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Profitability and Product Quality: Economic Determinants of Airline Safety Performance

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This study investigates product safety choices in the airline industry, with particular attention to the role of financial conditions. The analysis uses data on 35 large scheduled passenger airlines over the 1957–86 period to estimate the effect of profitability and other aspects of financial health on accident and incident rates. The results indicate that lower profitability is correlated with higher accident and incident rates, particularly for smaller carriers. These findings support a broad class of theoretical models that suggest links between financial conditions and product quality and may have significant implications for the allocation of safety inspection and enforcement resources.

This study analyzes the effect of airlines' financial conditions on their safety choices. Various theoretical models incorporating liquidity constraints on investment behavior, decision making near bankruptcy, and reputation formation suggest potential linkages between financial

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variables and firms' product quality or product safety choices. Despite a large body of theoretical work, however, there have been few empirical studies of the determinants of firms' quality choices.

This paper addresses the general issue of what factors affect product quality choice while also contributing to the current policy debate on air carrier safety. Although the impact of financial pressures on airline safety is a long-standing public concern that has intensified since economic deregulation of the industry, there has been little empirical research on this issue. The results of this study suggest that reduced profitability is associated with higher accident and incident probabilities for at least some groups of carriers. While this does not argue for or against economic deregulation, the finding may provide guidance on how to allocate Federal Aviation Administration (FAA) safety regulation resources.[1]

Earlier studies of the determinants of air carrier safety have used only short time series of prederegulation data for domestic operations of U.S. trunk carriers (see Graham and Bowes 1979*a*, 1979*b*; Sobin and Armore 1980; Golbe 1986). While these studies find little correlation between financial variables and airline accident rates, the infrequency of accidents combined with their small sample sizes limits the power of their statistical tests.[2] The present analysis improves on previous research in several ways. First, it employs a more extensive data set consisting of information on 35 large scheduled passenger air carriers over the 1957–86 period.[3] Second, the analysis controls for several variables that may affect safety performance but were excluded from previous work. Finally, the estimation technique based on the Poisson probability model explicitly treats the nonnormality of accident and incident distributions.

The study is structured as follows. Section I sketches the empirical model of airline safety performance. Data and estimation techniques are outlined in Section II. Section III reports analyses of carriers'

[1] The implications of this result for economic deregulation require an estimate of the effect of economic deregulation on profitability and a determination of whether safety was over-, under-, or optimally provided under regulation.

[2] In a previous paper (Rose 1989), results from ordinary least squares regressions using a subsample of the current data suggested a possible correlation between profitability measures and airline accident performance. Evans (1989) also finds evidence of a marginally significant profitability-accident relationship. His study extends the analysis presented in this article to include a larger set of carriers over a shorter time period, alternative statistical models, and estimates of differential accident rates for old and new carriers since deregulation.

[3] Most of these are large airlines certificated under pt. 121 of the Federal Aviation Regulations. Commuter carriers (pt. 135 carriers) are excluded from the analysis because of data limitations; see Oster and Zorn (1984, 1989) for discussions of commuter safety. The sample differs from that used in Rose (1989) in its inclusion of new entrants and former intrastate and charter carriers.

accident rates based on the model developed in the first section; Section IV reports corresponding results for incident rates. The results from a broad range of specifications suggest that lower profitability is associated with higher accident and incident rates, particularly for smaller and midsize carriers. The conclusion (Sec. V) discusses the implications of these findings.

I. Modeling the Determinants of Airline Safety

Airline safety is a function of two sets of factors: safety investments and operating conditions. Safety investments consist of actions undertaken by an airline to increase the safety of its operations. Examples include scheduling maintenance more frequently and using newer equipment to reduce the probability of equipment failure, relying on more experienced personnel and implementing more intensive training programs to decrease the frequency of human error, and purchasing newer aircraft that embody more advanced safety technology.

Operating conditions describe the environment in which an airline operates. Harsh climates may raise the probability of weather-related accidents, variations in airport quality and technology may entail differential risks, systemwide traffic congestion may increase certain hazards, and advances in aircraft and air traffic control technology may improve safety over time.[4] If there is a learning curve with respect to airline safety or operating efficiency, an airline's cumulative operating experience may reduce its risk or permit it to achieve the same level of safety with fewer resources.

These two sets of factors determine a risk distribution that characterizes the probability that a flight will be involved in a hazardous event, such as an accident or incident.[5] Actual accidents and incidents are randomly generated from this risk distribution and an airline's risk exposure, as measured by its number of flights (departures) and their average distance (stage length).

Air carriers choose their level of safety investment by balancing the cost of additional safety-enhancing investment with the benefits of reducing accident or incident risk. The benefits of risk reduction may include lower insurance premiums, lower wages, and higher prices.

[4] These vary greatly in their relative significance. For example, technological advances over the last 40 years have improved airline safety substantially. Increased congestion, on the other hand, is likely to have had a minimal effect on safety: midair collisions account for a small fraction of commercial air carrier accidents, and air traffic control was a primary factor in less than 5 percent of major commercial jet carrier accidents over the 1970–86 period (Oster and Zorn 1989).

[5] Accidents are events that involve fatalities, serious injuries, or substantial aircraft damage. Incidents are defined as hazardous events that do not culminate in fatality, serious injury, or substantial aircraft damage.

Airline passengers, employees, and insurance companies all have strong incentives to monitor carrier safety and to penalize airlines that underinvest in safety. If an airline has better information about its safety level than other market participants, however, the divergence of private and social incentives may lead to suboptimal levels of investment.[6] In this situation, or when there are constraints on airlines' investment choices, financial conditions may influence safety investments.

A variety of economic models provide insight into how such linkages might be generated. These include models of liquidity or financing constraints on investment (e.g., Fazzari, Hubbard, and Petersen 1988), models of decision making near bankruptcy under limited liability rules (see Bulow and Shoven 1978), and models of reputation formation and quality choice (see Klein and Leffler 1981; Shapiro 1982, 1983).[7] While these suggest that financial conditions may influence the choice of investment levels, risk, or product quality, the theoretical models are only suggestive. Empirical research is necessary to ascertain whether such linkages are substantively important. This study therefore focuses on an empirical test of financial influences on safety choices.

Although one cannot observe safety directly, safety outputs such as accidents and incidents provide information on the underlying distribution of airline risk. This study focuses on the total number of aircraft accidents as the primary measure of safety performance.[8] Incidents are used as an alternative measure of safety outputs, although these data are of lower quality. Both measures reflect the probability that a flight selected at random from the pool of available flights will be involved in a hazardous event.

[6] The selected level of safety could be higher or lower than the optimal (full-information) level. Airlines do not, however, choose safety investments solely on the basis of market incentives: they are subject to extensive federal safety regulation by the FAA. Only if FAA standards are below the level airlines prefer will market considerations alone govern safety investment levels. Otherwise, safety investment will be determined by both market and regulatory incentives. The degree of compliance will be influenced by the incremental cost of complying with FAA standards, the probability that violations will be detected, and the penalties imposed for detected noncompliance.

[7] A fourth class of models, in which firms locate at different points along a price-safety frontier, may suggest a correlation rather than causal relation between certain financial accounting data and safety choices. The predictions of these models for a profitability–product quality relationship are discussed further in an earlier version of this paper (Rose 1988).

[8] I emphasize models that combine fatal and nonfatal accidents for two reasons. First, fatal accidents are extremely rare events, making it difficult to estimate accident models with any precision. The mean number of fatal accidents per year in the sample is 0.165 (standard deviation, 0.440); the mean number of total accidents is 1.348 (1.939). Second, fatal and nonfatal accidents seem likely to be generated by the same underlying process even though the ex post outcomes differ.

A structural model of safety performance could be estimated if adequate data on safety investments were available. Given the lack of data and difficulty in accurately quantifying airlines' real maintenance inputs, personnel and equipment quality, and company procedures, however, estimation of a reduced-form model of safety performance seems preferable.[9] The analysis below assumes that past financial variables are exogenous with respect to current safety outputs.[10] The reduced-form model therefore specifies accidents and incidents as functions of lagged financial variables, current operating conditions, and levels of risk exposure.

II. Data and Methodology

This study uses data collected on 35 large U.S. scheduled passenger air carriers for 1957–86 to estimate the statistical model of air carrier safety performance.[11] Many carriers are observed for only part of the sample: 11 exit the industry before 1986, most through merger or acquisition, and nine carriers enter scheduled interstate service after 1978.

The data collected on each carrier include total accidents (TOTACC), system departures in thousands (DEPART), system average stage length in thousands of miles (AVSTAGE), carrier type (trunk, local service, entrant, etc.), cumulative airline operating experience in billions of aircraft miles (EXPER), and operating margin (OPMARG), a measure of operating profitability. I include year-specific time effects or a time trend (TIME) to control for variations in conditions that affect underlying risk over time.[12] To control for possible differ-

[9] This is the standard approach taken in the other analyses of airline safety cited above.

[10] Some empirical support for this is provided by Golbe (1986), who fails to reject the hypothesis of exogeneity for profitability measures. Using lagged values reduces potential simultaneity problems: last period's profits will not be contaminated by costs that are incurred because of accidents this period such as repair or replacement of aircraft, damage claims, higher insurance premiums, or traffic reductions (see, e.g., Borenstein and Zimmerman 1988). Lagged values also are likely to be appropriate since effects on investment levels are unlikely to have an immediate effect on safety outcomes.

[11] Sample firms and their average accident rates are reported in Appendix table B1. Three main classes of carriers were excluded from the sample because of lack of data and noncomparability of operations: commuter airlines and air taxis, charter and "supplemental" carriers, and cargo carriers.

[12] Factors such as regulatory stringency, air traffic control conditions, congestion, and technology were not readily quantifiable. To the extent that these factors vary primarily through time rather than across carriers, we can control for their effects by including time trends or year fixed effects in the analysis. Trends will be appropriate if the effects of omitted factors move smoothly with time. Time fixed effects, which condition on the average accident rate for each year, allow for nonlinear effects that vary through time.

ences in the risk of operations at foreign airports, the analysis includes the fraction of total departures that are international flights (INTL). A dummy variable for Alaskan carriers (ALASKA) picks up the effect of adverse climate and operating conditions within that state.[13] The data also include the number of incidents reported to the FAA during the 1981–86 period (TOTINC).

Accidents, though rare, constitute the highest-quality data on safety outputs. Because these are events that involve fatalities, serious injuries, or substantial aircraft damage, they are difficult to conceal and reporting is likely to be quite accurate. In contrast, the inherent subjectivity of what constitutes an incident, defined as a "hazard or potential hazard to safety," and the difficulty of detecting nonreporting of these hazards increase the noise in incident data and may induce systematic biases across carriers. For example, safety-conscious carriers may report a higher fraction of their incidents than less safe competitors. Accident data also may more closely reflect differences in outcomes attributable to air carriers. Most accidents are attributed to causes under the control or influence of air carriers, such as pilot or crew error, maintenance deficiencies, and inadequate training. Incidents include a higher proportion of events that may be partially or wholly attributable to air traffic and ground controller errors, such as near midair collisions and runway incursions. Accident data do, however, have one major drawback: the relative infrequency of airline accidents reduces the power of statistical tests of accident determinants.[14] Because of this, the model is estimated using information on both accidents and incidents.

The analysis of financial effects on safety performance focuses on the role of operating margins (OPMARG), which reflect profitability before capital expenses and taxes.[15] Additional financial variables, collected for the 1970–86 period, include interest coverage (INTCOV), a measure of leverage differences across carriers, and working capital (WKCAP) and current ratios (CURRAT), which reflect liquidity differences. While the accident data do not appear to have enough power to distinguish the effects of alternative financial measures, these measures are included in models of incident rates. All financial measures are calculated for air carrier operations only, excluding

[13] Inspection of accident rates in Appendix table B1 suggests substantially higher average accident rates for Alaskan carriers during the 1950s and 1960s.

[14] The sample aggregate accident rate is three per million departures over the 1980–86 period, compared to the sample aggregate incident rate of 87 per million departures for the 1981–86 period.

[15] The variable OPMARG measures pretax returns to equity and interest payments scaled by operating revenues (sales). Because depreciation is included in operating expenses, OPMARG more closely reflects profits than cash flow. It is likely to be correlated with underlying cash flow, liquidity, and solvency, however.

unrelated subsidiary operations. One-period lags of financial variables are used to minimize possible simultaneity bias.[16]

Sample means and standard deviations for variables included in the analysis are reported in column 6 of table 1. The sources and construction of the data are detailed in Appendix A.

Statistical Assumptions and Methodology

The Poisson probability distribution provides a natural stochastic specification for airline accidents. This distribution captures the infrequent and discrete nature of accidents and incidents and has been applied extensively as a model of accident probabilities.[17] If one assumes that each flight has some probability of being involved in an accident, the expected number of accidents for firm i in year t, n_{it}, can be modeled as a function of the accident rate per thousand departures, λ_{it}, and the number of departures in thousands, D_{it}. I parameterize the accident rate as an exponential function of an airline's financial and operating characteristics, which ensures that the estimated accident rates are nonnegative.[18] If the exogenous variables are denoted by the vector $\mathbf{X}_{it}$, the accident rate is given by $\lambda_{it} = \exp(\mathbf{X}_{it}\beta)$ and the expected number of accidents is

$$E(n_{it}) = D_{it} \cdot \exp(\mathbf{X}_{it}\beta). \tag{1}$$

I assume that incidents are generated by a similar process, although I allow for different parameters in the accident and incident processes.

If accidents are distributed as Poisson random variables with a conditional mean given by (1), the parameters of the model can be efficiently and consistently estimated by maximizing the log likelihood function, LL:

$$\mathrm{LL} = \sum_{i=1}^{N} \sum_{t=1}^{T_i} [-\exp(\mathbf{X}_{it}\beta)D_{it} + n_{it}\mathbf{X}_{it}\beta + n_{it}\ln(D_{it}) - \ln(n_{it}!)], \tag{2}$$

where N denotes the number of carriers and T_i denotes the number of years over which carrier i is observed. The one potentially troublesome feature of the Poisson distribution—its implied equality of the conditional mean and conditional variance of the distribu-

[16] In preliminary tests, the data did poorly at identifying separate effects of longer lags or moving averages.

[17] See Barnett, Abraham, and Schimmel (1979), Golbe (1986), Barnett and Higgins (1989), and Evans (1989) for applications to air carrier accidents.

[18] This functional form has been used widely in studies using count data (see, e.g., Hausman, Hall, and Griliches 1984).

TABLE 1

AIRLINE ACCIDENT RESULTS, 1957–86 (N = 726)

VARIABLE	TOTAL ACCIDENTS (1)	(2)	(3)	(4)	FATAL ACCIDENTS (5)	SAMPLE MEANS (6)
Constant	−4.405	−4.086	Fixed effects	Fixed effects	−8.334	...
	(.209)	(.075)			(.441)	
$OPMARG_{t-1}$	−.969	−.580	−1.686	−.882	−3.821	.040
	(.537)	(.442)	(.421)	(.329)	(1.488)	(.076)
AVSTAGE	.796	.771	.034	.113	1.174	.427
	(.189)	(.161)	(.301)	(.241)	(.513)	(.348)
EXPER	−.022	−.023	−.016	−.030	−.195	.980
	(.032)	(.025)	(.031)	(.025)	(.095)	(1.621)
INTL	.351	.385	.338	.493	.473	.102
	(.170)	(.152)	(.478)	(.425)	(.482)	(.266)
ALASKA	1.293	1.287	...	...	1.457	.095
	(.173)	(.170)			(.440)	(.293)
TIME	Fixed effects	−.076	Fixed effects	−.065	Fixed effects	15.401
		(.005)		(.006)		(8.889)
Log likelihood	−5,468.45	−5,488.41	−3,152.88	−3,173.36	−906.410	...

NOTE.—Asymptotic standard errors are in parentheses (standard deviations in col. 6). Firm fixed effect models (cols. 3 and 4) are estimated by conditional maximum likelihood.

tion—does not appear to be violated in these data.[19] The analysis therefore relies on maximum likelihood estimation of the Poisson model in (2).

III. Results: Accident Data

This section reports estimates of the Poisson model of airline accidents. Following the earlier discussion, the results should be interpreted as a reduced form rather than as a structural model of the accident-generating process. The basic Poisson model to be estimated is derived by substituting for $\mathbf{X}_{it}\beta$ in equation (2):

$$\begin{aligned}\mathbf{X}_{it}\beta = \beta_0 + \beta_{1t} + \beta_2 \cdot \mathrm{OPMARG}_{i,t-1} + \beta_3 \cdot \mathrm{AVSTAGE}_{it} \\ + \beta_4 \cdot \mathrm{EXPER}_{it} + \beta_5 \cdot \mathrm{INTL}_{it} + \beta_6 \cdot \mathrm{ALASKA}_{i},\end{aligned} \tag{3}$$

where β_{1t} denotes the fixed time effect for year t and the remaining variables are as defined in Section II. Following the discussion of airline accidents in Section I, we expect EXPER and OPMARG to be negatively correlated with accident rates and AVSTAGE, INTL, and ALASKA to be positively correlated with accident rates. The time effects control for any conditions—such as technological change, regulation, and congestion—that vary through time but not across carriers. We expect these to indicate a generally declining trend in accidents through time, mirroring the substantial decline in aggregate accident rates over the 1957–86 period (see Rose 1989), although the specification allows the data complete flexibility in estimating average accident rates over time.[20] The elements of the coefficient vector have the interpretation that a one-unit change in variable X_j will lead to a $\beta_j \times 100$ percent change in the accident probability.

Variations of this basic specification include replacing the time effects with TIME and allowing for the possibility of carrier-specific fixed effects. Carrier fixed effects condition on a carrier's average

[19] I use the procedure described in Hausman et al. (1984) to test this assumption of the Poisson model. Their test for overdispersion is based on a regression of the log of the estimated variance of the residuals for each firm (σ^2) on the log of the conditional mean for each firm (λ): $\log(\sigma^2) = \beta 0 + \beta 1 \cdot \log(\lambda)$. If the Poisson distribution is correct, $\beta 1$ should equal one. For the basic Poisson results presented in col. 1 of table 1, $\beta 0$ is estimated at 0.027 (standard error, 0.133) and $\beta 1$ is estimated at 0.830 (0.106). The test statistic for the hypothesis $\beta 1 = 1.0$ is -1.597, distributed as $t(35)$, which fails to reject even at the 10 percent significance level. I also test the assumption of independence of carriers' residuals through time. A regression of current residuals on lagged residuals yields a coefficient of 0.076 (0.038), which is statistically distinguishable from zero although not substantively large. Because the results presented below do not treat this autocorrelation, the reported standard errors may be slightly understated.

[20] The data could, but do not, indicate an increase in accident risk following economic deregulation of the industry in 1978 or following the air traffic controller strike in 1981.

accident rate, measuring how deviations from carriers' long-run average values of the independent variables affect firms' deviations from their average accident rates. Because of this, the carrier fixed effect specification excludes much of the variation in the data. This specification is reported primarily as a test of the consistency of the parameter estimates in the basic model.

Table 1 reports results for a number of variations of the total accident model in columns 1–4. Column 5 reports results from estimation of the basic model using only fatal accidents. Sample means and standard deviations (in parentheses below the means) are reported in column 6.

The coefficients in the basic specification, shown in column 1, all have the expected signs, and most are statistically distinguishable from zero. The primary coefficient of interest, OPMARG, is estimated at -0.969 (standard error, 0.537), implying that higher operating profits are associated with lower accident rates.[21] An increase of 7.6 percentage points in OPMARG (one standard deviation) will reduce the expected accident rate by 7.4 percent. For a carrier with the 1981–86 sample aggregate accident rate, this would imply a decrease from 3.42 to 3.17 accidents per million departures.

These results are strikingly robust to changes in the specification. The OPMARG coefficient in the fatal accident model (col. 5) is larger but less precisely estimated, although it is statistically distinguishable from zero. Most significant are the results from the carrier fixed effects specifications in columns 3 and 4, in which the effect of OPMARG on accidents is both larger and more precisely estimated.[22] This provides strong evidence against the hypothesis that the profit-accident correlation is driven primarily by an unobservable "managerial competence" effect, which posits that some airlines are run by managers who are good at both making profits and maintaining safety and others are run by managers who are bad at both activities. The results also suggest that the profit-safety relation is not simply an artifact of using accounting profits that include a substantial return to safety investment, which might lead to a correlation between investment and OPMARG in the cross section (as might have been predicted from simple reputation or heterogeneous quality choice mod-

[21] Further support for this result is provided by Evans (1989), who finds a negative coefficient on the current operating margin (he does not include lagged values) for his sample of 105 carriers over the 1970–87 period. While less precise, his point estimates are nearly identical to those presented here.

[22] These specifications are estimated by conditional maximum likelihood following Hausman et al. (1984). Because the reported log likelihoods are defined only up to a constant, they are not comparable across the maximum likelihood and conditional maximum likelihood estimates.

els). Since the carrier-specific fixed effect models condition on a carrier's total number of accidents during the period, the results imply that variations in profitability play an important role in explaining subsequent variations in accident rates over time for a given carrier. This supports a causal interpretation of the profitability-safety relationship.

In the basic specification, longer flights (AVSTAGE) are associated with a higher probability of accidents, as expected from their increased risk exposure, with a 350-mile (one-standard-deviation) increase in average flight length raising accident rates per thousand departures by 27.9 percent. The coefficient on EXPER is not statistically distinguishable from zero, although the negative sign would be consistent with some learning-by-doing effects.[23] Finally, both foreign and Alaskan operations are associated with higher risks over the sample period. Foreign flights (INTL) are associated with 35 percent higher accident risks, while Alaskan carriers had accident rates roughly three and one-half times those of comparable non-Alaskan carriers.

The coefficients on these variables generally are stable across the different specifications. In the fatal accident specification, the magnitude of the estimates tends to increase and their precision tends to decrease. In the firm fixed effect specifications, the point estimates are quite similar to those in the basic model, with the exception of AVSTAGE. The effect of AVSTAGE essentially vanishes in the carrier fixed effect specifications, suggesting that it may be an airline's average route structure that is important in determining accident risk rather than year-to-year variations in average flight distance.[24] The precision of the coefficients is substantially less in these specifications, however, typically preventing one from bounding these coefficients away from zero.

The data also allow us to test whether profitability effects vary across different groups of carriers.[25] To implement this, firms are grouped into size categories (SMALL, MED, and LARGE) on the basis of their average annual departures over the sample period.[26] Equation (3) is then modified to allow both the intercept and the

[23] Only in the estimates based on fatal accidents is the experience effect large and statistically significant.

[24] The variable AVSTAGE also could reflect fleet composition effects since different types of route structures will be associated with different configurations of aircraft. If this effect were substantial, however, it would tend to make the coefficient negative: airlines with the shortest average stage length historically relied more heavily on propeller planes, which tend to be riskier than jet aircraft.

[25] Earlier work using a subset of the data and nonlinear least-squares estimation suggested that profitability effects may vary with firm size.

[26] The results are not substantively changed by including the number of departures as a separate variable.

TABLE 2

AIRLINE ACCIDENT RESULTS, SIZE-VARYING PROFIT EFFECTS, 1957–86 (N = 726)

Variable	Total Accidents (1)	Total Accidents (2)	Total Accidents (3)	Fatal Accidents (4)
Constant	−4.527	−4.224	Fixed effects	−8.407
	(.217)	(.115)		(.583)
SMALL	.062	.091	...	.150
	(.183)	(.172)		(.633)
LARGE	.113	.143	...	.323
	(.134)	(.119)		(.412)
SMALL × OPMARG	−2.282	−2.044	−2.777	−5.973
	(1.878)	(1.192)	(.943)	(3.382)
MED × OPMARG	−.853	−.436	−1.803	−2.644
	(.814)	(.695)	(.637)	(3.031)
LARGE × OPMARG	.017	.165	−.685	−2.848
	(.989)	(.732)	(.580)	(3.648)
AVSTAGE	.756	.718	.026	1.141
	(.195)	(.168)	(.302)	(.516)
EXPER	−.042	−.048	−.005	−.244
	(.038)	(.030)	(.032)	(.120)
INTL	.504	.546	.410	.723
	(.190)	(.176)	(.480)	(.544)
ALASKA	1.346	1.328	...	1.514
	(.239)	(.229)		(.838)
TIME	Fixed effects	−.071	Fixed effects	Fixed effects
		(.006)		
Log likelihood	−5,465.62	−5,485.20	−3,152.12	−905.26

NOTE.—Asymptotic standard errors are in parentheses. Firm fixed effect model (col. 3) is estimated by conditional maximum likelihood.

operating margin coefficient to vary with firm size. Results from variations of this specification are reported in table 2.

Table 2 suggests that profitability effects may be most pronounced for smaller carriers, although the imprecision of the estimates prevents one from rejecting the hypothesis of equality at conventional significance levels.[27] In the total accident models, the operating margin coefficient for small firms ranges from −2.044 (1.192) to −2.777 (0.943) and is statistically significant at the 10 percent level or better. The effect for medium firms is smaller and statistically distinguishable from zero only in the carrier fixed effect specification (col. 3). For large firms, operating margin has no clear effect on accidents in terms of either point estimates or statistical precision. Coefficients on the remaining variables are quite robust across tables 1 and 2.[28]

[27] For the basic specification in col. 1, the likelihood ratio test statistic for the null hypothesis that SMALL = LARGE = 0 and SMALL × OPMARG = MED × OPMARG = LARGE × OPMARG is 5.65, which is distributed as $\chi^2(4)$.

[28] Point estimates in the fatal accident specification again tend to increase from those in the total accident models, but the increase in standard errors swamps this effect, making it difficult to bound most coefficients away from zero.

The persistence of negative point estimates for operating margin coefficients suggests that profitability and accident rates are inversely correlated for at least some groups of carriers. The data are powerful enough to detect profitability relationships in the full sample, although efforts to divide the sample into separate carrier groups or separate time periods yield statistically inconclusive results.[29] Including other financial measures in the model adds little in terms of explanatory power or increased precision. This leads naturally to an examination of airline incidents, to determine whether these data are able to provide more decisive tests.

IV. Results: Airline Incidents

This section explores the determinants of airline incidents, defined as nonaccident events involving actual or potential hazards to safety. To the extent that incidents reflect the same type of adverse outcome that accidents represent, the factors used to model accident rates should help to explain the pattern of incident rates across carriers and through time.

Table 3 reports estimates from a Poisson model of incident counts using data on 26 carriers over the 1981–86 period. All estimates include both firm and time fixed effects and are estimated by conditional maximum likelihood.[30] The basic specification in column 1 includes size-varying profitability effects; columns 2 and 3 include alternative measures of financial conditions. Sample means and standard deviations are reported in column 4.

The results provide strong support for the profitability relationship detected in the accident data and decisively reject the hypothesis of equality across carrier size groups.[31] Low operating margins are strongly correlated with higher reported incident rates for small firms, with coefficient estimates for OPMARG × SMALL ranging

[29] For example, when the data are separated into 10-year prederegulation and postderegulation periods, the coefficient on OPMARG remains negative throughout but the standard errors double. Likelihood ratio tests of the equality of parameters over the entire 1957–86 period do not reject this restriction. This feature of the data may explain why earlier studies of airline safety, which relied on quite small samples, were unable to detect any profitability-safety relationship.

[30] Preliminary estimates suggested that a number of the coefficients were quite sensitive to the inclusion of firm-specific effects. In addition, the assumption of a smooth time trend is implausible for the incident data. For example, the adoption of computer software to automatically report violations of aircraft separation limits on air traffic control screens appeared to increase the number of reported near midair collisions in the mid-1980s independent of any changes in the actual occurrence of such incidents.

[31] The likelihood ratio test statistic for the hypothesis SMALL × OPMARG = MED × OPMARG = LARGE × OPMARG in col. 1 is 10.94, distributed as $\chi^2(2)$. The critical value for the .005 significance level is 10.6.

TABLE 3

AIRLINE INCIDENT RESULTS, SIZE-VARYING FINANCIAL EFFECTS, 1981–86 (N = 137)

Variable	(1)	(2)	(3)	Sample Means (4)
TIME	Fixed effects	Fixed effects	Fixed effects	. . .
SMALL × OPMARG	−4.187	−8.350	−4.124	−.008
	(.462)	(1.255)	(.490)	(.077)
MED × OPMARG	−2.719	−2.550	−1.915	.019
	(.160)	(.175)	(.177)	(.073)
LARGE × OPMARG	.730	1.419	1.048	.023
	(.138)	(.217)	(.142)	(.047)
SMALL × INTCOV	. . .	.164	. . .	.414
		(.034)		(2.092)
MED × INTCOV	. . .	−.011	. . .	1.502
		(.003)		(3.564)
LARGE × INTCOV	. . .	−.017	. . .	2.119
		(.004)		(2.615)
SMALL × WKCAP	. . .	. . .	3.520	−.021
			(.990)	(.121)
MED × WKCAP	. . .	. . .	−1.467	−.055
			(.123)	(.100)
LARGE × WKCAP	. . .	. . .	1.710	−.040
			(.135)	(.053)
AVSTAGE	.293	.257	.350	.605
	(.024)	(.025)	(.025)	(.366)
EXPER	−.390	−.411	−.348	2.044
	(.017)	(.018)	(.018)	(2.524)
INTL	−3.393	−3.035	−4.475	.050
	(.351)	(.366)	(.360)	(.113)
Log likelihood	−4,256.16	−4,254.36	−4,248.28	. . .

NOTE.—Asymptotic standard errors are in parentheses (standard deviations in col. 4). All models are estimated by conditional maximum likelihood and include time fixed effects. Means and standard deviations for size × financial variables are calculated only for observations in size class.

from −4.19 (0.46) to −8.35 (1.26). These imply that a one-percentage-point increase in OPMARG would lead to a 4–8 percent reduction in reported incident rates. The variable OPMARG has a smaller but still large and statistically significant influence on reported incident rates for medium-size carriers; the point estimates range from −1.92 (0.18) to −2.72 (0.16). For large carriers, however, higher profitability seems to be correlated with higher incident reporting rates.[32] The qualitative results are robust to the inclusion of alternative financial measures, although the addition of interest

[32] Models without carrier fixed effects suggest that both small and large carriers report fewer incidents per thousand departures than medium-size carriers, other things equal. For the specification in col. 1 without firm effects, the coefficient on SMALL implies 30 percent fewer incidents and the coefficient on LARGE implies 17 percent fewer incidents.

coverage measures increases the magnitude of the operating margin coefficient for small and large carriers.

Although the incident data are able to distinguish the effects of some alternative financial measures, the results for these measures are mixed.[33] For medium-size carriers, all financial measures have a negative and significant effect on incident reporting rates. Reported incidents increase with working capital for large carriers, however, and increase with both interest coverage and working capital measures for small carriers. While variations in operating margins tend to explain more of the variation in incident rates than interest coverage or working capital measures do, the positive coefficients on these alternative measures are difficult to interpret. This anomaly notwithstanding, the data provide quite strong support for the hypothesis of a link between profitability and incident rates for small and medium-size carriers.[34]

The results for most of the remaining variables also are broadly consistent with the results from the accident models. Longer flights raise reported incident rates, with a coefficient on AVSTAGE of 0.293 (0.024) in the basic model. This implies that a 350-mile increase in average flight distance would increase expected incidents by 10.8 percent. Experience exerts a strong negative effect on incident reports, with a one-standard-deviation increase (2.5 billion miles) corresponding to a 63 percent reduction in incident reports. The only result that is sharply at odds with the accident model is that for international operations: INTL is estimated with a large negative coefficient in all specifications, ranging from -3.04 (0.37) to -4.48 (0.36), implying that international flights have virtually no reported incidents (1–5 percent of the incidents expected for domestic flights, other things equal). It seems likely that this is due at least in part to reporting biases: nonreporting is more difficult to detect, and the FAA is likely to have less accurate information on incidents that occur

[33] The restriction that all interest coverage coefficients are zero cannot be rejected at conventional levels of significance; the likelihood ratio test statistic is 3.6, distributed as $\chi^2(3)$. The restriction that all working capital coefficients are zero can be rejected at the .005 level, with a test statistic of 15.8, distributed as $\chi^2(3)$. Results using the current ratio are qualitatively similar to the working capital results.

[34] As discussed earlier, caution should be exercised in interpreting the incident results. While random noise in the data—such as the inclusion of events beyond the carrier's direct control—will reduce the precision of the estimates, it will not bias the results. Without better data or a model of the decision to report, however, it is impossible to disentangle systematic differences in reporting rates across carriers from systematic differences in the actual occurrence of incidents. Fortunately, the endogeneity of reporting seems most likely to bias results against the findings presented here for small and medium carriers. If financially marginal carriers report a lower fraction of incidents, e.g., we would expect to observe a positive relation between financial variables and incident rates even if the true underlying relationship were negative.

outside domestic airspace. Without additional information, it is difficult to assess the significance of this explanation relative to the alternative of a genuine difference in incident occurrence during international operations.

V. Conclusion

This study finds that airline profitability is directly correlated with airline safety. After one controls for operating conditions that affect airline risk—including average stage length, cumulative airline flight experience, the prevalence of international operations, and time-varying effects of technology and other system conditions—higher airline operating profit margins are associated with reduced accident and incident rates. The effect seems strongest for smaller carriers and is particularly pronounced in recent airline incident data.[35]

The strength of the profitability-safety link for small and medium-size carriers may reflect a greater degree of freedom for these carriers in choosing their safety investment levels. Information asymmetries or liquidity constraints may be less important for the largest firms in the industry, or the FAA may more tightly constrain these carriers through safety inspection and enforcement.[36] These factors could make safety investments by the largest carriers less variable, reducing the correlation between their safety performance and profitability. Smaller firms may, in contrast, have greater discretion in choosing safety investment and therefore may be more responsive to fluctuations in the economic environment. This pattern could guide the allocation of marginal FAA safety enforcement resources.

The empirical findings are consistent with models in which corporate investment, including investment in product safety, is affected by financing constraints, limited liability, and reputation formation. Although the present data are not strong enough to distinguish among these competing explanations, additional power might be gained from direct analysis of safety investments and other measures of airline quality. If the relationship between financial conditions and safety levels is causal, we would expect to observe similar financial

[35] Note that the smaller firms in this study are among the larger firms in the airline industry, however. Most regional carriers and all commuters are excluded from this analysis.

[36] This might be expected because their larger size both makes it worthwhile to invest in any fixed cost of information generation and implies that accident and incident statistics provide more precise information on underlying risk levels. (Since accidents and incidents are rare events, very large numbers of flights are necessary to increase the precision of estimated risks.) In addition, large firms may have better access to external financing or "deeper pockets" for internal financing.

effects on both safety investment levels and other aspects of airline quality. The results presented in this paper argue strongly for further empirical research along these lines.

Appendix A

Data Description and Sources

A. Accidents and Incidents

An *accident* is defined by the National Transportation Safety Board (NTSB) as "an occurrence associated with the operation of an aircraft which takes place between the time any person boards the aircraft with the intention of flight until such time as all persons have disembarked, in which any person suffers death or serious injury as a result of being in or upon the aircraft or by direct contact with the aircraft or anything attached thereto, or in which the aircraft receives substantial damage." An *incident* is defined as "an aircraft occurrence not classified as an accident in which a hazard or potential hazard to safety is involved."

Individual air carrier accident data are taken from the U.S. Civil Aeronautics Board (CAB), *Resume of Accidents, U.S. Air Carriers, Rotorcraft and Large General Aviation Aircraft* (annual, 1953–59); CAB, *Statistical Review and Briefs of U.S. Air Carrier Accidents* (annual, 1960–65); NTSB, *Annual Review of Aircraft Accident Data, U.S. Air Carrier Operations* (succeeds the CAB accident publications; 1966–82); NTSB, *Preliminary Analysis of Aircraft Accident Data, U.S. Civil Aviation* (1979–82); and NTSB accident briefs (unpublished computer printout; 1983–86).

Incident data for the period 1981–86 were obtained from the FAA, AFS-4 (computer printout). These data are taken from the FAA's Accident-Incident Data System data base, maintained by the National Safety Data Branch of the FAA in Oklahoma City. They include both self-reported incidents and those reported by the FAA (such as air traffic control–related near midair collisions).

B. Operations Data

Annual scheduled passenger domestic and international revenue departures in thousands and aircraft miles completed in millions are from CAB, *Air Carrier Traffic Statistics* (various issues, 1954–83) and U.S. Department of Transportation (DOT), *Air Carrier Traffic Statistics* (continues the CAB publication; various issues, 1983–86). Average stage length (AVSTAGE) is computed as system miles per system departure and is scaled in thousands of miles. The proportion of international departures, INTL, is international departures per system departure.

Airline experience (EXPER) in year t is calculated as the cumulative system aircraft miles completed (in billions) in scheduled interstate passenger service from 1954 through year $t - 1$. When two or more carriers in the data set merge operations, the experience for the larger carrier is used as a base for the merged carrier's experience. For example, when Texas International and Continental merged operations in 1982, miles after 1982 were added to Continental's cumulative mileage to compute the merged carrier's experience.

When ownership is merged but operations are not, experience continues to be separately calculated for each carrier (e.g., New York Air and Continental). Experience for former intrastate and charter carriers is cumulated only after their entry into scheduled interstate passenger service. This treatment is due primarily to the lack of data on intrastate service and also to a desire to maintain consistent treatment across the two types of entrants.

Carrier size is defined on the basis of average annual departures over the full sample. Small carriers are defined as those with fewer than 75,000 average annual departures, medium carriers are defined as those with more than 75,000 and fewer than 225,000 departures, and large carriers have over 225,000 departures. There are 15 small, 14 medium, and 6 large carriers. The small carriers include all Alaskan, Hawaiian, and territorial carriers as well as Northeast, Air California, Air Florida, Capitol International, World, Midway Airlines, and New York Air. The large carriers include American, Delta, Eastern, Trans World Airlines, United, and USAIR. The remaining carriers constitute the medium category.

C. *Financial Data*

Annual airline system operating revenues and operating expenses are taken from CAB, *Air Carrier Financial Statistics* (various issues, 1954–83), and DOT, *Air Carrier Financial Statistics* (continues CAB publication; various issues, 1983–86). The system operating margin, OPMARG, is calculated as 1 − (operating expenses/operating revenues).

Additional financial measures were retrieved from the DOT data tapes of form 41 quarterly schedules P1, P3, and B1 for 1970–86. Further documentation including form 41 account numbers from which the measures were constructed is available from the author on request. The variables used in the analysis include (1) INTCOV = interest coverage = earnings before interest and taxes/total interest payments; (2) CURRAT = current ratio = current assets/current liabilities; (3) WKCAP = working capital = (current assets − current liabilities)/total assets.

Appendix B

TABLE B1

ACCIDENT AND INCIDENT RATES BY CARRIER BY TIME PERIOD (per Million Departures)

Carrier	Accidents 1957–60	1961–65	1966–70	1971–75	1976–80	1981–86	Incidents 1981–86
Trunks:							
American	24.75	14.20	7.68	9.07	6.44	3.82	162.14
Braniff	7.87	10.80	9.03	4.52	4.65	4.02	88.55
Continental	13.17	20.94	7.34	4.06	8.38	7.82	121.14
Delta	10.87	11.69	11.20	11.60	4.92	1.61	56.60
Eastern	16.39	15.47	6.71	8.13	2.88	4.07	65.49
National	15.24	10.35	9.03	9.52	6.48	...	...
Northeast	19.85	17.34	12.59	.00	...	...	...
Northwest	33.19	16.84	5.72	12.17	.00	1.80	114.22
Pan Am	40.32	30.23	24.41	17.24	7.65	6.08	96.05
TWA	19.44	21.53	8.07	15.36	2.77	1.56	200.86
United	11.48	12.64	12.62	4.56	1.56	4.52	104.29
Western	12.35	9.53	6.04	2.63	5.04	1.05	79.85
Local service:							
Frontier	9.82	11.97	6.95	9.70	2.04	2.50	61.36
Ozark	11.52	6.88	5.60	2.70	.00	6.30	89.75
Piedmont	8.40	10.22	8.29	4.50	1.18	3.14	45.87
Southern/Republic	8.88	7.82	5.48	2.95	.80	1.64	91.18
Texas Intl.	12.44	2.05	7.98	8.67	8.50	6.35	126.90
USAIR	12.53	7.72	6.65	6.08	4.71	3.62	63.04

Alaskan and Hawaiian:							
Alaska	95.58	41.19	17.71	7.57	9.51	3.35	. . .
Aloha	.00	9.59	14.74	7.25	5.38	.00	12.77
Hawaiian	.00	6.50	4.78	.00	.00	7.15	35.73
Northern Consol.	117.95	31.35	24.47	. . .	. . .	. . .	. . .
Wien Air Alaska	51.23	89.79	40.79	11.10	2.87	3.55	17.73
Territorial:							
Caribbean Atlantic	.00	6.98	26.52				
Pacific Northern	.00	.00	.00				
Pan-Am-Grace	47.51	.00	.00				
Former intrastate and charters:							
Air California					21.29	4.74	14.22
Air Florida					24.55	12.52	. . .
Capitol Intl.					.00	.00	. . .
Pacific Southwest					.00	1.48	32.65
Southwest					.00	2.85	42.73
World					.00	42.03	231.19
New entrants:							
Midway						4.86	189.72
NY Air						4.14	45.53
People Express						1.95	76.03
Aggregate:							
Total accidents	203	214	204	176	83	99	2,487
Departures (millions)	11.73	15.22	21.11	21.87	22.50	28.97	28.49
Accident rate	17.30	14.06	9.67	8.05	3.69	3.42	87.30

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