incident, not an accident. For example, damage limited to the landing gear or a single engine due to a collision is considered an incident. Golbe (1986) uses only accidents for analysis, while Rose (1990) considers fatal accidents, all accidents, and incidents separately. Dionne *et al.*'s (1997) study encompasses all kinds of accidents in Canada from many deaths to a broken landing gear but excludes incidents. We do not distinguish between incidents and accidents or between fatal and non-fatal accidents 'because the difference between a situation that leads to a minor accident and a major accident is quite small' (see Oster *et al.*, 1992, p. 159–162). In addition, fatal accidents are so rare that a study relying on such events is unlikely to obtain reliable or statistically strong results. Further, we include all mishaps without regard to fault since any assignment of fault is necessarily subjective.

Our sample consists of only major airlines (e.g. Delta Airlines, American Airlines, and United Airlines) and national airlines (e.g. Valujet, Braniff, and Midway) as defined by the Department of Transportation. We exclude regional carriers (e.g. ASA) from our analysis. This restriction is made for two reasons. First, there is a difference in safety expectation of large carriers and small carriers due to differences in aircraft used, differences in markets served, and the level of operating experience. Usually large carriers concentrate on high-density routes while small carriers act as feeder airlines or concentrate on low-density routes. Like Golbe's, our study is confined to US certificated route carriers 'to have a reasonably homogeneous sample'. Second, bonds of most of the smaller airlines are not rated by rating agencies such as Standard and Poor's and Moody's and we require these ratings as the primary explanatory variable. Also, regional carriers that are subsidiaries of major carriers typically would not have independently issued bonds.

The normalization variable, N_{it}, is chosen such that the dependent variable is proportional to the normalization variable, other regressors held constant. Several variables are potential candidates viz., passenger emplanements, passenger-miles flown, hours flown, number of departures, etc. Since more than 70% of the mishaps occur during takeoff and landing,[10] most studies use the number of departures (we use the log, *LNDEP*) as the measure of exposure to risk,[11] as do we. The data relating to physical operations (such as number of departures) are obtained from Bureau of Transportation Statistics' Form 41 Tape 10 and includes both domestic and international operations.

Finally, the primary explanatory variable is Standard and Poor's rating of the airline. Standard and Poor's rates all public corporate debt issues over $50 million. Rating is based on analyzing several business risk factors such as industry characteristics, competitive position, and management and financial risk factors such as financial policy, profitability, capital structure, cash flow protection, and financial flexibility. Fortunately, Standard and Poors identifies the rating factors in detail for the airline industry. They consider (i) market share, trend in market share, market share of CRS owned/shared by the airline, (ii) position in specific markets and the competition in those markets, (iii) revenue generation capacity based on yields, load factors, reputation, and productivity, (iv) labor cost, fuel costs, and commissions, and (v) current aircraft fleet, aircraft orders, and options related to the current and projected needs, and aircraft characteristics.

The ratings data have been obtained from the Research Department of Standard & Poor's Rating Services. These are issuer ratings rather than bond ratings so they are less affected by the seniority/maturity of outstanding debt.[12] We have made one change to the ratings: if an issuer rating is not available then the bond rating is used instead. In over 95% of the cases where both issuer rating and bond rating are available, the issuer rating is the same as the rating for senior bonds.[13]

Other measures have been employed in the literature to predict financial distress such as actual bankruptcy filing, abnormal returns, leverage, interest cover ratio, book to market ratio, Tobin's Q, and size (see Shumway, 2001; Altman, 1968). In our opinion, ratings have several advantages as an indicator of financial health over other measures—chief amongst them is their forward looking nature and the fact that most of these indicators are subsumed in the debt ratings. Nonetheless, ratings have several limitations. They tend to be sticky and the smaller commuter airlines are not rated which limits us to only publicly traded airlines. The way in which these ratings are actually used in regressions is discussed in the next section.

While previous researchers have used an airline's experience as an independent variable, we choose not to because the number of departures already adequately controls for experience. As a matter of fact, we do not have any prediction on the coefficient on any additional experience variable due to the departures variable. Experiments with different experience variables reveal the instability of the coefficients on additional experience variables. Thus, we believe that the departures variable, which we measure as the log of departure, *LNDEP*, is a sufficient control for experience.

There is some concern that international operations may have an adverse effect on the accident rate. Therefore, we control for this by including the proportion of monthly revenue-passenger-miles that are international (*RPINL*). There are other variables that may govern the incidence of accidents such as airport congestion, severity of weather, etc. We do not include such variables in the regression because of data limitations.

Finally, a dummy (*Year*) is added for 15 of the 16 years to control for industry-wide changes in airline safety due to technological improvements. The final regression specification is given by Equation (2).[14]

$$\begin{aligned}\ln\lambda_{it} &= (X_{it}\beta) = \beta_0 + \beta_1 \times Rating_{it} + \beta_2 \\ &\quad \times LNDEP_{it} + \beta_3 \times RPINL_{it} \\ &\quad + \sum_{t=1}^{15} \beta_{4t} \times Year_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

Table 1. Descriptive Statistics of Airlines and Mishaps (January 1983 to December 1998)

Airline name	Classification	Period of inclusion	Mean monthly departures	Mean monthly hours flown	Mean monthly mishaps	Mishaps per million departures
American Airlines	Major	1/83–12/98	60 412	127 620	0.703	12
Alaska Airlines	National/Major[a]	1/83–12/98[b]	9091	14 345	0.092	10
Braniff Inc.	National	3/84–11/89	3358	6309	0.043	13
Continental Airlines	Major	1/83–12/98[b]	33 816	64 776	0.416	12
Delta Airlines	Major	1/83–12/98	68 142	109 869	0.557	8
Eastern Airlines	Major	1/83–1/91	37 305	54 006	0.608	16
Tower Air	National	7/98–12/98	471	2200	0	0
Frontier Airlines	National	1/83–11/85	11 364	12 809	0.114	10
America West	National/Major[a]	4/86–12/98	16 279	24 106	0.088	5
Valujet Air	National	3/95–3/98	4984	6531	0.171	34
Midway Airlines	National	9/89–11/91	8500	13 455	0.111	13
Northwest Airlines	Major	2/83–12/98	37 829	70 875	0.288	8
Ozark Airlines	National	1/83–4/83	8960	9271	0	0
Pan Am World Airways	Major	1/83–12/91	12 064	28 620	0.231	19
Piedmont Airlines	Major	1/83–7/89	31 027	29 528	0.241	8
Pacific Southwest Air	National	1/83–9/87	11 301	10 798	0.053	5
Republic Airlines	Major	1/83–9/86	33 490	36 160	0.267	8
TransWorld Airlines	Major	1/83–12/98	22 562	43 955	0.244	10
United Airlines	Major	1/83–12/98	55 837	116 029	0.625	11
USAir Inc.	Major	1/83–12/98	55 455	70 198	0.339	6
Western Airlines	Major	1/83–3/87	13 875	20 234	0.059	4
Southwest Airlines	National/Major[a]	1/83–12/98	35 835	35 586	0.115	3
World Airways	National	1/83–10/86	708	2578	0	0

[a] Alaska Airlines was designated a Major carrier by the Department of Transportation from February 1994 while America West Airlines and Southwest Airlines are considered Major carriers from March 1988.
[b] Airlines are included for the period that their bonds are rated. The following airlines have a discontinuity in their ratings. The periods of their inclusion are indicated: Alaska (1/83 to 1/87, 8/88 to 6/89, and 5/92 to 12/98), and Continental Airlines (1/83 to 4/93 and 3/96 to 12/98).

RESULTS

Frequency of Mishaps

Table 1 lists airlines in the sample and the period of their inclusion. The study begins with January 1983, the first month for which the accidents and incidents data of the National Transportation Safety Board are available in a computer readable format from the NTSB/FAA. The sample period extends to December 1998. The critical condition for inclusion of an airline in the sample is the availability of a Standard and Poor's bond rating for that airline. The table also indicates the Department of Transportation's classification for each airline. The mean monthly number of departures and mean monthly hours flown are indicative of firm size. Delta Airlines is the largest based on the average number of monthly departures while American Airlines is the largest based on the average number of monthly hours flown. World Airways is the smallest airline.

The frequency of mishaps is given in the last two columns. Initially, we term all accidents and incidents listed in NTSB's database as mishaps.[15] Our sample consists of 783 accidents and incidents during 1983–1998 for airlines with credit ratings. Golbe (1986) has a total of 601 accidents for airline companies (excluding commuter carriers) during 1952–1972. Rose (1990) has 726 accidents during 1957–1986 for all carriers. Among the Major carriers, Pan Am was the airline most prone to mishaps while Western Airlines was the airline least likely to experience safety-threatening events based on the last column.

Twenty-three ratings, ranging from AAA to D, are assigned by Standard and Poor's, for issuers and their bonds. To make these ratings manageable, we construct broader categories. The broadest categorization is between 'investment grade' bonds and 'below investment grade' bonds (or junk bonds). A rating at or above BBB- is considered investment grade while any rating at BB+ or below is considered below investment grade. This classification is suggested by Standard and Poor's and widely accepted by the financial institutions. To convey some sense of airline bond ratings, we also include Table 2 which lists each

Table 2. Descriptive Statistics of Airline Bond Ratings (January 1983 to December 1998)

Airline name	Classification	Period of inclusion	Median bond rating	Best bond rating	Worst bond rating	Proportion of period as invtestment grade (%)
American Airlines	Major	1/83–12/98	BBB	A	BB+	64
Alaska Airlines	National/Major[a]	1/83–12/98[b]	BB	BBB	B–	29
Braniff Inc.	National	3/84–11/89	D+	D+	D+	0
Continental Airlines	Major	1/83–12/98[b]	B	BB	C–	0
Delta Airlines	Major	1/83–12/98	A–	A	BB	72
Eastern Airlines	Major	1/83–1/91	CCC	B	D+	0
Tower Air	National	7/98–12/98	CCC+	CCC+	CCC+	0
Frontier Airlines	National	1/83–11/85	BBB	BBB	B+	59
America West	National/Major[a]	4/86–12/98	CCC+	B+	C–	0
Valujet Air	National	3/95–3/98	B–	BB	B–	0
Midway Airlines	National	9/89–11/91	B	B+	B–	0
Northwest Airlines	Major	2/83–12/98	BB	A	B–	42
Ozark Airlines	National	1/83–4/83	B+	B+	B+	0
Pan Am World Airways	Major	1/83–12/91	B–	B	C–	0
Piedmont Airlines	Major	1/83–7/89	BBB–	BBB+	BB–	60
Pacific Southwest Air	National	1/83–9/87	B+	B+	B+	0
Republic Airlines	Major	1/83–9/86	B+	BB+	B	0
TransWorld Airlines	Major	1/83–12/98	B–	BBB–	CCC	27
United Airlines	Major	1/83–12/98	BB+	BBB	BB	50
USAir Inc.	Major	1/83–12/98	BBB–	A	B–	51
Western Airlines	Major	1/83–3/87	B–	A–	B–	2
Southwest Airlines	National/Major[a]	1/83–12/98	A–	A	A–	100
World Airways	National	1/83–10/86	CCC	CCC	CCC	0

[a]Alaska Airlines was designated a Major carrier by the Department of Transportation from February 1994 while America West Airlines and Southwest Airlines are considered Major carriers from March 1988.
[b]Airlines are included for the period that their bonds are rated. The following airlines have a discontinuity in their ratings. The periods of their inclusion are indicated: Alaska (1/83 to 1/87, 8/88 to 6/89, and 5/92 to 12/98), and Continental Airlines (1/83 to 4/93 and 3/96 to 12/98).

airline's median bond rating for the period that airline is included in the study. We also list each airline's best and worst bond ratings for the period, together with the proportion of time the airline had a bond rating of BBB- or better. Southwest was financially the most healthy airline and Braniff least so. It is evident from the range of bond ratings for a given airline that ratings change slowly and infrequently. This has implications for the econometric aspects of the study that we discuss in the following section on regression estimates.

A preliminary examination of the relation between the frequency of mishaps and an airline's financial health is presented in Table 3. As discussed above, the financial health of an airline is measured by its bond rating. To account for possible industry-wide improvements in airline safety, the results are presented for three different time periods. Going from left to right, there is a consistent pattern of an overall decrease in the frequency of mishaps. This improvement in airline safety is well documented (see Oster and Zorn, 1989).

The rows in the table represent different bond ratings. The difference in the frequency of mishaps between the investment grade and 'junk' categories is presented first. It can be seen that the frequency of mishaps is always greater for the 'below investment grade' category suggesting that airlines with lower rated bonds are at a greater risk.

Using unsigned letter ratings gives another categorization scheme. Thus, A+, A, and A− form one category, all BBBs form another category, etc. Unsigned categories are frequently used in research (see Hand *et al*. 1992). Results based on unsigned categories are presented next in Table 3. There is deterioration in safety, as the bond rating falls in most though not all cases. In general, it appears that bond rating and safety are correlated. We examine this issue in greater depth relying on a Poisson regression model.

Regression Estimates for All Mishaps

The Poisson regression model specified in Equation (2) is estimated for all mishaps. The first explanatory variable in Equation (2) is the bond rating. We use three different categorization schemes for bond rating in the estimation: unsigned letter ratings, signed letter ratings, and yield-based ratings.[16] Rather than rely on the qualitative nature of letter ratings, we assign them cardinal values following Hand *et al*. (1992). They assign a value of 28 to the highest class (AAA), a value of 25 to the AA class, a value of 22 to the A class, and so on with a value of 1 to class D. We use the same classification and call it 'Unsigned letter-rating'. To obtain a finer level of categorization, we assign cardinal values to *Signed* letter ratings using the same order as for unsigned letter ratings: AAA is assigned 28, but in addition,

Table 3. Frequency of Mishaps by Rating and Period

Rating Class	For the 5-year period 1983 to 1987		For the 5-year period 1988 to 1992		For the period 1993 to 1998	
	Departures	Mishaps per million departures	Departures	Mishaps per million departures	Departures	Mishaps per million departures
Total	23 800 000	11.2	28 192 000	8.3	33 376 000	8.4
Junk/non-Junk bonds						
Investment grade	13 300 000	10.1	17 295 000	7.5	7 034 000	7.5
Below investment grade	10 500 000	12.9	10 897 000	9.5	26 342 000	8.7
Letter-based classes						
A+, A, A−	7 724 000	9.5	8 408 000	7.0	4 058 000	3.2
BBB+, BBB, BBB−	5 576 000	10.9	8 887 000	7.9	2 976 000	13.4
BB+, BB, BB−	2 911 000	13.4	2 761 000	7.2	16 913 000	9.2
B+, B, B−	4 558 000	10.9	4 583 000	10.7	7 500 000	6.8
CCC+, CCC, CCC−	2 415 000	14.9	1 600 000	8.1	1 468 000	10.2
CC and lower	596 000	16.7	1 953 000	9.3	462 000	17.3

The frequency of mishaps is given by different rating categories for three different 5-year periods (except 1993 to 1998 which is a 6-year period). All airlines in Table 1 are included here for the months that they are rated.

AAA+ is assigned 29 and AAA− is assigned 27. This method continues the assignment process to lower ratings up to a value of 1 for the 'D' rating.

The cardinal values assigned by Hand *et al*. are arbitrary and seemingly without justification. That assignment implies that the difference between two adjacent letter ratings is equivalent: for example, the difference between AAA (28) and AA (25) is assumed to equal the difference between BBB (19) and BB (16). This is not necessarily true: while AAA and AA ratings are not considered very different, BBB and BB are considered different since BBB represents an 'investment grade' rating but BB does not.[17] To take account of these differences, we devise another scheme of assigning values that are based on the risk premium for different categories of corporate bonds. These risk premiums are obtained from market sources. According to Salomon Brothers',[18] the spread (difference between corporate bonds and treasury bonds) was 40 basis points for 10-year AAA rated bonds, 50 basis points for AA bonds, 60 basis points for A rated bonds, 85 basis points for BBB rated bonds, 260 basis points for BB rated bonds, and 350 basis points for B rated bonds. For lower grade bonds, we assume the spreads to be 500 basis points for CCC rated bonds, 700 basis points for CC rated bonds, and 1000 basis points for C bonds. For firms in default, the spread is assumed at 2000 basis points. Values are assigned as follows such that they represent the differences in the spread (or the risk premium): 25 for AAA, 20 for AA, 15 for A, 12 for BBB, 4 for BB, 3 for B, 2 for CCC, 1 for CC & C, and 0.5 for D rated bonds. This classification is called 'Yield-Rating'. Though the value assignments are based on one-time yield spreads, data limitations preclude us from updating the yield spreads periodically. A crude comparison of some yield spreads for other periods reveals no systematic bias in our assumption of yields.

Poisson regression results are reported in Table 4.[19] For a correctly specified Poisson model, the conditional mean should equal the conditional variance, i.e. ϕ should be equal to one in the equation $V(\mu) = \phi\mu$. If this assumption is violated, the situation is analogous to heteroskedasticity in ordinary least squares models: the standard errors are inconsistent. If ϕ is greater than one then the data are over-dispersed, if less than one then the data are under-dispersed. The dispersion can be measured by the deviance divided by the degrees of freedom. This is indicated as Deviance/DF in the tables. We test and correct for over-dispersion and for under-dispersion by adjusting or scaling the covariance matrix (see McCullagh and Nelder, 1989).

Table 4. Monthly Bond Ratings and All Airline Mishaps

	Letter based values for signed ratings		Letter based values for unsigned ratings		Yield based values for ratings	
	AR(1)	EXCH	AR(1)	EXCH	AR(1)	EXCH
Constant	−13.178	−11.864	−13.100	−11.854	−12.899	−11.314
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lagged letter based values	−0.041	−0.034	−0.040	−0.030		
	(0.01)	(0.03)	(0.01)	(0.07)		
Lagged yield based values					−0.026	−0.010
					(0.08)	(0.42)
Log of total departures (*LNDEP*)	1.201	1.069	1.193	1.064	1.132	0.976
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Proportional international (*RPINL*)	1.093	0.997	1.093	0.999	1.034	0.963
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Yearly dummies	Included		Included		Included	
Deviance/DF	0.78		0.78		0.78	
Log likelihood	−1887		−1887		−1884	
Observations	2492		2492		2492	

Estimates for a Poisson regression model are presented. The dependent variable is the number of mishaps for an airline during a month, and the explanatory variables are listed in the left column and described in the text. The correlation structure of the residuals is specified as AR(1) or exchangeable. The mishaps include all accidents and incidents. p-values are in parentheses.

Though there are 2492 observations (airline-months) for the 16-year period, stickiness in bond ratings implies that the assumption of independence across observations may be invalidated and that the error terms may be correlated.[20] One way to mitigate the problem is to employ firm fixed-effects estimators in our regressions. However, Zhou (2001) demonstrates the use of fixed-effects estimators can eliminate between-firm variation.[21] Specifically, he shows that when an explanatory variable which may have substantially different values across firms, changes slowly in time for an individual firm, the use of fixed-effect estimators may result in a failure to observe a relationship between the explanatory variable and dependent variable even if one exists.[22] Also, as a result of using fixed effects, some of the variation in the dependent variable may be ascribed to the firm rather than the ratings variable. Because of this, and since our major explanatory variable, issuer ratings, changes too slowly for a given airline to provide the within-firm variation necessary to detect a relationship between ratings and mishaps, we do not use fixed-effect estimators in our regressions.[23] We do, however, control for correlations among the error terms for observations of the same airline by estimating robust standard errors, using both an AR(1) and exchangeable correlation structure.[24] In the exchangeable structure, the correlation between observations for the same airline is as follows: $\mathrm{Corr}(Y_{ij}, Y_{ik}) = 1$ for $j=k$, and α for $j \neq k$.

The results for each rating scheme are presented in a columnar fashion in Table 4 under the assumption of both an AR(1) and exchangeable correlation structure. Looking at the first column, for the AR(1) structure it can be observed that the signed rating measure has a negative coefficient, -0.041, that is statistically significant. The economic significance of the coefficient the signed rating is determined as follows. The mean value of the dependent variable, $\ln \lambda_{it}$, is -13.178, which is equal to a rate of 1.89 accidents per million departures. For airlines with a rating one signed value higher, the mean value of the dependent variable is –13.219 (= –13.178–0.041). This translates into a rate of 1.81 accidents per million departures. This result indicates that each higher signed rating has a 4% lower number of mishaps.

The results with the exchangeable correlation structure are qualitatively similar. The coefficient of the signed letter-rating variable is negative and significant, and each higher rating has a 3.5% lower mishap rate. Since higher rated firms are assigned higher values, the negative coefficient is consistent with the notion that higher rated firms exhibit a lower frequency of mishaps. The second rating categorization scheme, values based on unsigned letter ratings, generates results almost identical to those for signed letter ratings because the assignment of cardinal numbers is similar. Both signed and unsigned schemes suggest that a drop in letter ranking translates to around a 15% increase in the rate of accidents. Finally, the yield-rating categorization also reveals a picture not different from what we observed for the other rating schemes, though the results are not as statistically strong. The difference in the yield based values for a B rated bond and an A rated bond is 12, from the Hand *et al.* rating scheme. Based on the coefficient of -0.026 for the AR(1) correlation structure, this translates into a difference of about 10% in the accident rate. Overall, an airline with a higher letter bond rating is associated with at least a 10% lower probability of mishaps.

The coefficient of LNDEP is positive and statistically significant as expected, indicating that the more an airline flies, the greater its risk of mishap. The coefficient on RPINL is positive and statistically significant. The positive coefficient suggests that, controlled for size, the greater the international exposure, the greater is the accident rate. This is a reasonable expectation as, in general, foreign airports do not have the same emphasis on safety that the domestic airports do.

The results in Table 4 strongly suggest that there is a correlation between an airline's bond rating and its likelihood of a mishap. Except for the yield-based coefficient under the exchangeable correlation structure, all three rating schemes employed have statistically significant coefficients at least the 8% level of confidence. All coefficients have the right sign. The number of accidents/incidents is at least 10% less for airlines with a higher letter rating than for airlines with one lower.

Since there has been a general positive trend in safety, we estimate our regression equation with year as a trend variable. The bond rating variable is robust to this specification and the results do exhibit that the frequency of mishaps is negatively correlated with the passage of time as can be observed from Table 3.

ROBUSTNESS CHECKS AND EXTENSIONS

In this section, we explore the robustness of the above results and discuss possible extensions to the study.

Mishaps with Aircraft Damage

The results presented above are based on airline accidents and incidents in the NTSB database. We choose to include both incidents and accidents because except for fortuitous circumstances, the incident could easily be an accident. One major criticism of including incidents in a safety analysis is that the reporting of some of those incidents is voluntary. Airlines that are more safety conscious are more likely to report such incidents than less safety conscious airlines. Thus, the self-selection bias makes it more difficult to find a correlation between the frequency of incidents and occurrence of serious accidents. At the other extreme, inclusion of an event as an accident does not necessarily imply safety compromises made by an airline. Some serious injuries occur because of the failure of passengers to fasten their seatbelts when entering an area of turbulence despite requests from the cockpit and cabin crew. Similarly, a fatal accident is recorded for a stowaway who hid in an unheated and un-pressurized area of the plane.

We intend to overcome some of these criticisms by using a new measure of safety: aircraft damage. That is, we consider only those incidents or accidents where the aircraft was damaged. Aircraft damage is less subject to differences in interpretation and more likely to be reported because it can be easily verified and detected by the FAA or NTSB. Mishaps with aircraft damage may be better correlated with future events because if some damage occurs to an aircraft, it can be assumed that similar circumstances at another time might result in a more serious accident. Excluding incidents or accidents where no damage occurred to the aircraft will also exclude events that are unrelated to the airline's ability to maintain and operate aircraft. Thus, we assume that aircraft damage is a better indicator of unsafe practices and better correlated with the possibility of a serious accident than a sample consisting of accidents and/or incidents. While aircraft damage is a better measure, it is by no means perfect. Near mid-air collisions are not included either in the aircraft damage sample or in the incidents and accidents sample. And third party errors, for example, errors by the air traffic control, are attributed to the airline if they result in damage to the aircraft.

The new criterion reduces the sample of mishaps: there are only 418 mishaps with aircraft damage compared with 783 mishaps without this condition during the 1983–1998 period. The results based on mishaps with aircraft damage are presented in Table 5, again for both the AR(1) and exchangeable correlation structures. These findings convey information that is similar to the conclusions drawn with all mishaps in Table 4. If anything, the coefficients on the bond rating variables indicate a marginally stronger correlation with the number of mishaps, with, once again, the coefficient under the exchangeable structure for yield-based ratings being the only one not significant at 8% or better. The accident rate for an airline whose bonds are rated one higher letter grade drops by at least 10%.

Annual Data

The above analysis relies on monthly data relating to accidents and issuer ratings. It seems unlikely that either the financial health of an airline or its strategy towards safe operation will change on a monthly basis. A worsening financial condition might encourage the airline to buy older planes or relax its criteria for hiring new pilots or mechanics. However, the effect of strategic changes may take several months to affect safety.

Therefore, an alternative is to study the relationship between mishaps and credit ratings on an annual basis. Monthly ratings are aggregated to an annual rating by taking the mean rating for each calendar year. Similarly, mishaps for each calendar year are taken instead of for a month. Some airline-years have fewer than 12 airline-months if the airline entered the sample after January 1983, terminated operations before December 1998, or was otherwise unrated in the interim. However, these observations do not affect the results.

Regression results are presented in Table 6. The results are similar to those obtained with monthly data though weaker, perhaps, on account of loss of information in the data due to aggregation. Only bond rating coefficients under the AR(1) correlation structure remain statistically significant

Table 5. Monthly Bond Ratings and Mishaps involving Aircraft Damage

	Letter based values for signed ratings		Letter based values for unsigned ratings		Yield based values for ratings	
	AR(1)	EXCH	AR(1)	EXCH	AR(1)	EXCH
Constant	−14.793	−14.092	−14.680	−14.123	−14.370	−13.391
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lagged letter based values	−0.051	−0.050	−0.049	−0.047		
	(0.01)	(0.01)	(0.01)	(0.01)		
Lagged yield based values					−0.030	−0.023
					(0.08)	(0.14)
Log of total departures *(LNDEP)*	1.310	1.245	1.299	1.245	1.217	1.123
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Proportion international (*RPINL*)	1.161	1.102	1.158	1.110	1.084	1.034
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Yearly dummies	Included		Included		Included	
Deviance/DF	0.56		0.56		0.56	
Log likelihood	−1837		−1838		−1834	
Observations	2492		2492		2492	

Estimates for a Poisson regression model are presented. The dependent variable is the number of mishaps for an airline during a month and the explanatory variables are listed in the left column and described in the text. The correlation structure of the residuals is specified as AR(1) or exchangeable. The mishaps are restricted to accidents and incidents where the aircraft sustained damage. *p*-values are in parentheses.

Table 6. Annual Bond Ratings and All Airline Mishaps

	Letter based values for signed ratings		Letter based values for unsigned ratings		Yield based values for ratings	
	AR(1)	EXCH	AR(1)	EXCH	AR(1)	EXCH
Constant	−11.085	−9.840	−11.115	−9.862	−11.205	−9.915
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lagged letter based values	−0.030	−0.019	−0.030	−0.018		
	(0.07)	(0.18)	(0.07)	(0.23)		
Lagged yield based values					−0.029	−0.017
					(0.10)	(0.25)
Log of total departures *(LNDEP)*	1.240	1.110	1.244	1.111	1.234	1.098
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Proportion international (*RPINL*)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.25)	(0.65)	(0.25)	(0.67)	(0.35)	(0.72)
Yearly dummies	Included		Included		Included	
Deviance/DF	1.71		1.71		1.71	
Log likelihood	233		235		235	
Observations	198		198		198	

Estimates for a Poisson regression model are presented. The dependent variable is the number of mishaps for an airline during a calendar year and the explanatory variables are listed in the left column and described in the text. The correlation structure of the residuals is specified as AR(1) or exchangeable. The mishaps include all accidents and incidents. Monthly ratings are aggregated to arrive at an average annual rating. *p*-values are in parentheses.

at 10% or better, though all coefficients exhibit the predicted sign. Since aggregation of data leads to loss of information, we prefer to rely on the results with monthly data.

Levels versus Changes in Bond Ratings

In the foregoing analysis, we have used levels of bond ratings and not changes in bond ratings.

Some observers have questioned the use of levels. We rely on the level of bond rating because the level, not the change, is a measure of the financial soundness of the firm. A firm that is downgraded from AA to A is not in a worse financial condition than a firm that is upgraded from a CC to CCC. While changes in bond ratings are relevant for stock returns, the current financial condition is the hypothesized determinant of safety.

Nonetheless, for the sake of completeness, we examine how changes in ratings (upgrades and downgrades) affect subsequent safety performance of airlines. If there is an effect of a rating change then we would expect it to occur soon after the rating change, so we restrict our observation period to 24 months after the rating change. The post-event period is compared with a pre-event period of the same length, 24 months. To ensure that multiple rating changes bunched together in time do not result in multiple observations, we consider only the first rating change that occurs. For a subsequent rating change to enter the sample, it must occur more than 24 months later. Further, if during the pre-event observation period or during the post-event observation period, another rating change occurs that is of a different kind then that observation is dropped. This implies that an upgrade (downgrade) must not be preceded or followed by a downgrade (upgrade) during the ± 24 month period around the upgrade (downgrade). However, that upgrade (downgrade) can be followed or preceded by another upgrade (downgrade) within a 24 month period but the other upgrade (downgrade) will not constitute an additional rating change.

The following model is estimated:

$$\ln\lambda_{it} = (X_{it}\beta) = \beta_0 + \beta_1 \times Rating_{it} + \beta_2 \times LNDEP_{it} + \beta_3 \times RPINL_{it} + \sum_{t=1}^{15} \beta_{4t} \times Year_{it} + \beta_5 \times Change, \quad (3)$$

where ‘Change’ is the new variable added to the model in Equation (2). Change is set to 1 for the 24-month period following an upgrade, is set to -1 for the 24-month period following a downgrade, and zero otherwise. The results of this analysis are presented in Table 7.

The number of rating changes depends on the level of discrimination provided by the rating

Table 7. Changes in Bond Ratings

	Letter based values for signed ratings		Letter based values for unsigned ratings		Yield based values for ratings	
	AR(1)	EXCH	AR(1)	EXCH	AR(1)	EXCH
Constant	−13.026	−11.909	−12.529	−12.382	−12.198	−11.957
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Change in rating	0.060	0.107	0.037	0.051	0.019	0.031
	(0.26)	(0.15)	(0.66)	(0.57)	(0.84)	(0.75)
Lagged letter based values	−0.033	−0.038	−0.040	−0.040		
	(0.05)	(0.01)	(0.01)	(0.01)		
Lagged yield based values					−0.025	−0.024
					(0.03)	(0.03)
Log of total departures (*LNDEP*)	1.191	1.108	1.170	1.153	1.099	1.071
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Proportion international (*RPINL*)	1.164	1.115	1.287	1.292	1.245	1.249
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Yearly dummies	Included		Included		Included	
Deviance/DF	0.78		0.82		0.82	
Log likelihood	−1646		−1241		−1239	
Observations	2131		1621		1621	
Upgrades	22		16		16	
Downgrades	30		22		22	

Estimates for a Poisson regression model are presented. The dependent variable is the number of mishaps for an airline during a month and the explanatory variables are listed in the left column and described in the text. The correlation structure of the residuals is specified as AR(1) or exchangeable. The mishaps include all accidents and incidents. p-values are in parentheses.

scheme. Signed letter ratings with 29 categories are the most discerning and result in a total of 52 rating changes while the unsigned and yield-based categories provide only 38 rating changes. The number of upgrades and downgrades is reported in the last two rows of Table 7. The number of observations depends on the number of rating changes.

The regression results reveal that the new variable 'Change' is not statistically significant with any of the rating schemes, i.e. the change in rating does not provide additional information regarding the likelihood of accidents. This implies that the level of ratings, rather than a downgrade/upgrade, is more important in determining the number of accidents. Not surprisingly, the coefficient on the level of rating becomes significantly negative in all rating schemes.

Causality

While the correlation between bond ratings and incidence of mishaps is clear from Tables 4–7, causality is more difficult to establish. Though we use ratings lagged by a month and by a year, the stickiness in bond ratings precludes us from claiming causality.[25]

Do accidents/incidents result in poor financial performance that then causes a lowering of bond ratings? Or is a financially weak airline more susceptible to accidents? To the best of our knowledge, no airline has gone bankrupt because of accidents. Of 783 accidents/incidents in the sample, only about 2–3% were serious enough to cause the airline financial pain. For the airlines in the sample, such serious accidents constitute about once a lifetime occurrence. Following such an accident, the affected airline will probably pay extra attention to safety,[26] which in turn is likely to result in an improved safety record. If Standard and Poor's lowers the rating on the airline's bonds following the accident, we would be likely to see a negative correlation, i.e. lower rating is associated with safer operation rather than the current observation of higher rating associated with greater safety.

As mentioned in Methodology and Data above, the frequency of airline accidents does not seem to play a direct role in assignment of a particular rating by Standard and Poor's; rather financial performance, market share, competitive position, etc. seem to be the key determining factors in bond rating. Further, financial performance is affected more quickly, and more frequently, by economic downturns or bad management, than by an isolated accident.

On the other hand, as intuition and theoretical models suggest, airlines in poor financial condition are likely to compromise safety because stockholder value is best maximized in that manner. This behavior may usually be noticeable only at the margin of distress, however, but the incentive for stockholders to expropriate wealth always exists in the absence of perfect contracting. In this sense, the issue of causality may not be one that is susceptible of an easy resolution.

Possible Extensions

If an airline compromises safety, it is likely to compromise quality as well. Therefore, quality of service provided by an airline can be used as an alternative to safety. The two best measures of quality are the number of consumer complaints and on-time performance. However, these measures are unreliable. Consumer complaints vary significantly depending on the mood of the consumers and publicity in the media. During the mid-1980s following a wave of consolidations in the airline industry, the consumers perceived deterioration in quality. The number of complaints rose to several times the normal number until, responding to the popular mood, Congress passed a bill to protect passengers. Similarly, on-time performance depends on the airline's policy. Some airlines tend to understate the flying time so that time-conscious travelers will fly with them. Other airlines overstate the flying time so that their on-time performance will be superior. Therefore, we choose to use only accidents and incidents for the study. The relation between financial health and provision of quality by airlines is an interesting issue and an area for future research.

Another interesting extension to this work is to examine how managerial attributes such as insider ownership, compensation packages, and labor participation influence the firm's response to financial distress. It is likely that labor may resist a firm's neglect of safety to protect their jobs. Finally, similar issues might exist in other industries like health care where financially distressed firms may have the incentive and ability to impose high social costs.

CONCLUDING REMARKS

That the financial health of an airline will impact its ability or willingness to provide safety seems intuitive. In this paper, we provide empirical evidence to support this notion. Relying on lagged bond rating to judge the financial health of an airline and using accidents and incidents as a measure of airline safety, we find that financially strong airlines are significantly less at risk than financially weak airlines. The difference in the accident rate from a whole letter rating change is about 10%. These findings are robust to alternative definition of mishaps, ratings, and other variations. If the financial condition of airlines is important in the pursuit of safety, the FAA should consider allocating relatively more resources to the oversight of financially weak airlines than to financially strong ones.

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NOTES

1. Since equity value can be represented by a call option on the value of the firm, stockholders attempt to maximize value of that option. For calls *not* deep in-the-money, accepting less risky projects with positive NPV *can* decrease the value of that option because call value is positively correlated with risk and with firm value. Realizing this, stockholders of firms close to bankruptcy may choose not to invest in positive NPV projects if those projects make the firm less risky.
2. As the probability of bankruptcy increases managers may be more concerned with keeping the firm solvent and retaining their jobs. At that time, managers may have their incentives aligned with those of the stockholders, i.e. they may accept riskier projects of such projects increase the probability if survival more than acceptance of safe projects.
3. Empirical evidence of Chevalier (1995) and Phillips (1995) is consistent with Dasgupta and Titman (1998).
4. See, for example, Golbe (1986), Rose (1990), and Dionne *et al*. (1997).
5. In a similar vein, Pulvino (1998) studies the effect of financial constraints on asset sales in the airline industry.
6. Airline firms may become highly leveraged without accessing debt markets, due to loss of equity value around economic downturns.
7. We do not mean to imply that the externality arises only at the bankruptcy margin. Bankruptcy behavior is a continuum and benefits from constant monitoring.
8. See Standard and Poor's Compustat manual.
9. The observation that the papers cited examine *changes* in bond ratings while we use the *level* of bond ratings does not invalidate the use of ratings in this study. The cited papers must condition their study on changes in bond ratings to evaluate the effect on stock prices. By contrast, we examine how the level of bond rating (or financial condition) affects quality.
10. Barnett and Higgins (1989) claim that over 90% of the mishaps occur upon landing or takeoff while Weener and Wheeler (1992) state that around 70% of accidents have occurred during these stages.
11. See, for example, Golbe (1986), Barnett and Higgins (1989), and Rose (1990).
12. For comparison, however, we have also considered bond ratings in addition to issuer ratings. The results are similar. Bond ratings are also provided by S&P. Where ratings are not available for senior unsecured debt, the Research Department of Standard and Poor's has calculated an implied rating for senior unsecured debt from other debt ratings. In the bond rating information provided to us by S&P, United Airlines had been assigned a "AAA" rating for the period May 1988 to March 1989. This seemed to be in error since the rating prior to May 1988 was BBB and the rating post-March 1989 was also BBB. After verifying with the Standard & Poor's Bond Record, the senior bond rating for United Airlines has been changed from AAA to BBB for the period May 1988 to March 1989. This change has no perceptible effect on the results.
13. Since bond rating is a more commonly used term, we prefer to use that term instead of "issuer rating".
14. It can be argued that a downgrade is more valuable than an upgrade where the probability of an accident is concerned. Accordingly, the regression model should place a non-symmetric weight on upgrades and downgrades. However, such a system implies that a firm with an upgrade followed by a downgrade has a higher probability of default than a firm that remains in the same rating. Clearly, such a conclusion is erroneous.
15. Later, we consider only those events where the aircraft sustained damage.
16. The investment grade dummy is not used in the regression analysis because it is a crude measure of ratings which exhibits very little variation over time.
17. It is also true that the direction of the move in ratings is important. A move down is worse than a move up is better. We discuss changes in ratings in the following section of the paper.

18. Bond Report dated July 14, 1995.
19. For a Poisson model, SAS reports the log likelihood estimates after dropping terms involving factorials of the observed counts, which tends to make these estimates look large, especially with annual data.
20. In addition, factors such as route structure, pilot experience, among others, are all likely to result in less variation within than between airlines.
21. Hermalin and Weisbach (1991) face a similar problem and, asserting that it is between-firm variation that drives their results, eschew the fixed-effects approach.
22. Zhou's paper is essentially a critique of Himmelberg *et al*. (1999), which uses fixed effects in panel data to show that there *may not* be a relationship between managerial ownership and performance.
23. For the purpose of illustration, we did repeat the regression in Table 4 with fixed firm effects. We find that the coefficients on all forms of the bond ratings variable are no longer significant. When we use cumulative revenue passenger miles as a proxy for airline experience, the letter-based bond ratings are significant—the unsigned rating at 2% and the signed at 10%. This result holds whether we control for the international services or not.
24. Specifically, we employ generalized estimating equations using the SAS procedure GENMOD, which, according to the SAS Institute, uses sandwich estimators. The procedure, however, requires that we specify a correlation structure for the error terms in question. Testing using SAS's PROC ARIMA and studying the partial autocorrelations, gives a strong indication that the correlations in the residuals are AR(1). Intuitively, the best predictor of a given period's bond rating is the previous period's bond rating, which is a special case of AR(1). However, such a structure may be too restrictive. Consequently, we estimate our regressions using an exchangeable correlation structure as well. We are grateful to the referee for alerting us to the use of sandwich estimators, the restrictive nature of the AR(1) correlation structure, and for suggesting the exchangeable correlation structure.
25. Longer lags continue to show a significant correlation between the number of accidents and bond ratings.
26. Anecdotal evidence seems to support the notion of greater emphasis on safety following a serious accident by both the airline and the regulatory authorities. All Valujet aircraft were grounded and inspected following the crash in the Florida Everglades in May 1996 before Valujet was allowed to fly again several months later. Additionally, Valujet reduced the number of aircraft types to simplify maintenance and improve safety. To monitor safety more closely on its aircraft, Alaska Airlines created a new post of Vice President of Safety after its plane crashed into the ocean near Los Angeles in January 2000. The FAA conducted many interviews with the mechanics at several maintenance facilities and increased oversight of Alaska Airlines following the accident.

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