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PROFITABILITY AND PRODUCT QUALITY: ECONOMIC DETERMINANTS OF AIRLINE SAFETY PERFORMANCE

Nancy L. Rose
MIT

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MASSACHUSETTS
INSTITUTE OF TECHNOLOGY
50 MEMORIAL DRIVE
CAMBRIDGE, MASSACHUSETTS 02139

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ABSTRACT

PROFITABILITY AND PRODUCT QUALITY:
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Nancy L. Rose
MIT School of Management
Cambridge, MA 02139

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Despite an extensive theoretical literature on product quality choice, there have been few empirical tests of the determinants of firms' quality decisions. This study uses data on the airline industry to investigate financial influences on product safety. Data on 35 large scheduled passenger airlines over the 1957 through 1986 period are used to estimate the effect of profitability and other aspects of financial health on accident and incident rates, controlling for operating characteristics that may exert independent effects on safety levels. The results from a broad range of statistical specifications suggest that lower profitability is correlated with higher accident and incident rates, particularly for smaller carriers in the sample.

A variety of theoretical models suggest the existence of possible causal linkages between financial variables and firms' product quality or product safety choices. These include models of cash flow or liquidity constraints on investment behavior, decision-making near bankruptcy, and reputation formation in the presence of asymmetric information.[1] Despite a large body of theoretical work, there have been few empirical studies of the determinants of firms' quality choices. This paper uses data from the airline industry to test whether a relation exists between firms' financial conditions and their safety performance.

Although there has been extensive public concern that financial stress leads to reduced air carrier safety, there has been little empirical research on this question. Three studies that have examined this issue-- Graham and Bowes (1979a,b), Sobin and Armore (1980), and Golbe (1986)-- use relatively short time series of pre-deregulation data and look only at domestic operations of U.S. trunk carriers. While these studies find little evidence of correlations between financial variables and airline accident rates, the infrequency of accidents combined with their small sample sizes limits the power of their statistical tests. Results from longer time series of data and larger sets of carriers suggest that more powerful tests may be able to detect a correlation between profitability measures and airline accident performance (see Rose, forthcoming).[2]

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[1] See, for example, Shapiro (1982, 1983) on reputation models, Bulow and Shoven (1978) on limited liability effects, and Fazzari, Hubbard, and Petersen (1988) on financing constraints. A fourth class of models, in which firms locate at different points along a price-safety frontier, may suggest a correlation but not causal relation between certain financial accounting data and safety choices.

[2] This earlier work examined aggregate accident patterns through time and used a subset of the present data to estimate OLS regressions of accidents rates on profitability.

This study re-examines the relationship between firms' financial health and their safety performance as measured by total accident and incident rates.[3] It differs from earlier analyses in several ways. First, a more extensive data set is employed, consisting of information on 35 large scheduled passenger air carriers over the 1957 through 1986 period.[4] Second, the study controls for a broader range of variables that may affect safety performance than have been included in most previous work. Finally, the analysis explicitly accounts for the unusual statistical properties, including non-normality, of accident and incident distributions.

The study is structured as follows: Section 1 describes the statistical model of airline safety performance and discusses the channels through which firms' financial conditions may influence their safety levels. Section 2 outlines the data and estimation techniques. Section 3 reports regression analyses of carriers' accident rates based on the model developed in the first section; section 4 reports corresponding results for incident rates. The results from a broad range of statistical specifications suggest that lower profitability is associated with higher accident and incident rates for smaller air carriers in the sample. A brief conclusion follows in section 5.

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[3] See the appendix for the precise definition of accidents and incidents. The distinction between the two is essentially one of realized versus potential hazard.

[4] Most of these are large airlines certificated under Part 121 of the Federal Aviation Regulations (FAR); hereafter referred to as "Part 121" carriers. Commuter carriers (part 135 carriers) are excluded from the analysis due to data limitations; see Oster and Zorn (1984, forthcoming) for discussions of commuter safety. The sample differs from that used in Rose (forthcoming) in its inclusion of new entrants and former intrastate and charter carriers.

1. MODELING THE DETERMINANTS OF AIRLINE SAFETY

This study models airline safety performance as a direct function of two sets of factors: the first, which will be referred to as "safety investments," consists of conditions under an airline's immediate influence, such as maintenance procedures, personnel quality, and equipment quality and age. The second, denoted as "operating conditions," is comprised of factors that are independent of the current actions of any individual airline, including airline operating experience, weather or climate conditions, airport quality, and aircraft and air traffic control technology. 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. Observed safety outputs are generated from this risk distribution and airline exposure levels (the number of flights and average distance). A third set of factors may indirectly influence safety performance through their effects on airline safety investment decisions.[5] These include the direct costs of higher risks, the airline's financial condition, and the stringency of Federal Aviation Administration (FAA) safety regulation. This model of airline safety performance is sketched in Figure 1. It can be summarized as a system of two equations:

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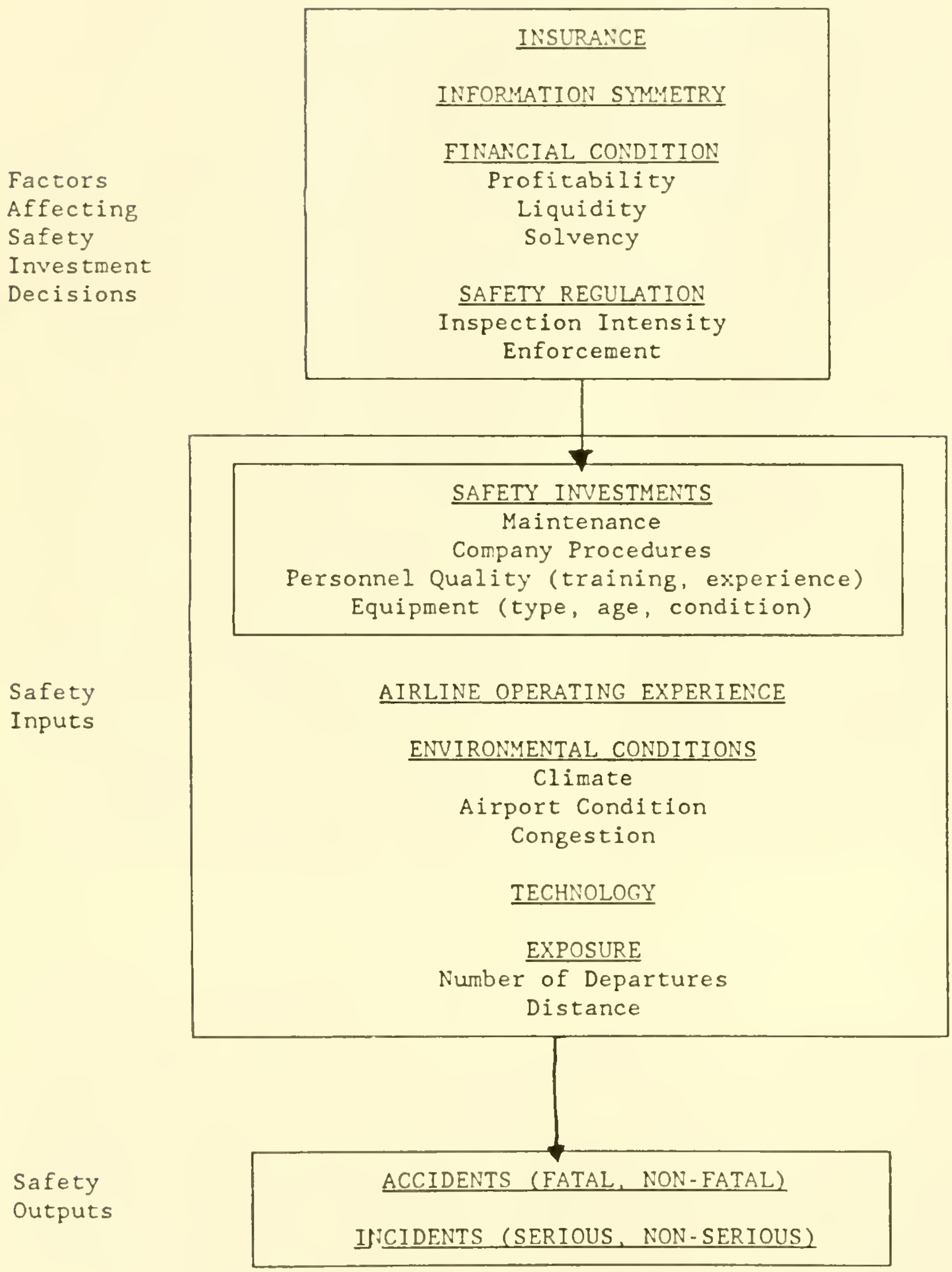
[5] The topic of safety investment is a sensitive one in the airline industry. Although many airline executives claim that safety is their top priority and is never compromised, it is unlikely that any airline attempts to provide the maximum level of safety attainable; nor would such an objective be socially desirable. Once we accept that airlines do not undertake every investment that might reduce risks, we must ask how carriers trade off the costs and benefits of safety investment. This study explores factors that may influence firms' decisions in this area.

Figure 1

A MODEL OF AIRLINE SAFETY PERFORMANCE



(1) Safety Investment = f(Risk Premia, Financial Conditions, Regulatory Constraints)

(2) Safety Outputs = g(Safety Investment, Operating Conditions, Exposure)

The components of the model are described in further detail below.

Factors that affect airlines' safety investment decisions

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. Airline passengers, employees, and insurance companies all have strong incentives to monitor carrier safety and to penalize airlines that underinvest in safety. Insurance companies will demand higher premiums from firms with higher accident risks. Airlines that are perceived to be less safe will, other things equal, tend to lose passengers and employees to safer competitors. Pilots, flight attendants, and other frequent flyers will resist reductions in safety or require compensating wage or price differentials for higher risk exposure.[6]

If an airline has better information about its safety level than have its customers, employees, insurance firms, and creditors, however, the divergence

[6] The wage effect is likely to be strongest when wages are set competitively. If airline wages are above the opportunity wages for these workers, safety reductions may erode workers' quasi-rents instead of raising wages. It also should be noted that employees may have an incentive to frame labor relations disputes in terms of safety if this improves their bargaining position. Disentangling true safety concerns from negotiation tactics may prove difficult in practice.

of private and social incentives may lead to suboptimal levels of safety investment. In this situation, or when there are constraints on airlines' investment choices, airlines' financial conditions may influence their 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, decision-making under limited liability rules, and reputation-formation and quality choice. Although the airline safety data do not in fact appear strong enough to distinguish among these explanations, it seems useful to describe a number of ways in which such financial-safety relationships might arise.

Cash flow constraints on investment may provide the most plausible channel through which financial conditions might influence safety investment behavior. If there is asymmetric information about the quality of available investment projects or if it is difficult to monitor and discipline management, adverse selection and moral hazard effects may create a wedge between the cost of internally-generated capital and the cost of raising new capital. In this case, investment levels in general may depend on firms' cash flows: for low cash flow firms, the marginal cost of capital will be high, leading to less investment than would otherwise take place. Recent empirical work by Fazzari, Hubbard and Petersen (1988) suggests that these liquidity or financing constraints may have significant effects on firms' investment patterns. For airlines, safety investment may be particularly susceptible to these problems. Airline equipment can be leased and airport-specific investment may be easily collateralized, reducing outside investors' risks. Safety investments, such as those in human capital or the development of maintenance facilities and programs, are likely to be the most difficult to monitor or collateralize, and asymmetric information about safety levels may confound estimates of returns to additional investment. This suggests that safety investments may be most sensitive to the level of firms' internally-generated cash flows. This model is compatible with the concern expressed by many airline industry observers and participants that cash-constrained airlines may be unable to finance desired safety investments.

Informational asymmetry also may affect safety investment by interacting with limited liability and bankruptcy laws. Given limited liability, firms that are near insolvency may find it attractive to reduce safety expenditures in an effort to avoid bankruptcy, even if this increases the risk of accidents (see Bulow and Shoven, 1978, and Myers, 1977). The impossibility of writing complete contingent contracts and perfectly monitoring safety may lead to a relation between safety investments and carriers' liquidity and leverage positions. These predictions depend on the magnitude of bankruptcy costs; high bankruptcy costs may counteract the incentives created by limited liability. The net impact on safety investment depends on the relative magnitudes of offsetting effects.

In reputation-based models of firms' quality choices under asymmetric information, firms trade off the costs of building or maintaining a reputation for providing high quality service with the benefits (profits) associated with that reputation (see, for example, Klein and Leffler, 1981, Shapiro, 1982 and 1983, and Allen, 1985). Profitability may influence safety choices through at least two channels. First, a decline (increase) in marginal returns to quality could reduce (raise) safety investment as firms equate the marginal costs of safety investment to these returns. Second, a discrete reduction in profits that leaves marginal returns unaffected could reduce safety investment if the total revenue earned by a high quality reputation falls below the costs of maintaining such a reputation (a zero profit threshold). Finally, a cross-sectional relation between profitability and safety levels may be observed even in the absence of any causal relations. If safety investments generate a flow of returns over more than one period (i.e., they are investments, not current expenses), high safety investment should generate high total returns (reflecting a normal return on the investment). Since profitability data measure accounting rather than economic profit, observed profits will tend to be high for firms with significant safety investments, leading one to estimate a positive correlation in the cross-section though not in the time series dimension.[7]

Note that these channels do not require the presence of asymmetric information: even under perfect information, carriers' locations along a price-quality spectrum will be influenced by the marginal returns to quality and zero profit investment criteria. However, an assumption of perfect information on individual airlines' safety levels may be strained. Empirical studies suggest some reputation effects, although it is difficult to assess their magnitude. Barnett and Lofaso (1983) find little evidence of passenger responses to the 1979 DC-10 crashes; Borenstein and Zimmerman (1987) find relatively small responses in their sample of fatal airline crashes since 1962. Mitchell and Maloney (1988) estimate larger average wealth losses and insurance cost increases from fatal accidents in which pilot error is suspected.[8] These estimates

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[7] If a firm reduces investment this period, accounting profits will remain high or increase (depending on the treatment of safety expenditures). Since safety next period will fall, this will tend to induce a negative correlation between profitability last period and safety this period.

[8] Borenstein and Zimmerman find that expected profits decline by an average of $4.5 million (1985 dollars) while traffic volume effects appear to be significant only in the post-deregulation period and are quite short-lived. Mitchell and Maloney estimate wealth declines of $19 to $27 million and insur-

may understate the full impact of potential reputation losses if revisions to reputation from a single accident are minimal (consumers expect even safe airlines to experience an occasional accident) or if safety levels are above the optimum (profits are not increasing in safety).

Finally, in evaluating these models it is important to recognize that airlines do not choose safety investment levels solely on the basis of private incentives. In particular, airlines are subject to extensive federal safety regulation by the Federal Aviation Administration (FAA). This regulation takes the form of maintenance and operations standards rather than performance standards; as such, it regulates airline inputs into the safety production process.[9] Only if FAA standards are below the level the airlines prefer will market considerations alone govern safety investment levels.[10] Otherwise, safety investment will be determined by both market and regulatory incentives. The degree of airline 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 non-compliance.

<u>Factors that affect safety outputs</u>

Two types of inputs enter the safety production process: carriers' safety investments and operating conditions that influence underlying risks or the

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ance cost increases of $8 to $9 million (all 1987 dollars). Chalk (1987) estimates larger effects of accidents on aircraft manufacturers' profits when aircraft defects are suspected in the crash, although this does not imply that airline <u>passengers</u> are able to evaluate manufacturers' reputations.

[9] Standards specify training and experience levels for personnel, equipment requirements, maintenance schedules, operating procedures, and reporting and record-keeping requirements.

[10] This is <u>a priori</u> plausible, however.

efficiency of safety investments. Investments are actions undertaken by an airline to increase the safety of its operations. More frequently scheduled maintenance and newer equipment may reduce the probability of equipment failure, relying on more experienced personnel and implementing more intensive training programs may decrease the frequency of human error, newer aircraft may embody more advanced safety technology, and so on. While safety is assumed to be non-decreasing in these investments, the impact of additional investment on performance is likely to suffer diminishing returns. This suggests that safety investment levels may provide quite imperfect measures of relative safety levels in the absence of specific information on the form of the safety production function.

Operating conditions may exert an independent effect on safety performance. If there is a learning curve with respect to airline safety or operating efficiency, an airline's cumulative operating experience may raise its safety or permit it to achieve the same level of safety with fewer resources. Environmental conditions in which airlines operate may alter underlying risks: harsh climates probably raise the probability of weather-related accidents, variations in airport quality and technology may entail differential risks, system-wide traffic congestion may increase certain hazards.[11] Finally, advances in aircraft and air traffic control technology will improve aviation safety through time.

Safety investments and operating conditions combine to produce some risk distribution ("safety level") for an airline's flights. This distribution

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[11] It is easy to overstate the significance of congestion and air traffic control factors, however. Mid-air collisions account for a small fraction of commercial air carrier accidents; air traffic control was a primary factor in less than 5 percent of major commercial jet carrier accidents over the 1970-1986 period (Oster and Zorn, forthcoming).

determines the probability that a given flight will be involved in an adverse event such as an accident or incident. The number of adverse events experienced by an airline will depend on its exposure to risk as well as on its risk distribution: how many flights take place and over what distance.

Measuring safety outputs

Although we cannot observe safety directly, safety outputs such as accidents (fatal, serious, and minor) and incidents (serious and minor) 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. These are events that involve fatalities, serious injuries, or substantial aircraft damage.[12] Aircraft incidents, defined as hazardous events that do not culminate in serious injury or substantial aircraft damage, are also used as a 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. Using the number of flights involved in accidents or incidents instead of passenger-based measures implicitly assumes that 10 accidents with ten fatalities each reflect a lower safety level, all else equal, than a single accident that kills 100 passengers.

While accidents are rare events, they comprise the highest quality data on safety outputs. Accident reporting is likely to be quite accurate; fatalities,

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[12] The analysis combines fatal and nonfatal accidents. For individual carriers, fatal accidents are extremely rare events and it may be quite difficult to estimate accident determinants from these measures. Moreover, it seems likely that fatal and nonfatal accidents are generated by the same underlying process even though the *ex post* outcomes differ. Future work will explore the effect of separating accidents by severity or proximate cause.

serious injuries, and substantial aircraft damage are difficult to conceal. Incident reporting is likely to be measured with much more error: judgment of what constitutes a "potential hazard" is subjective and detecting non-reporting is more difficult. This may induce systematic biases across carriers. For example, safety-conscious carriers may report a higher fraction of their incidents than do less safe competitors. Accident data also may more closely reflect differences in outcomes attributable to air carriers. The National Transportation Safety Board attributes the substantial majority of accidents 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 mid-air 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. Because of this, the model also is estimated using information on reported incidents, which are more frequent events.[13] The trade-off between the larger number of incidents and the larger amount of noise in these data must be recognized, however.

Given the endogeneity of safety investment decisions, safety performance models may be estimated one of two ways. If adequate data on safety inputs were available, a two-equation structural model of safety performance could be estimated following equations (1) and (2). Given the difficulty in accurately quantifying airlines' maintenance levels, personnel and equipment quality, and company procedures, however, estimation of a reduced form model of safety

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[13] The sample aggregate accident rate is 3 per million departures over the 1980-1986 period, compared to the sample aggregate incident rate of 87 per million departures for the 1981-1986 period.

performance seems preferable.[14] This approach specifies current safety performance as a function of exogenous variables only; that is, those variables that are independent of current decisions. The analysis below assumes that past financial variables are exogenous with respect to current safety outputs[15] and specifies the model as

(3) Safety Outputs = h(Risk Premiums, Financial Conditions, Regulatory Conditions, Operating Conditions, Exposure)

where the financial measures are values from prior periods.

2. Data and Methodology

This study uses data collected on 35 large scheduled passenger air carriers over the period 1957 to 1986 to estimate the statistical model of air carrier safety performance. Using the old Civil Aeronautics Board groupings, these consist of twelve domestic and international trunks, six local service carriers, five intra-Alaskan and intra-Hawaiian airlines, three territorial carriers, six former intrastate or charter operators, and three new jet carrier

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[14] A natural extension of this study would model the determinants of safety investment. I currently am exploring the use of detected safety violations and maintenance expenditures as proxies for investment levels in such a model. This analysis may provide the foundation for estimating a model closer to the structural model of equations (1) and (2).

[15] Some empirical support for this is provided by Golbe (1986), who finds that her data fail 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 due to accidents this period such as repair or replacement of aircraft, damage claims, higher insurance premiums, or traffic reductions. Lagged values may also be appropriate since the impact of reduced profits on accidents is unlikely to be immediate. On a practical level, the exogeneity assumption is required by the dearth of reasonable instruments.

entrants.[16] Many carriers are observed for only part of the sample; eleven 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 revenue departures in thousands (DEPART), system revenue aircraft miles and average stage length in thousands of miles (AVSTAGE), the share of flights involving foreign airports (PINTL), carrier type (trunk, local service, entrant, etc.), cumulative airline operating experience (EXPER), TIME (a linear time trend), and a number of financial measures. In addition, I was able to obtain the number of incidents reported to the FAA (TOTINC) over the 1981-1986 period.

The financial variables measure aspects of carriers' profitability, liquidity, and leverage. They include: operating margins (OPMARG), which reflect profits before capital expenses and taxes; interest coverage (INTCOV) which measures leverage differences across carriers; and working capital (WKCAP) and current ratios (CURRAT), which reflect liquidity differences. All financial measures are calculated for air carrier operations only, excluding unrelated subsidiary operations.[17] Of the financial variables, operating margins were collected for the entire time period; the remaining variables are

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[16] Sample carriers and average accident rates are reported in appendix tables A1 and A2. Almost all the carriers would be classified as "major" or "national" carriers under current Department of Transportation groupings. Three classes of air carriers were excluded from the sample due to lack of data and non-comparability of operations: commuter airlines and air taxis (Part 135 carriers), nonscheduled passenger carriers (charters or "supplemental" carriers), and cargo carriers.

[17] The measures are constructed from accounting data reported on Department of Transportation Form 41. These data apply only to the airline portion of corporate accounts for conglomerate firms. While accounting data reflect true economic or financial conditions only imperfectly, they appear to be the best we can do.

available only for a 1970-1986 subsample. Because preliminary work suggested that OPMARG provided the strongest, most stable estimates of financial-accident links, this study focuses on the OPMARG results. I interpret this variable as primarily reflecting differences in profitability, although it is likely to be correlated with underlying cash flow, liquidity, and solvency.[18] Unfortunately, the accident data do not appear strong enough to distinguish decisively among these various components. As noted above, lagged financial variables are used to minimize possible simultaneity bias.

Data on a number of the factors described in equation (3) were not readily available. These include indices of regulatory stringency, climate, airport quality or conditions, congestion, and technology. 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.[19] Regulatory stringency, congestion and technology seem likely to be most consistent with this assumption although there may be some inter-carrier variations that this approach will not capture. Cross-sectional variations in airport quality are accounted for to the extent that foreign airports involve different risks than U.S. airports by controlling for the fraction of

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[18] OPMARG, defined as 1 - (operating expenses)/(operating revenues), includes pre-tax 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. Future work will collect depreciation information to determine whether the results are more sensitive to profitability or cash flow differences.

[19] Time trends will be appropriate if the effects of omitted factors move smoothly with time. Time fixed effects, which amount to estimating separate average accident rates for each year, will pick up any type of nonlinear effects that vary only through time.

total departures that are international flights (PINTL).[20] Climate is assumed to matter only when extreme, so I include a dummy variable for Alaskan carriers (ALASKA).[21]

Table 1 provides information on the sample means and standard deviations for all variables in the analysis. The sources and construction of the data are detailed in the appendix.

Statistical Assumptions and Methodology

The number of accidents for firm i in year t, n_{it}, is a function of an (unknown) accident rate per thousand departures, λ_{it}, and the number of departures in thousands, D_{it}. It seems most reasonable to assume that accident risk is proportional to the number of departures (flights) rather than to elapsed time, particularly given the considerable variation in the scale of airlines' operations. 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 non-negative.[22] Denoting these exogenous variables by the vector X, the accident rate is given by $\lambda_{it} = \exp(X_{it}\beta)$ and the expected number of accidents is:

$$(4) \quad E(n_{it}) = D_{it} \exp(X_{it}\beta)$$

[20] Barnett, Abraham and Schimmel (1979) argue that carriers can influence airport quality by choosing which airports to serve. This endogeneity would suggest excluding finer controls for variations in airport quality.

[21] Inspection of accident rates--see appendix table A2--suggest substantially higher average accident rates for Alaskan carriers during the 1950s and 1960s.

[22] This functional form has been used widely in studies using count data; see, for example, Hausman, Hall, and Griliches (1984, hereafter HHG).

TABLE 1

VARIABLE DEFINITIONS AND DESCRIPTIVE STATISTICS

Full Sample, 1957-1986

Variable	Description	Sample Mean	Standard Deviation
ACCDEP	Accidents per thousand departures	.011	.023
ALASKA	1 if Alaskan carrier; else	.095	.293
AVSTAGE	Average Stage Length (000 miles)	.427	.348
BIG	1 if mean DEPART > 225,000; else 0	.248	.432
DEPART	Departures (000)	167.207	151.188
EXPER	Experience (billions of miles)	.980	1.621
LACCDEP	ln(ACCDEP) if ACCDEP > 0; else 0	-2.516	2.289
OPMARG	Operating Margin	.040	.076
PINTL	Int'l Departures/Total Departures	.102	.266
SMALL	1 if mean DEPART < 75,000; else 0	.289	.454
TIME	Years since 1954	18.400	8.890
TOTACC	Total Accidents	1.348	1.939
ZERODUM	1 if TOTACC = 0; else 0	.428	.495
	Number of observations in sample	726	

Financial Sample, 1971-1986:

INTCOV	Interest Coverage Ratio	1.820	2.900
WKCAP	Working Capital Ratio	-.030	.140
CURRAT	Current Ratio	.980	.340
	Number of observations in sample	352	

Incident Sample, 1981-1986:

INCDEP	Incidents per thousand departures	.090	.093
INCIDENT	Total Incidents	17.034	19.180
	Number of observations in sample	146	

I assume that incidents are generated by the same type of process, although the parameters of that process are estimated independently.

This conditional expectation can be estimated consistently without imposing particular assumptions on the statistical distribution of accidents, using nonlinear least squares (NLLS) or other "pseudo-maximum likelihood" techniques (see Gourieroux, Monfort, and Trognon, 1984; hereafter GMT). While the estimation does not require that the accident or incident distribution be known, more efficient estimates can be obtained when a particular distributional assumption can be maintained. The Poisson probability distribution provides a natural stochastic specification for this purpose. This distribution captures the infrequent and discrete nature of accidents and incidents and has been applied extensively as a model of accident probabilities (see Barnett, Abraham, and Schimmel (1979), Barnett and Higgins (1987), and Golbe (1986) for applications to air carrier accidents).[23] If accidents are distributed as Poisson random variables with a conditional mean given by (4), the parameters of the model can be efficiently and consistently estimated by maximizing the log-likelihood:

$$(5) \quad \text{LogL} = \sum_{i=1}^{N} (\sum_{t=1}^{Ti} (-\exp(X_{it}\beta)D_{it} + n_{it}X_{it}\beta + n_{it}\ln(D_{it}) - \ln(n_{it})$$

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[23] The one potentially troublesome feature of the Poisson distribution--the equality of the mean and the variance of the distribution--can be relaxed with minor modifications if necessary. See GMT (1984); HHG (1984); and Cameron and Trivedi (1986) for discussions of Poisson models and their variants.

3. Results: Accident Data

In this section I report estimates of the accident rate model using a variety of statistical specifications. Following the earlier discussion, the results should be interpreted as a reduced form rather than as a structural model of the accident-generating process. For comparability with earlier studies, I first report results using ordinary least squares (OLS) techniques. Although these provide a benchmark, the existence of zero accident observations leads to consistency problems with the estimates. Nonlinear least squares (NLLS) estimates, which are consistent under a broad range of distributional assumptions, and maximum likelihood Poisson estimates, which trade off a more tightly parameterized model against potential efficiency gains, follow the OLS results.

OLS Results

The model of accidents in equation (4) can be linearized by dividing both sides by the number of departures and taking logs to yield the equation: $\ln(n_{it}/D_{it}) = X_{it}\beta$. Since the log will be undefined for observations with zero accidents, I follow Pakes and Griliches (1980) and HHG (1984) in setting the log equal to zero for these observations and introducing a dummy variable, ZERODUM, equal to one for these observations and zero for all others.[24] This procedure, while _ad hoc_, provides a metric for comparing results to those of previous studies, most of which use OLS (see Graham and Bowes (1979a,b), Golbe (1986), and Rose (forthcoming)). The elements of the estimated coefficient

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[24] This procedure is much more dubious for my accident data than it is for the data used in these patent studies. About 7 percent of the observations in the Pakes and Griliches and HHG studies had zero patents, as compared to 43 percent zero accident observations in this study. Only 8 percent of the observations in the incident subsample record zero incidents.

vector have the interpretation that a one unit change in the corresponding variable in X_j will lead to a β_j*100 percent change in the accident or incident probability.

The basic OLS specification of carrier i's accident rate in year t is:

$$(6)\quad \ln(TOTACC_{it}/DEPART_{it}) = \beta 0 + \beta 1{*}TIME_{it} + \beta 2{*}AVSTAGE_{it} + \beta 3{*}EXPER_{it} + \beta 4{*}OPMARG_{i,t-1} + \beta 5{*}PINTL_{it} + \beta 6{*}ALASKA_{it} + \beta 7{*}ZERODUM_{it}$$

where the variables are as defined earlier and in the appendix. The model described in section 1 implies that time, experience, and operating margins should be negatively correlated with accident rates while average stage length, proportion international, and Alaskan operations should be positively correlated with accident rates. ZERODUM is a correction factor for the treatment of zero accident years and therefore is not reported in the tables below. Variations on this specification replace the time trend with time fixed effects and replace the constant with carrier fixed effects. The time effects control for any conditions--such as technological change, regulation, and congestion--that vary through time but not across carriers. Carrier fixed effects condition on a carrier's average accident rate; it measures how deviations from carriers' long-run average values of the independent variables affect firms' current accident rates.[25]

Table 2 reports results from variations of equation (6) in the first four columns. These are estimated on the full data set of 726 carrier-year observations over the 1957-1986 period. Column 5 reports results estimated from the

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[25] The carrier fixed effect specification may eliminate much of the important variation in the data. It takes out, for instance, the effect of cross-sectional differences in average profitability--although this may be precisely the dimension that matters most.

TABLE 2

OLS REGRESSION ANALYSIS OF ACCIDENT RATES
1957-1986

Variable	BASIC MODEL	MODEL 2	MODEL 3	MODEL 4	MODEL 5
CONSTANT	-4.043 (.054)	-4.015 (.120)	FIXED EFFECTS	FIXED EFFECTS	-3.908 (.085)
TIME	-.020 (.003)	FIXED EFFECTS	-.024 (.004)	FIXED EFFECTS	-.035 (.004)
AVSTAGE	.321 (.101)	.317 (.098)	.078 (.206)	.086 (.203)	.725 (.239)
EXPER	-.154 (.024)	-.156 (.022)	-.094 (.033)	-.102 (.032)	-.220 (.037)
OPMARG	-1.124 (.287)	-1.190 (.316)	-.972 (.329)	-1.130 (.353)	-2.130 (.442)
PINTL	.210 (.100)	.201 (.098)	-.007 (.387)	.048 (.375)	.427 (.214)
ALASKA	.722 (.104)	.724 (.101)	--	--	1.498 (.106)
SSR	231.31	224.34	200.14	194.63	145.85
Adj. R^2	.344	.363	.432	.447	.586
NOBS	726	726	726	726	415

* Mean and standard deviation of dependent variable.

White heteroskedastic-consistent standard errors in parentheses. Coefficient on ZERODUM is not reported. Adjusted R^2 is calculated as: (1-SSR/SST'), where SST' is the SSR from a regression of ln(TOTACC/DEPART) on a constant and zerodum.

non-zero observations only (discussed below). The coefficients in the basic specification, shown in column 1, all have the expected signs and are statistically distinguishable from zero. The primary coefficient of interest, OPMARG, is estimated at -1.124 (standard error, .287), implying that higher operating margins (profits) are associated with lower accident rates, other things equal. An increase of 7.6 percentage points in OPMARG (one standard deviation) will reduce the expected accident rate by 8.5 percent. For a carrier with the 1981-86 sample aggregate accident rate, this would imply a decrease from 3.42 accidents per million departures to 3.13 accidents per million departures.

Accident rates decline over time (TIME) at a rate of 2.0 (0.3) percent per year. 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 11.2 (3.5) percent. The coefficient on experience (EXPER) is consistent with strong learning-by-doing effects. Increasing cumulative airline experience by one standard deviation (1.62 billion aircraft miles) reduces the expected accident rate by 25 (3.89) percent. The experience coefficient may, however, also reflect nonlinear time effects (as experience trends strongly through time until the entry of inexperienced entrants in the late 1970s and early 1980s) or size effects (since carriers that have flown more historically tend to be larger). These possibilities are discussed below.[26] Finally, both foreign and Alaskan operations are associated with

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[26] The experience coefficient also may reflect a selection bias in the data: if airlines with high accident rates exit the industry, then long-lived airlines will be those with few accidents over their history. As reported below, however, the experience coefficient remains significant (though it declines somewhat) when carrier fixed effects are included in the model. Since the fixed effect model uses time series rather than cross-sectional variation to identify the coefficients, this result argues against selection bias as the

higher risks over the sample period. Foreign flights (PINTL) are associated with 22 percent higher accident risks, while Alaskan carriers had accident rates roughly double those of comparable non-Alaskan carriers.

The estimates are robust to the inclusion of time effects (columns 2 and 4) but the inclusion of carrier fixed effects (columns 3 and 4) considerably reduces the precision of the estimates and weakens a number of the results. The smaller experience coefficient in carrier fixed effect specifications suggests that this variable may partially reflect the influence of carrier size, which is correlated with experience in the cross-section. The robustness of the coefficient to inclusion of time effects argues against the interpretation of experience as a proxy for nonlinear time patterns. The influence of AVSTAGE essentially vanishes in specifications that include carrier fixed effects, suggesting that it may be an airline's average route structure that is important rather than year-to-year variations in average flight distance.[27] PINTL is small and negative in column 3, small and positive in column 4, with enormous standard errors in both. In contrast, the estimated time trend in the fixed effect equation is somewhat larger and still quite significant.

The weaker performance of carrier fixed effect specifications is not entirely surprising: this specification conditions on carriers' long-run average accident rates and identifies the impact of variables through deviations from long-run averages. This conditioning is likely to absorb much of the inter-

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dominant explanation.

[27] 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 significant, however, it would tend to make the coefficient negative: airlines with the shortest average stage lengths relied more heavily on propeller planes, which generally are thought to be more risky than are jet aircraft.

esting variation, making it more difficult to identify the coefficients: one might expect that long-run values of financial and other variables exert more influence on investment decisions (and therefore accident rates) than do transitory deviations from these values. Given this, it is quite encouraging that the effect of OPMARG, though slightly smaller and less precisely estimated in column 3, remains relatively large and statistically distinguishable from zero in both fixed effects specifications (columns 3 and 4).

This result provides evidence against the hypothesis that the profit-accident rate correlation is driven primarily by an unobservable "managerial competence" effect, in which some airlines are run by managers that are good at both making profits and maintaining safety and others are run by managers that are bad at both activities. The result also suggests that relation is not simply an artifact of OPMARG including a substantial component of return to safety investment, leading to a correlation between investment and OPMARG in the cross-section (as might have been predicted from simple reputation or heterogeneous quality choice models). Even when cross-sectional variation is ignored, variations in profitability appear to play an role in explaining accident rates. I interpret this as supporting a causal interpretation of the profitability-safety relationship, although the data may not be strong enough to conclude this decisively.

Finally, column 5 reports results estimated over the 415 non-zero accident observations only. For these observations, the log of the accident rate is defined without resort to the ZERODUM adjustment discussed earlier. Because this sample censors the data on the dependent variable, the coefficient estimates will not be consistent for modeling the entire accident generating process. The estimates provide some information on how the variables affect accident probabilities conditional on an accident occurring. Most coefficients increase in magnitude for this sample, with OPMARG almost doubling, to -2.130 (.442). This suggests that OPMARG is less strongly correlated with the change from 0 to 1 accidents in the data than it is with the movement from 1 to 2 or 2 to 3 (etc.) accidents.

Nonlinear Least Squares

Although OLS provides estimates comparable to those of earlier studies, the presence of a substantial number of zero accident observations limits the reliance we can place on the OLS estimates. An alternative technique that will provide consistent estimates (assuming the basic model is correctly specified) is nonlinear least squares applied to equation (4). This yields an equation of the form:

$$(7)\quad TOTACC_{it} = D_{it} \cdot \exp(\beta 0 + \beta 1{*}TIME_{it} + \beta 2{*}AVSTAGE_{it} + \beta 3{*}EXPER_{it} + \beta 4{*}OPMARG_{i,t-1} + \beta 5{*}PINTL_{it} + \beta 6{*}ALASKA_{it})$$

The variance in total accidents is likely to increase with an airline's total departures, implying heteroskedasticity in equation (7).[28] While the reported standard errors are consistent even in the presence of heteroskedasticity,[29] more efficient estimates can be obtained by weighting the observations to eliminate the heteroskedasticity. I consider three weighting schemes:

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[28] If accidents are distributed as Poisson, the error variance will be proportional to the conditional mean, $D_{it}\exp(X_{it}\beta)$. This is treated in the MLE specification.

[29] The standard errors are calculated using White's heteroskedastic-consistent estimator.

unweighted, weighted by the inverse of the square root of departures, and weighted by the inverse of departures. Efficiency can be further enhanced if one is willing to accept more tightly parameterized specifications of the accident distribution, such as the Poisson specification discussed in section 2.

Table 3 reports NLLS estimates of equation (7) in columns 1-3 and maximum likelihood estimates (MLE) of the Poisson specification in column 4. The NLLS and MLE results differ from the OLS results in a number of respects. The NLLS/MLE standard errors are much larger, perhaps in part due to inconsistency of the OLS standard errors.[30] While most of the OLS coefficients could be bounded away from zero in tests of statistical significance, many of the NLLS and MLE coefficients cannot be. The point estimates also exhibit some differences from the patterns in the OLS results. The coefficients on OPMARG look quite similar to those estimated by OLS, apart from the larger standard errors, as do the coefficients on PINTL. Both AVSTAGE and ALASKA are estimated to have larger effects in the NLLS and MLE specifications, more than double their effect in the OLS equations reported in table 2. The experience effect essentially vanishes: the point estimates of EXPER are small, extremely imprecise, and quite unstable.

All the equations include time fixed effects and therefore can be thought of as estimating the effect of changing a carriers' position relative to the industry average for each year. In equations that include time trends rather than fixed effects (not reported here), TIME has a much larger impact than was

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[30] The inclusion of ZERODUM artificially increases the fit of the OLS equations, reducing the estimated variance.

TABLE 3

NONLINEAR LEAST SQUARES AND MLE ESTIMATES OF ACCIDENT RATES
BASIC MODEL: 1957-1986

Weighting:	Depart	$\sqrt{\text{Depart}}$	Unweighted	Poisson
TIME	FIXED EFFECTS	FIXED EFFECTS	FIXED EFFECTS	FIXED EFFECTS
AVSTAGE	1.291 (.394)	.946 (.246)	.669 (.287)	.795 (.189)
EXPER	-.020 (.102)	.047 (.043)	.009 (.044)	-.022 (.032)
OPMARG	-2.202 (1.331)	-.756 (.694)	-1.067 (.714)	-.967 (.537)
PINTL	-.114 (.334)	.305 (.214)	.460 (.260)	.352 (.168)
ALASKA	1.849 (.164)	1.678 (.154)	1.293 (.161)	1.293 (.173)
SSR/LOG-LIKE.	.218	7.900	1053.33	-5468.44
R-SQUARE	.427	.385	.614	--
NOBS	726	726	726	726

Standard errors in parentheses.
White heteroskedastic consistent standard errors reported in columns 1-3.

estimated in table 2--accidents decline at 7 to 10 percent per year.[31] The coefficient estimates generally are robust to the treatment of time and carrier fixed effects, with the notable exception of the AVSTAGE coefficients. These estimates decline by half or more in fixed effect estimates, echoing the earlier OLS results. However, the standard errors on all coefficients tend to increase substantially in carrier fixed effects models, making it difficult to bound almost anything away from zero.

Preliminary results for subsamples of the data set suggested that operating margin coefficients often were sensitive to the weighting factor used.[32] While it is difficult to assess the importance of this instability given the imprecision of the estimates, a more flexible model would allow the effects of the coefficient to change with firm size. I implement this by grouping firms into size categories based on their average annual departures over the sample period. SMALL firms are defined as those with fewer than 75,000 mean departures; BIG as those with more than 225,000 mean departures; and MED as all others.[33] Table 4 reports results for specifications that allow both the intercept and the operating margin coefficient to vary with firm size.[34] Most other coefficients are robust to this change in specification; I therefore focus on the operating margin coefficients. The results suggest that profit-

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[31] OPMARG is estimated with much smaller coefficients in these specifications, although the point estimates are within one standard error of the point estimates reported in table 3.

[32] Different weights should affect only the precision of the coefficient estimates and not their magnitude.

[33] These are based on natural breakpoints in the data. The classification of firms is detailed in the appendix.

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

TABLE 4

NONLINEAR LEAST SQUARES AND MLE ESTIMATES OF ACCIDENT RATES
SIZE-BASED DIFFERENCES: 1957-1986

Weighting	Depart	$\sqrt{\text{Depart}}$	Unweighted	Poisson
TIME	FIXED EFFECTS	FIXED EFFECTS	FIXED EFFECTS	FIXED EFFECTS
SMALL	-.182	-.112	-.015	.062
	(.297)	(.216)	(.254)	(.183)
BIG	-.215	-.052	.242	.112
	(.224)	(.134)	(.143)	(.134)
AVSTAGE	1.268	.896	.572	.746
	(.419)	(.272)	(.293)	(.195)
EXPER	-.022	.052	-.035	-.042
	(.108)	(.051)	(.051)	(.038)
OPMARG*SMALL	-2.788	-1.249	-1.804	-2.282
	(1.672)	(1.327)	(1.367)	(1.188)
OPMARG*MED	-.849	-.913	-1.267	-.851
	(1.615)	(1.022)	(1.381)	(.814)
OPMARG*BIG	.926	.084	-.841	.016
	(1.942)	(1.103)	(.987)	(.989)
PINTL	-.059	.353	.754	.504
	(.373)	(.259)	(.282)	(.190)
ALASKA	2.007	1.785	1.394	1.346
	(.301)	(.272)	(.312)	(.239)
SSR/ LOG-LIKELIHOOD	.217	7.883	1040.38	-5465.62
R-SQUARE	.431	.386	.618	--
NOBS	726	726	726	726

Standard errors in parentheses.
White heteroskedastic consistent standard errors reported in columns 1-3

ability effects may be most pronounced for smaller carriers, although the imprecision of the estimates prevents one from rejecting the hypothesis of equality at any conventional level of significance.[35] The operating margin coefficients for small firms (OPMARG*SMALL) range from -1.249 (1.327) to -2.788 (1.672) and are statistically distinguishable from zero at the ten percent level in columns 1 and 4. The effect for medium firms is smaller, ranging from -.849 (1.615) to -1.267 (1.381) and never statistically significant. For big firms, operating margin has no clear effect on accidents, with coefficients ranging from +.926 (1.942) to -.841 (.987) and standard errors substantially larger than the point estimates.

While these results and the general persistence of negative point estimates for operating margin coefficients suggest that profitability and accident rates are inversely correlated for at least some groups of carriers, the imprecision of the results limit the strength of any conclusions one can draw from the data. The data are strong enough to detect marginally significant profitability relationships in the full sample, but most efforts to divide the sample into separate carrier groups or separate time periods yield statistically inconclusive results.[36] Including other financial measures in the model also seems to add little in terms of explanatory power or increased precision. The

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[35] For the Poisson specification, for example, the likelihood ratio test statistic for the null hypothesis that SMALL = BIG = 0 and SMALL*OPMARG = MED*OPMARG = BIG*OPMARG is 5.64, which is distributed as chi-square(4).

[36] For example, when the data are separated into 10-year pre-deregulation and post-deregulation periods, the coefficient on OPMARG remains negative throughout but the standard errors double. A likelihood ratio test of equality throughout the 1957-1986 period (for the Poisson specification) yields a test statistic of 3.268, distributed as chi-square(20). 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.

inability of the accident data to provide very powerful tests of the relationships of interest leads naturally to an examination of airline incidents, to determine whether these data are able to more decisively test some of the hypotheses hinted at in the analysis of airline accidents.

4. Incident results

This section explores the determinants of airline incidents, defined as non-accident 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.

Differences in the way incidents are measured suggest some caution in interpreting the results. Incidents are likely to measured with substantial and perhaps systematic errors.[37] Random noise in incident data--such as the inclusion of events beyond the carrier's direct control--will reduce the precision of the estimated coefficients but will not bias the results. Absent information on reporting accuracy, however, it will be impossible to disentangle systematic differences in reporting rates across carriers from systematic differences in the actual occurrence of incidents.[38] The endogeneity of reporting could lead to perverse results. For example, if financially marginal

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[37] Accidents by definition involve serious injuries or substantial aircraft damage, making it difficult to conceal their occurrence. Incidents by definition involve events in which no one is seriously injured and any damage is at most minor. This makes it difficult to detect non-reporting of incidents. Indeed, there is substantial anecdotal evidence that official reports of incidents understate their occurrence.

[38] If one were willing to impose specific distributional and functional form assumptions on the incident occurrence equation and a decision-to-report equation, these effects might be separately identified. I have no reason to believe that such assumptions would be justified for these data.

carriers report a lower fraction of incidents, we might observe a positive relation between financial variables and incident rates even if the true underlying relationship is negative. With this caveat in mind, it nevertheless seems useful to examine the incident data, since the much higher frequency of incidents relative to accidents may improve the power of statistical tests of the determinants of safety outputs.

Table 5 reports estimates of the basic incident equation for 26 carriers over the 1981-1986 period. I report Poisson results for the basic model in column 1. As the OPMARG coefficients seem particularly unstable across different weightings, however, I focus on equations that allow for size-based differences in both the level of incidents and the effect of profitability (as suggested by the accident models). These are reported in columns 2-5. All estimates include time fixed effects as the assumption of a smooth time trend is particularly implausible for the incident data.[39] Columns 2-4 report NLLS results weighted by different functions of departures; column 5 reports MLE Poisson results; sample means and standard deviations are reported in column 6.

The results provide surprisingly strong support for the profitability relationship detected in the accident data. The results in column 1 suggest an average operating margin effect of -.612 (.202). This average masks significant variation across different size groups, however. Low operating margins are strongly correlated with higher reported incident rates for small firms, with coefficient estimates for OPMARG*SMALL ranging from -6.640 (.595) in the Poisson model to -10.744 (3.203) in the specification weighting by the square

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[39] For example, the adoption of computer software to automatically report violations of aircraft separation limits on air traffic control screens increased the number of reported near mid-air collisions in the mid-1980s, independent of any changes in the actual occurrence of such incidents.

TABLE 5

ANALYSIS OF INCIDENT RATES: BASIC MODEL
1981-1986

Weighting:	Poisson	Depart	$\sqrt{\text{Depart}}$	Unweighted	Poisson	Sample Mean Std. Dev.
CONSTANT	-3.182	-2.678	-3.207	-3.562	-3.180	--
	(.049)	(.154)	(.191)	(.244)	(.055)	
SMALL	--	-.264	-1.080	-1.399	-.443	.267
		(.225)	(.348)	(.437)	(.073)	(.444)
BIG	--	.320	.239	.159	-.054	.247
		(.216)	(.212)	(.209)	(.054)	(.433)
AVSTAGE	1.970	.859	1.894	2.713	2.050	.586
	(.073)	(.206)	(.296)	(.324)	(.089)	(.357)
EXPER	-.018	-.002	-.045	-.080	-.022	1.961
	(.005)	(.034)	(.035)	(.035)	(.011)	(2.476)
OPMARG	-.612	--	--	--	--	.010
	(.202)					(.079)
OPMARG*SMALL	--	-9.734	-10.744	-8.746	-6.640	-.001
		(1.732)	(3.203)	(3.619)	(.595)	(.037)
OPMARG*MED	--	-.177	.071	-.450	-.827	.005
		(.563)	(.833)	(1.091)	(.259)	(.065)
OPMARG*BIG	--	-2.451	-.626	.528	.664	.006
		(1.819)	(1.591)	(1.199)	(.388)	(.025)
PINTL	-2.179	-.489	-1.629	-2.621	-2.386	.047
	(.247)	(.502)	(.458)	(.454)	(.259)	(.110)
SSR/LOG-LIKE.	-8270.30	.452	43.10	8732.18	-8253.59	
R-SQUARE	--	.641	.692	.836	--	
NOBS	146	146	146	146	146	146

All equations include time fixed effects.

root of departures. These imply that a 1 percentage point increase in OPMARG would lead to a 6 to 10 percent reduction in reported incident rates. OPMARG has much less influence on reported incident rates for medium size carriers; the point estimates are relatively small and variable and the standard errors are quite large. The point estimates of OPMARG for big carriers are quite unstable but not statistically distinguishable from zero except in the Poisson specification, where the estimated effect is positive (.664, standard error .388).

Small carriers appear to report fewer incidents per thousand departures (SMALL), other things equal, while medium and big carriers appear to have similar average incident rates (compare BIG). AVSTAGE exerts a strong positive effect on incident rates, though the point estimates vary across different weightings. Longer flights appear to raise reported incident rates by more than they raised accident rates, with point estimates varying from .859 (.206) to 2.713 (.324). Experience is negatively but weakly correlated with incident reports in all four specifications.

The only result that is at odds with the accident model is that for PINTL. PINTL is estimated with a large negative coefficient in all four specifications, ranging from a statistically insignificant -.489 (.502) to -2.621 (.454). It is possible this reflects reporting biases: FAA incident counts may record fewer incidents that occur outside domestic airspace.[40] Without additional information, it is difficult to assess the plausibility of this explanation against the alternative of a genuine difference in incident occurrence among carriers with substantial international operations.

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[40] For example, near mid-air collisions that would be reported by U.S. air traffic controllers may go unrecorded if they occur outside the U.S. air traffic control system.

These data are better able than were the accident data to distinguish the effects of alternative financial measures, such as interest coverage (INTCOV), working capital (WKCAP) and current (CURRAT) ratios. These variables are available for 137 of the 146 observations in the incident sample. For economy of presentation, only Poisson and NLLS equations weighted by the square root of departures are reported. The results of these specifications, reported in table 6, are mixed. On the one hand, the OPMARG results seem reasonably robust to inclusion of most other financial variables. Interest coverage measures appear to add somewhat to the explanatory power of the model, with larger effects for smaller firms. For small carriers, an increase in the interest coverage ratio from 1.0 to 2.0 reduces the reported incident rate by 5.7 (7.4) to 10.5 (2.9) percent. The effect for other carriers is roughly one-fifth as large.[41] On the other hand, the results in columns 3-6 suggest that incident rates for small carriers are positively correlated with liquidity measures. Increases in working capital ratios are associated with substantially higher incident rates for small firms (coefficients of 3.899 (1.719) to 5.364 (1.166)) as are increases in the current ratio (coefficients of .818 (.355) to 1.090 (.220)). Since higher values of both variables should be associated with more liquidity and stronger financial health, this relation is difficult to explain. This anomaly notwithstanding, the data provide reasonably strong support for the hypothesis of a link between profitability and measures of safety outputs for smaller jet carriers.

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[41] Interest overage effects suggest that leverage or capital financing constraints may play a role, since these effects would not be predicted by reputation models or by perfect information heterogeneity explanations.

TABLE 6

ANALYSIS OF INCIDENT RATES: ALTERNATIVE FINANCIAL MEASURES
1981-1986

	(1)	(2)	(3)	(4)	(5)	(6)
Weighting:	$\sqrt{Depart}$	Poisson	$\sqrt{Depart}$	Poisson	$\sqrt{Depart}$	Poisson
CONSTANT	-2.750 (.132)	-2.752 (.041)	-2.820 (.138)	-2.816 (.041)	-2.839 (.225)	-2.749 (.073)
SMALL	-.467 (.197)	-.328 (.114)	-.393 (.357)	-.350 (.130)	-1.195 (.554)	-1.514 (.300)
BIG	.186 (.210)	-.051 (.049)	.143 (.168)	-.053 (.049)	.123 (.166)	-.072 (.050)
AVSTAGE	1.223 (.201)	1.239 (.041)	1.284 (.184)	1.292 (.041)	1.285 (.184)	1.281 (.050)
EXPER	-.026 (.037)	.003 (.009)	-.022 (.031)	.002 (.009)	-.020 (.031)	.004 (.009)
PINTL	-1.161 (.416)	-1.411 (.188)	-1.080 (.481)	-1.355 (.178)	-1.128 (.480)	-1.373 (.177)
OPMARG*SMALL	-7.627 (1.476)	-6.317 (2.435)	-8.490 (2.519)	-5.883 (1.084)	-9.049 (2.519)	-6.472 (.986)
OPMARG*OTHER	-.806 (1.289)	-.928 (.339)	-1.222 (.974)	-1.070 (.369)	-1.344 (.996)	-1.198 (.352)
INTCOV*SMALL	-.105 (.029)	-.057 (.074)	--	--	--	--
INTCOV*OTHER	-.022 (.013)	-.014 (.008)	--	--	--	--
WKCAP*SMALL	--	--	3.899 (1.719)	5.364 (1.166)	--	--
WKCAP*OTHER	--	--	-.293 (.600)	-.368 (.231)	--	--
CURRAT*SMALL	--	--	--	--	.818 (.355)	1.090 (.220)
CURRAT*OTHER	--	--	--	--	.041 (.221)	-.047 (.076)
SSR/LOG-LIKE.	44.50	-8233.8	44.31	-8221.51	44.50	-8224.75
NOBS	137	137	137	137	137	137

5. CONCLUSION

The analysis provided in this study suggests the possible existence of financial influences on airline safety production. After controlling for operating conditions that affect airline risk and safety production--including average stage length, cumulative airline flight experience, international operations, and time-varying effects of technology and other system conditions--higher airline operating margins appear to be correlated with lower accident and incident rates. The effect seems strongest for the smaller Part 121 scheduled passenger carriers and is particularly pronounced in recent airline incident data. This finding suggests that firms' quality or safety choices may be influenced by their financial condition, in the spirit of many models of financing constraints, investment under limited liability, and reputation-formation. The data analyzed in this study do not appear strong enough to distinguish among these competing explanations, however. Additional power in testing these various models 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 effects on both safety investment levels and other aspects of airline quality. The results presented in this paper argue strongly for further empirical research on the existence of such effects.

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APPENDIX

DATA DESCRIPTION AND SOURCES

1. 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" (U.S. Department of Transportation, 1980, p.18). 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 from the U.S. Civil Aeronautics Board (CAB), Resume of Accidents, U.S. Air Carriers, Rotorcraft and Large General Aviation Aircraft (annual, 1953-1959); U.S. CAB, Statistical Review and Briefs of U.S. Air Carrier Accidents (annual, 1960-1965); U.S. NTSB, Annual Review of Aircraft Accident Data, U.S. Air Carrier Operations (succeeds the CAB accident publications; 1966-1982); U.S. NTSB, Preliminary Analysis of Aircraft Accident Data, U.S. Civil Aviation (1979-1982), and U.S. NTSB Accident Briefs (unpublished computer printout, for 1983-1986).

Incident data for the period 1981-1986 were obtained from the Federal Aviation Administration, AFS-4 (computer printout). These data are from the FAA's Accident-Incident Data System (AIDS) 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 mid-air collisions).

2. Operations data: Annual scheduled passenger domestic and international revenue departures in thousands and aircraft miles completed in millions are from U.S. CAB, Air Carrier Traffic Statistics (various issues, 1954-1983) and U.S. Department of Transportation (DOT) Air Carrier Traffic Statistics (continues the CAB publication, various issues 1983-1986). Average stage length (AVSTAGE) is computed as system miles/system departures and is scaled in thousands of miles. PINTL, the proportion of international departures, is international departures/system departures.

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 (for example, 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 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 big carriers have over 225,000 departures. There are 15 small, 14 medium, and 6 big carriers. The small carriers include all Alaskan, Hawaiian, and Territorial carriers as well as Air California, Air Florida, Capitol International, World, Midway Airlines, and New York Air. The big carriers are comprised of American, Delta, Eastern, TWA, United, and USAIR. The remaining carriers constitute the medium category.

3. Financial data: Annual airline system operating revenues and operating expenses are from the U.S. CAB, Air Carrier Financial Statistics (various issues, 1954-1983) and U.S. DOT, Air Carrier Financial Statistics (continues CAB publication, various issues, 1983-1986). The system operating margin, OPMARG, is calculated as 1 - (operating expenses)/(operating revenues).

Additional financial measures were retrieved from the U. S. Department of Transportation data tapes of Form 41 quarterly schedules P1, P3, and B1 for 1970-1986. These measures are constructed as described in table 2; further documentation including form 41 account numbers from which the measures were constructed is available from the author upon request. These 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 TABLE A1
SAMPLE AIR CARRIERS

	Full Data	Financial Data
Trunk Carriers:		
American Airlines	1954-1986	1970-1986
Braniff Airways	1954-81,84-86	1970-81,84-86
Continental Air Lines	1954-1986	1970-1986
Delta Air Lines	1954-1986	1970-1986
Eastern Air Lines	1954-1986	1970-1986
National Airlines	1954-1979	1970-1979
Northeast Airlines	1954-1971	---
Northwest Airlines	1954-1986	1970-1986
Pan American Airlines	1954-1986	1970-1986
Trans World Airlines	1954-1986	1970-1986
United Airlines	1954-1986	1970-1986
Western Air Lines	1954-1986	1970-1986
Local Service Carriers:		
Frontier Airlines	1954-1986	1970-1986
Ozark Air Lines	1954-1986	1970-1986
Piedmont Aviation	1954-1986	1970-1986
Southern Airways/Republic [a]	1954-1986	1970-1986
Texas International	1954-1982	1970-1982
USAir/Allegheny	1954-1986	1970-1986
Alaskan and Intra-Hawaiian:		
Alaska Airlines	1954-1986	1970-1986
Aloha Airlines	1958-1986	1970-1986
Hawaiian Airlines	1954-1986	1970-1986
Northern Consolidated	1954-1967	---
Wien Air Alaska [b]	1954-1984	1970-1984
Territorial Carriers:		
Caribbean Airlines	1954-1970	---
Pacific Northern	1954-1966	---
Pan American-Grace	1954-1966	---
Former Intrastate and Charters		
Air California	1979-1986	1979-1986
Air Florida	1979-1983	1979-1983
Capitol International	1979-1984	1979-1984
Pacific Southwest Airlines	1979-1986	1979-1986
Southwest Air	1979-1986	1979-1986
World Airways	1979-1986	1979-1986
New Jet Entrants:		
Midway Airlines	1980-1986	1980-1986
New York Air	1981-1986	1981-1986
People Express	1981-1986	1981-1986

[a] Data reflects Southern Airways operations prior to merger into Republic in 1979, and Republic operations thereafter.

[b] Data reflects Northern Consolidated operations prior to its merger with Wien Airlines in 1968, and combined operations thereafter.

APPENDIX TABLE A2

ACCIDENT AND INCIDENT RATES BY CARRIER BY TIME PERIOD
(per million departures)

	Accidents						Incidents
Carrier	1957-60	1961-65	1966-70	1971-75	1976-80	1981-86	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	0.00	--	--	--
Northwest	33.19	16.84	5.72	12.17	0.00	1.80	114.22
PanAm	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	0.00	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	0.80	1.64	91.18
Texas Int'l	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	0.00	9.59	14.74	7.25	5.38	0.00	12.77
Hawaiian	0.00	6.50	4.78	0.00	0.00	7.15	35.73
Wien Air Alaska	51.23	89.79	40.79	11.10	2.87	3.55	17.73
Northern Consol.	117.95	31.35	24.47	--	--	--	--
Territorial							
Caribbean Atlantic	0.00	6.98	26.52	--	--	--	--
Pan-Am-Grace	47.51	0.00	0.00	--	--	--	--
Pacific Northern	0.00	0.00	0.00	--	--	--	--
Former Intrastate and Charters							
Air California	--	--	--	--	21.29	4.74	14.22
Air Florida	--	--	--	--	24.55	12.52	--
Capitol Int'l	--	--	--	--	0.00	0.00	--
Pacific Southwest	--	--	--	--	0.00	1.48	32.65
Southwest	--	--	--	--	0.00	2.85	42.73
World	--	--	--	--	0.00	42.03	231.19
New Entrants							
Midway	--	--	--	--	--	4.86	189.72
NYAir	--	--	--	--	--	4.14	45.53
People Express	--	--	--	--	--	1.95	76.03
Aggregate							
Total Accidents	203	214	204	176	83	99	2487
Departures (000,000)	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