Market Incentives for Safe Commercial Airline Operation

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Airlines are insured against most direct costs of an accident, but they cannot insure against demand loss. Our estimation of deviations from expected demand following accidents finds little or no effect prior to airline deregulation and weak indication of a response to recent crashes. These results are consistent with the changes in an airline's equity value following an accident, which are statistically significant, but quite small relative to the total social cost of the accident.

Central to the debate over the need for government regulation of product safety is the incentive that the private market provide for producing safe goods and services. This incentive comes from the costs imposed upon firms responsible for unsafe products. With the economic deregulation of airlines, the industry has become a focus for this debate. Some argue that increased competition may lead airlines to skimp on investments in safety.[1] Others respond that airline safety is still monitored by the Federal Aviation Administration (FAA) and that the private market discipline unsafe operations, as well. Using a sample of nearly all fatal U.S. airline accidents between 1960 and 1985, this paper attempts to quantify the costs that airlines incur due to crashes. The potential costs include those due to loss of life and equipment, tort liability, increased regulatory oversight, and loss of demand as consumers turn away from products perceived to be unsafe.

We begin by examining the losses incurred by shareholders when a major accident occurs. Airlines carry insurance against many of the costs of a crash, such as equipment loss and tort liability. Hence, the decline in firm value comes from those losses that are uninsured and from the increased insurance costs that might result as insurance companies update their information about the safety of a particular airline or of the industry in general.

A potentially important uninsured loss is the reduction in demand that an airline might suffer. Consumers may respond to an accident in several different ways. If they interpret the news as evidence that flying in general is more dangerous than previously thought, total industry demand may decline. To the extent that all airlines suffer from one carrier's accident, the firms have an interest in enforcing common safety standards. If, however, the information is interpreted as firm-specific, demand for the involved airline may fall while total traffic of competing airlines increases as passengers switch carriers. Finally, consumers may exhibit little or no reaction to an accident, either because they believe that there is no new information in the event, or because the change in their subjective probabilities of an accident has very little effect on the overall value they receive from the product.

We find that an airline's shareholders suffer a statistically significant wealth loss when the airline experiences a serious accident. The average loss in equity value, however, is

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[1] Nancy Rose, 1988, addresses this question directly by examining the relationship between safety record and an airline's financial health.

much smaller than the total social costs of an accident, reflecting the fact that airlines are insured against many of the costs of a crash. This result is also consistent with our finding of little or no effect of an accident on demand. Prior to deregulation, the demand that a carrier faced was virtually unaffected when it experienced an accident. We find some evidence of demand effects in the post-deregulation period, but the statistical significance of this result is weak. Finally, in both the pre- and post-deregulation periods, there appears to be very little evidence of an externality effect, positive or negative, caused by one airline's accident on the demand for other carriers' services.

I. Previous Findings of Market Incentives for Safe Products

Several studies have examined incentives provided by the private market for safety in autos, pharmaceuticals, and air travel. Steven Crafton, George Hoffer, and Robert Reilly (1981), and Reilly and Hoffer (1983) examined the effect of product recalls on the demand for automobiles. Their research suggests that in the month after a product recall the demand for the model type subject to the recall is reduced. Further, they found that similar-sized models of other producers are also adversely affected by the product recall. They did not, however, examine the persistence of the effect and the cost to the automobile manufacturer.

Gregg Jarrell and Sam Peltzman (1985) studied the loss to shareholders from a product recall. Using data for the automobile and pharmaceutical industries, they examined equity value changes associated with the announcement of a product recall. Their analysis suggests that recalls lead to substantial wealth loss for shareholders of the firms involved. They found that the total loss sustained due to recalls far exceeds the readily available estimates of the direct costs of the recall. They attributed this large difference to loss of goodwill, for example, the decline in future expected demand, but they did not measure such losses directly. They also found that the financial losses spill over to competing firms not directly involved in the recall. Jarrell and Peltzman's results relating to the auto industry, however, have been called into question recently by Hoffer, Stephen Pruitt, and Reilly (1988), who found that the results are very sensitive to sample selection and econometric technique.

A number of previous studies have examined the effect of airline accidents on the equity value of airlines and aircraft manufacturers. Andrew Chalk (1986, 1987) examined the effects of commercial air crashes on the value of the firm that manufactured the aircraft. The first paper studied the effect of a single crash, the American Airlines DC-10 accident in Chicago on May 25, 1979. Following the accident, McDonnell-Douglas suffered a loss of about $200 million, which, Chalk concludes, exceeds any reasonable estimate of regulatory or liability costs. The results suggest that the market anticipated a decline in future sales of McDonnell-Douglas aircraft.[2]

Chalk's second paper studied a set of 76 accidents, comparing the change in the manufacturer's equity value following each of 23 crashes that were possibly due to defects in the aircraft ("suspect cases") with the value change after the 53 accidents that were due to other causes. He found significant effects when the manufacturer may be at fault, but no change when the accidents are clearly attributable to other factors. In the 19 suspect cases that involved aircraft still in production, the manufacturer's equity value declined by an average of $21 million. Chalk compared the loss in firm value of these 19 accidents with the four suspect cases that involved aircraft no longer in production. The results are not significant for the latter group, from which Chalk concluded, somewhat tentatively, that the change in firm value in the 19 "in-production" cases is driven in part by expectations of lost future sales of the aircraft.[3]

[2] We find that the effect of this accident on American Airlines was much smaller than Chalk's estimate for McDonnell-Douglas and the effect on American was not statistically significant.

[3] A statistical test for the difference in means between the 19 suspect "in-production" cases and the 4 suspect "past production" cases fails to reject the hypothesis that the means are equal.

Two recent papers examine the airline equity value response to crashes. Don Chance and Stephen Ferris (1987) and Mark Mitchell and Michael Maloney (1988) each looked at samples of fatal accidents from the 1960s through the mid-1980s. Each study found statistically significant effects of the crashes on the stock of the airline involved. Chance and Ferris found no statistically significant effect of crashes on other airlines. Mitchell and Maloney distinguished between crashes that are the airline's fault and those that are due to some other cause. For the 31 crashes in their sample that were the airline's fault, they found a statistically significant 2.2 percent decline in equity value (2 post-crash trading days). For 18 crashes that were not the airline's fault, they found a 1.2 percent decline in equity value (2 post-crash trading days) that is not statistically significant.[4] Mitchell and Maloney looked more closely at the impact of accidents on insurance premiums and concluded that changes in insurance rates explain about 34 percent of the loss in equity value. The remainder they attributed to expected loss of consumer demand.

Several of these studies attribute much of the lost firm value to declines in future demand for the firms' products. In this paper, we examine directly the consumer response to airline accidents and attempt to measure the financial loss suffered by shareholders because of the consumer demand response. We find small and statistically insignificant demand changes following an accident and show that little if any loss of airline equity value following accidents can be reliably attributed to consumer response.[5] Further, when the proportional stock value changes are translated into changes in total firm value (dollar value changes), it becomes clear that the losses to airlines are quite small.

II. "Rational" Consumer Responses to Airline Accidents

The reaction that one would expect from a consumer following an accident will depend on her prior distribution of beliefs about airline safety. If the distribution were massed at a single point, no updating would occur. The absence of response in this case would be a result of the consumer's strong beliefs that an airline is safe. If the individual's priors are more diffuse, however, updating from a single crash or a series of accidents is more likely.

Table 1 presents an example of such Bayesian updating where the consumer believes that the airline is probably "safe" (probability of a fatal accident is 1 in 500,000 for each flight, about equal to the average rate in the 1970s), but might be "unsafe" (probability of a fatal accident is 1 in 100,000), and she is able to update her beliefs based on a sample of 200,000 flights (which would be 1 year of operations for a medium-sized major airline).[6] Table 1 demonstrates that weaker prior beliefs about the safety of an airline can lead to significant updating based on accident rates that are

[4]From these results, they conclude that crashes only affect equity value when the accident is the airline's fault. However, their reported standard errors indicate that a test for differences in means would fail to reject the hypothesis that the average decline in equity value is the same for fault and non-fault accidents.

[5]Mitchell and Maloney take issue with our conclusions, arguing that one would not expect to see changes in quantity. Rather, they assert, one would see airlines respond to a decline in demand by lowering price, either directly to the consumer or indirectly with increased travel agent commissions, or by increasing quality, for example with greater flight frequency, better-quality food, or more courteous flight attendants. We control for price changes, though they are unlikely to matter much under regulation, because prices were set exogenously by the Civil Aeronautics Board (CAB) and changed infrequently. Likewise, during the regulation period from which most of our sample is drawn, travel agent commissions were set by the CAB. Though flight frequency on a given route may be altered in the short-run, systemwide flight frequency for an airline is constrained by its total fleet size, which cannot be changed substantially in 3 to 4 months without high transaction costs. Though we are unable to control for food quality or employee courtesy, a demand response that could be offset by such changes would not be a significant change to begin with.

[6]At this rate of operations, a "safe" carrier would average one fatal accident every 2 1/2 years and an "unsafe" airline would average 2 fatal accidents per year.

TABLE 1—EXAMPLE OF BAYESIAN UPDATING FROM ACCIDENT RECORD

	Prior Beliefs		
	Pr(safe)[a] = 0.9 Pr(Unsafe)[b] = 0.1	Pr(Safe) = 0.99 Pr(Unsafe) = 0.01	Pr(Safe) = 0.999 Pr(Unsafe) = 0.001
Number of Accidents in One Year	Posterior Beliefs		
0	Pr(Safe) = 0.978 Pr(Unsafe) = 0.022	Pr(Safe) = 0.998 Pr(Unsafe) = 0.002	Pr(Safe) = 1.000 Pr(Unsafe) = 0.000
1	Pr(Safe) = 0.899 Pr(Unsafe) = 0.101	Pr(Safe) = 0.990 Pr(Unsafe) = 0.010	Pr(Safe) = 0.999 Pr(Unsafe) = 0.001
2	Pr(Safe) = 0.641 Pr(Unsafe) = 0.359	Pr(Safe) = 0.951 Pr(Unsafe) = 0.049	Pr(Safe) = 0.995 Pr(Unsafe) = 0.005
3	Pr(Safe) = 0.263 Pr(Unsafe) = 0.737	Pr(Safe) = 0.797 Pr(Unsafe) = 0.203	Pr(Safe) = 0.975 Pr(Unsafe) = 0.025
4	Pr(Safe) = 0.067 Pr(Unsafe) = 0.933	Pr(Safe) = 0.440 Pr(Unsafe) = 0.560	Pr(Safe) = 0.888 Pr(Unsafe) = 0.112

Note: Updating based on accident record in 1 year, assumed = 200,000 flights.
[a]"Safe" = A 1 in 500,000 probability of a fatal accident on any flight.
[b]"Unsafe" = A 1 in 100,000 probability of a fatal accident on any flight.

actually observed for some airlines. Furthermore, the likelihood of significant changes in one's beliefs is much greater if multiple accidents are observed in a sample period.

The small consumer response that we have estimated could be a result of strong prior beliefs about the safety of air travel or confidence that the FAA will react to an accident with much closer monitoring. Alternatively, the weak reaction is also consistent with a significant change in subjective probabilities, but a low marginal valuation of safety. Because flying is an extremely safe form of travel, increases in the perceived danger of flying may have little effect on a consumer's expected cost of travel. The decrease in expected consumer surplus due to a substantial increase in subjective accident probabilities may still leave most of an airline's customers with positive consumer surplus from the product. The data do not allow us to distinguish among these possible explanations for weak demand responses to accidents.

III. Method of Study

The first part of this research examines the effect of an airline accident on the equity value of the airline. Drawing on the efficient markets literature (Eugene Fama, Lawrence Fisher, Michael Jensen, and Richard Roll, 1969), the change in equity value associated with an airline accident is taken as an unbiased estimate of the financial consequences of the accident. The market model is used to separate out changes in value caused by overall market effects from those changes caused by the accident itself.

The normal relation between the returns to a given stock and the market is given by

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}. \tag{1}$$

The parameter β_j measures the sensitivity of the jth firm's return, R_{jt}, to movements in the market index, R_{mt}, and is equal to β of the Sharpe-Litner capital asset pricing model. The term $\beta_j R_{mt}$ is the portion of the return to security j on day t that is due to marketwide factors. The parameter α_j measures that part of the average daily return on the stock that is not due to market movements. Lastly, ε_{jt} measures that part of the change in the value of firm j's stock on day

t that is not due to either movements in the market or to the firm's average daily return.[7]

On the day of an event, the deviation in an individual stock's daily return from what is expected based on equation (1), that is, the prediction error, is taken as an unbiased estimate of the financial effects of the event. Let PE stand for this prediction error:

$$PE_{jt} = R_{jt} - a_j - b_j R_{mt}, \tag{1'}$$

where a_j and b_j are, respectively, the estimates of α_j and β_j.

The average abnormal daily return for all accidents in the sample is calculated along with two measures of its statistical significance.[8] The first measure of significance aggregates into a single portfolio the abnormal returns of all airlines experiencing an accident for the day of each firm's crash. It then uses the daily variance of returns on this portfolio to calculate a t-statistic. Assuming that the N abnormal returns are independently distributed, the formula for this t-statistic is given by

$$t = \frac{\Sigma_1^N PE_{jt}}{\sqrt{\Sigma_1^N VAR(PE_{jt})}}, \tag{2}$$

where $VAR(PE_{jt})$ is the variance of the prediction error for firm j taken from the market model regression of equation (1).

The second significance test calculates a t-statistic for each firm's abnormal return for each accident-day. The sum of these individual t-statistics follows a distribution that is asymptotically normal with mean zero and variance equal to the number of observations. The z-statistic for the average is then the sum of the individual t-statistics divided by the square root of the number of observations. This test attributes less weight to observations of firms with a high variance in returns and is therefore less sensitive to distortions from very noisy observations. The formula for this z-statistic is

$$z = \frac{\Sigma_1^N \left(PE_{jt} / \sqrt{VAR(PE_{jt})} \right)}{\sqrt{N}}. \tag{3}$$

The share of the financial losses that can be attributed to demand response is examined in the following manner. For every airline for which sufficient monthly traffic data can be obtained, a demand function is estimated during months unaffected by the airline's accidents. Demand is modeled as a function of price, income, a time trend, and seasonal (dummy) variables. The month in which an airline experiences an accident and the three following months are excluded from the estimation of these parameters. The deviation of actual demand from predicted demand in these four monthly periods is the measure of demand response to the accident, and is estimated directly using dummy variables for each of the months. The function estimated for each firm during each time period is

$$\begin{aligned} \ln RPM_{jt} = {} & \lambda_j + \phi t + \alpha_j \ln P_{jt} \\ & + \beta_j \ln I_t + \sum_{i=1}^{11} \gamma_{ij} F_{it} \\ & + \sum_{l=1}^{L_j} \sum_{k=0}^{3} \delta_{jlk} C_{jlk} + \varepsilon_{jt} \end{aligned} \tag{4}$$

where:

RPM_{jt} = Revenue passenger miles for firm j in month t.

[7] The market model regressions were estimated using the 280 trading days before the accident. If 280 days of trading data before the date of the accident were not available, the model was estimated using the n days of data available before the accident and $280-n$ days beginning 40 days after the accident. The market return variable used was the equally weighted index. In a number of cases, the 280 days for one firm's market regression included an accident by another firm. The bias from such an overlap is almost surely negligible, however, because even the own-firm effects are found to last only one or two days, and because Chance and Ferris find the cross-airline equity value effects to be insignificant. See Section V, Part E.

[8] The day of the crash is counted as the first day of trading on the information if the crash occurred before 3 P.M. New York City local time and it was a trading day. Otherwise, the first day of the effect was taken to be the next trading day.

t = The number of the month within either the 72- or the 96-month sample period (see Section IV).

P_{jt} = Average revenue per passenger-mile (yield) for firm j in month t.

I_t = U.S. Personal income in month t.

F_{it} = Eleven seasonal dummy variables, each of which takes on a value of one in month i and zero otherwise, February omitted.

C_{jlk} = A vector that takes on the value 1 in the kth month after the lth crash that firm j experienced during the time period and zero otherwise. ($k = 0$ refers to the month in which the crash occurred.)

λ_j = The estimated constant term for firm j.

ϕ_j = The estimated time trend for firm j.

α_j = The estimated price elasticity of demand faced by firm j.

β_j = The estimated income elasticity of demand faced by firm j.

γ_{ji} = The estimated natural log of the proportional deviation of demand from the base month (February) in month i for firm j.

δ_{jlk} = The natural log of the proportional prediction error of the regression for demand k months after crash l experienced by firm j during the time period.

Equation (4) is estimated for each airline separately.[9] The equation is estimated for each of four time periods using a Cochrane-Orcutt procedure to correct for serial correlation in the disturbances. For the three time periods during which the airline industry was regulated by the CAB—1960–65, 66–71, and 72–77—price is treated as an exogenous variable. During these years, price was determined by regulators and it is assumed that price did not respond to short-run demand changes. Beginning around 1978, however, airlines were given much greater pricing freedom that ultimately led to complete deregulation. For this latter period, 1978–85, the demand equation is also estimated by two-stage least squares (2SLS). The instruments for price include the exogenous variables listed above and an index of airline costs that is described in the Data Appendix.

Analogous to the significance test of stock movements, we use two different approaches to test the significance of the impact of accidents on demand in the month of the crash and the three succeeding months. In each of the four post-crash months, we calculate the average of the estimated log proportional impact of a crash from the estimates of the δ parameters.[10] We also calculate the standard error of this estimate of the mean and perform a t-test of whether the log deviations from predicted demand in the months of the crashes and the first, second, and third following months are statistically different from zero.

As with the financial market study, such t-tests of the mean can be very sensitive to a few high-variance estimates. Again, this leads to the alternative calculation of a z-statistic for a test of statistical significance. For the "portfolio" of accidents, the following z-sta-

[9]Though the structure of the model appears to allow for use of Zellner's seemingly unrelated regressions technique, its use in this case would distort estimation of the effect of a crash. Unless one is willing to assume away externality effects on demand, correcting the estimated parameters for firm j, which experiences a crash at time t, based on the residuals in the estimates of other firms' demand functions at time t will inappropriately dampen (or enhance, if the externality effect is positive) the estimated effect of the crash on the demand faced by firm j. Zellner's *SUR* could be used if one excluded from all firms' regressions the periods following any firm's accident. This would eliminate too many of the observations to make demand estimation possible.

[10]In the two-stage least squares demand estimation for the deregulation period, there is a technical issue of whether one should use the residuals from the second-stage estimation (with $\hat{p}$ as a right-hand side variable) or, having estimated the parameters of the demand function, one should calculate the residuals from the expected quantity using the actual values of the endogenous variable, p. The latter approach would yield estimates of the *proportional change in the quantity demanded* due to the accident, while the former approach gives the *proportional shift in the demand function*. We use the former approach and thus measure the proportional change in quantity *for a given price*.

tistic is calculated for the month of the crash and each of the three succeeding months:

$$(5)\quad z_k = \frac{\sum_{j=1}^{J}\sum_{l=1}^{L_j}\left(\delta_{jlk}/\sqrt{VAR(\delta_{jlk})}\right)}{\sqrt{\sum_{j=1}^{J}L_j}},$$

where j indexes firms, l indexes crashes, k indexes the month following a crash, J is the number of airlines experiencing at least one crash during the period, and L_j is the number of crashes experienced by airline j. These tests attribute less weight to estimated demand effects from airlines with more volatile demands.

For each accident, the four monthly deviation parameters, δ_0 through δ_3, can be translated into percentage deviations from predicted demand. The sum of these percentage deviations indicates the magnitude of the total lost demand as a percentage of one month's traffic. This interpretation is not exact, because demand fluctuates seasonally and cyclically, so the percentage deviations in each of the four months are not deviations from the same predicted level. Still, the sum gives an indication of the overall demand effect of an accident.

Following estimation of the demand responses, an attempt is made to explain the variation in responses. The estimated δ_{jlk} coefficients are regressed on a set of variables explaining the magnitude of the demand effect during each month k after the crash. The explanatory variables are the number of fatalities ($FATAL$), the size of the airline as measured by revenue passenger-miles flown in the month before the crash ($RPMLAG$), whether the airline was primarily responsible for the accident ($FAULT$), the day of the month on which the crash occurred ($DATE$),[11] the recent accident records of the firm ($FATSUMOWN$), and the industry ($FATSUM$),[12] and two measures of the extent of newspaper coverage of the crash. These measures are the number of days of front page coverage ($PAGE1$) and the total number of articles appearing in the *New York Times* in the two weeks after the crash (ART).[13]

The regression of the estimated demand effects, δ_{jlk}, on causal variables allows calculation of a fitted value for demand change. The fitted value, $\hat{\delta}_{jlk}$, along with the quantity that is actually sold, can be used to calculate the quantity that the model would have predicted in the absence of the accident. The difference between the predicted and the actual quantity is an estimate of the loss in passenger traffic due to the crash.[14] This loss multiplied by the average yield (price) in the period is an estimate of revenue loss attributable to the accident.[15] The estimated revenue loss is then used as an independent variable in regressions that explain the change in the airlines' equity value. The *fitted* value for the demand response ($REVCHFIT$) is used in order to purge the estimate of errors due to nonsystematic influences on demand experienced in the months after a crash.[16]

Because the dependent variable in this procedure is the stock movement for the first and second trading days following the accident, estimates by traders of the likely demand impact of a crash can only be based

[11] If the demand impact decays monotonically over time, one would expect this variable to be positively correlated with the month-of-crash impact and negatively correlated with the impact during all later months. These signs may seem counterintuitive because a larger crash effect is a more negative abnormal demand.

[12] More precisely, these are the number of fatalities for, respectively, the firm and the industry in the 365 days prior to the accident.

[13] Because crashes in New York are covered more extensively by the *Times* than crashes elsewhere, newspaper coverage variables for New York crashes are taken from the coverage of the *Chicago Tribune*.

[14] $RPM - R\hat{P}M = RPM\cdot(\hat{\theta}_{jlk}/(1+\hat{\theta}_{jlk}))$, where $\hat{\theta}_{jlk}$ is the estimated percentage change in demand, $\hat{\theta}_{jlk} = \exp\hat{\delta}_{jlk} - 1$.

[15] In the deregulated period, the traffic loss is multiplied by the fitted price, $\hat{p}$, from the first stage of the two-stage least squares demand estimation procedure. Due to the brief time period over which the demand response seems to persist, when it is evident at all, we ignore the effect of discounting in analyzing the impact of lost revenue on the present value of future profits.

[16] Essentially, this is an instrumental variables procedure to correct for errors in a right-hand side variable.

on information available at that time. Thus, the extent of newspaper coverage in the following two weeks and whether or not the accident was primarily the carrier's fault are excluded as instruments in forming *REVCHFIT*.[17]

The variables used to estimate the $\hat{\delta}_{jlk}$ explain the variation in demand response rather poorly. Hence, revenue changes calculated from the actual estimated demand deviations (*REVCHACT*) are also used to explain the change in firm value. The results do not differ substantially for the *REVCHACT* and *REVCHFIT* variables. To obtain the dependent variable in these regressions, the percentage financial losses, as measured by the market model residuals, are converted to an absolute dollar loss. These losses are then regressed on the estimated loss in revenue and on other factors reflecting the direct costs of an accident.

The last issue addressed is the externality effect, the impact of one airline's accident on the demand faced by other airlines and on the equity values of other airlines. The approach is quite similar to the own-firm analysis. The abnormal return on equity for all major airlines other than the one experiencing the accident is estimated for the accident day and the following day. Similarly, the deviation from predicted demand for all other airlines in the month of the accident and the following month is calculated.[18] The residual from a carrier's demand equation in the month of another airline's crash is the best estimate of the impact of another carrier's accident on the quantity sold by the first airline.[19] Test statistics for demand and financial effects, analogous to the test statistics for own-firm effects described above, are then calculated.

IV. Description of the Sample

The base sample from which all the analysis is drawn is every accident aboard a U.S. certificated air carrier[20] from 1960 to 1985 involving at least one on-board fatality and some damage to the aircraft.[21] Demand or stock market data were not available for every firm at all times during the 26-year period, however, so the demand and financial studies omit some of these accidents. Table 2 lists all accidents included in either the demand or the financial analysis.

Only accidents occurring between 1962 and 1985 are included in the estimation of financial losses associated with airline accidents. This time period is chosen in order to allow use of the daily stock returns tape of the Center for Research in Security Prices (CRSP) of the University of Chicago. Use of this data source also limits the investigation to firms listed on either the New York or American Stock Exchanges. Seventy-four accidents met these criteria, but 7 were eliminated from the regression of value loss on injuries and revenue loss, because there was insufficient demand data to allow estimation of the effect of the crash on demand.[22]

[17] In place of the newspaper variables described above, a dummy variable for page 1 coverage on the day following the accident was used. Although the cause of the accident is occasionally known by investigators within the 48 hours following the accident, it is rarely stated publicly with any degree of certainty during this time.

[18] Because we found very little evidence of a demand externality in these periods, we did not extend the analysis for later months.

[19] In the demand analysis, months in which other airlines experienced accidents are not excluded from the estimation of an airline's demand functions. Because these observations are included, problems would arise if there were a significant demand externality and/or if other airlines' crashes were correlated with variables in the demand regressions. The combination of these two factors would create omitted variable bias in the parameter estimates for the included variables. In fact, accidents are not significantly correlated with any included variables. Even without such a correlation, omitting consideration of a demand externality, if it were present, would bias the reported standard errors in the demand regressions. As discussed in Section V, Part E, we find very little evidence of a demand externality.

[20] These are Part 121 certificated airlines and thus exclude air taxis and commuter operations.

[21] The dual conditions of on-board fatalities and aircraft damage eliminates from the sample those fatalities not directly related to air travel, for example, heart attacks, and fatalities of ground crew or other bystanders.

[22] In two of the seven cases eliminated, the same carrier had two crashes during the same month, so we

TABLE 2—LISTING OF ACCIDENTS AND INCLUSION IN ANALYSIS

Date	Carrier	Aircraft	Damage	FTL	SER	TOT	VALCH12 ($million)	Notes
600106	NA	DC-6B	D	34	0	34		X
600317	NW	L-188C	D	63	0	63		X
600523	DL	Convair 880	D	4	0	4		EX
600722	TX	DC-3	S	1	0	12		X
601004	EA	L-188	D	62	9	72		X
601028	NW	DC-4	D	12	0	12		AX
601216	TW	L-1049	D	44	0	44		AX
601216	UA	DC-8	D	84	0	84		X
610128	AA	B-707	D	6	0	6		AEX
610711	UA	DC-8	D	17	12	122		X
610721	AS	DC-6	D	6	0	6		DEX
610901	TW	L-049	D	78	0	78		X
610917	NW	L-188C	D	37	0	37		X
620301	AA	B-707	D	95	0	95		X
620522	CO	B-707	D	45	0	45		X
621019	AL	Convair 440	M	1	0	52	0.913	
621123	UA	Viscount	D	17	0	17	3.603	
621130	EA	DC-7	D	25	14	51	7.049	
630129	CO	Vickers 810	D	8	0	8	−0.083	
630212	NW	B-720B	D	43	0	43	9.503	
630603	NW	DC-7	D	101	0	101	−8.317	N
630702	MK	Martin 404	D	7	30	43	−0.224	
631208	PA	B-707	D	81	0	81	−2.575	
640225	EA	DC-8	D	58	0	58	13.842	
640312	FL	DC-3C	D	5	0	5		X
640709	UA	Viscount 745D	D	39	0	39	−40.560	
641115	BZ	Fairchild F-2	D	29	0	27		X
641123	TW	B-707 331	D	48	11	73	−5.003	
650208	EA	DC-7B	D	84	0	84	36.956	
650816	UA	B-727	D	30	0	30	−26.997	
650917	PA	B-707 121B	D	30	0	30	−6.324	
651108	AA	B-727	D	58	4	62	−18.300	
651111	UA	B-727	D	43	35	91	−107.327	
651204	EA	L1049C	D	4	34	54	−8.668	
660806	BN	British AC	D	42	0	42	−0.262	
661115	PA	B-727	D	3	0	3	52.299	DE
661120	PI	Martin M404	D	3	0	3		DEX
670309	TW	DC-9	D	25	0	25	39.824	
670330	DL	DC-8	D	6	0	6	−51.000	E
670623	MK	British AC-111	D	34	0	34	−8.225	
670719	PI	B-727	D	79	0	79		X
671106	TW	B-707	D	1	1	36	−20.959	O
671121	TW	Convair 880	D	69	13	82	−9.459	
671221	FL	DC-3C	D	2	0	2	−2.302	DE
680503	BN	L-188	D	85	0	85	54.942	
680612	PA	B-707	D	6	0	62	−32.354	
680810	PI	Fairchild 227	D	35	2	37		X
681025	NE	Fairchild 227	D	32	7	49	−19.973	
681212	PA	B-707	D	51	0	51	−107.342	
681224	AL	Convair 580	D	20	26	47	−7.372	
681226	PA	B-707	D	3	0	3	137.813	ODE
681227	NC	Convair 580	D	27	16	45		X
690106	AL	Convair 440	D	11	14	28	−0.899	
690118	UA	B-727	D	38	0	38	19.255	
690726	TW	B-707	D	5	0	5	86.667	E
690909	AL	DC-9	D	82	0	82	5.114	
691119	MK	Fairchild 227B	D	14	0	14	−1.311	
701114	SO	DC-9	D	75	0	75		X
710331	WA	B-720	D	5	0	5	−8.751	E

TABLE 2—CONTINUED

Date	Carrier	Aircraft	Damage	FTL	SER	TOT	*VALCH12* ($million)	Notes
710607	AL	Convair 580	D	28	3	31	−2.833	
710725	PA	B-707	D	4	0	4	17.336	DE
710904	AS	B-727	D	111	0	111	−5.490	
720303	MK	Fairchild 227B	D	16	32	48	0.559	A
720530	DL	DC-9	D	4	0	4	29.440	E
720629	NC	Convair 580	D	8	0	8		X
721208	UA	B-737	D	43	12	60	20.356	
721220	NC	DC-9	D	10	9	45		X
721229	EA	L1011	D	99	60	176	−168.905	
730722	PA	B-707	D	78	1	79	9.175	
730723	OZ	Fairchild 227B	D	38	6	44	−5.986	A
730731	DL	DC-9	D	88	1	89	−88.244	
730927	TX	Convair 600	D	11	0	11		X
731103	PA	B-707	D	3	0	3	3.634	DE
731103	NA	DC-10	S	1	0	128	−16.090	
740131	PA	B-707	D	96	5	101	−17.891	
740422	PA	B-707	D	107	0	107	2.798	
740908	TW	B-707	D	88	0	88	−8.877	
740911	EA	DC9-31	D	71	10	82	−19.389	
741201	TW	B-727	D	92	0	92	3.794	
741201	NW	B-727	D	3	0	3	18.236	E
750624	EA	B-727	D	112	12	124	0.933	
760405	AS	B-727	D	1	11	50	−2.927	
760427	AA	B-727	D	37	19	88	15.719	
770327	PA	B-747	D	327	55	396	−7.481	
770404	SO	DC-9	D	62	22	85		X
771218	UA	DC-8F	D	3	0	3	2.309	E
780118	FL	DHC-6	D	3	0	3	−0.535	E
780301	CO	DC-10	D	2	31	197	−2.260	
780508	NA	B-727	S	3	11	58	−2.154	A
780925	PS	B-727	D	135	0	135	−3.270	A
781228	UA	DC-8	D	10	23	198	−46.282	
790212	AL	Frakes M298	D	2	8	25	1.206	
790525	AA	DC-10	D	271	0	271	−7.714	
791031	WA	DC-10	D	72	13	89	−1.065	
820113	AF	737-222	D	74	5	79		X
820123	WO	DC-10	D	2	4	345	−1.785	
820709	PA	B-737-235	D	145	0	145	−14.234	
820811	PA	B-747	S	1	0	288	−1.146	O
830109	RC	Convair 580	S	1	1	33	−7.410	
830111	UA	DC-8-54F	D	3	0	3	27.214	E
850802	DL	L-1011-385-1	D	134	15	164	−27.142	

Notes. X = Insufficient equity price data to estimate equity value change. A = Insufficient demand data to estimate demand effect. O = Excluded from demand effect estimation due to complete overlap of observation with another accident by same airline.

D = Cargo, E = crew only, N = military charter.

Damage Notes: D = Destroyed, S = Substantial, M = Minor.

FTL = Fatalities; SER = Seriously injured; TOT = Total on board; *VALCH12* is in January 1985 constant dollars.

TABLE 3—CARRIERS INCLUDED IN THE DEMAND AND/OR FINANCIAL STUDIES

AA—American	FL—Frontier	PS—Pacific Southwest Airlines
AF—Air Florida	MK—Mohawk	RC—Republic
AL—US Air (formerly Allegheny)	NA—National	RW—Hughes Air West
AS—Alaska Air	NC—North Central	SO—Southern
BN—Braniff	NE—Northest	TW—TWA
BZ—Bonanza	NW—Northwest Orient	TX—Texas International (formerly Trans-Texas)
CO—Continental	OZ—Ozark	UA—United
DL—Delta	PA—Pan Am	WA—Western
EA—Eastern	PI—Piedmont	WO—World

Estimation of the demand functions was broken into four periods, 1960–65, 1966–71, 1972–77, and 1978–85. The first period covers the time of transition from piston engine to jet aircraft. The next period was relatively stable in both prices and technology. The third period covers the time of the CAB's Domestic Passenger Fare Investigation (DPFI) as well as increased use of wide-bodied aircraft.[23] The final period is taken to be the deregulation era, though the exact starting date can, of course, be questioned.[24] Although there are 27 airlines included in the demand study, every carrier is not included in every period. For an airline to be included during a period, data for at least 48 months of full operation during the period had to be available.[25] In the four periods, there are respectively, 15, 14, 12, and 12 airlines that experienced accidents and for which sufficient data are available. Table 3 lists the airline carriers included in the demand and/or financial studies.

V. Results of the Statistical Analysis

A. *The Average Effect of Accidents on Shareholder Wealth*

Table 4 presents the average abnormal returns for the portfolio of 74 accidents included in the financial analysis from two days before news of the accident reaches the market to 14 days after. The column labeled "CAR" shows the cumulative abnormal returns for the accident day and the following trading days. The *t*- and *z*-tests are presented for the daily and cumulative abnormal returns.[26]

Crashes are associated with, on average, a 0.94 percent loss in the equity value of the firm on the first trading day. This loss is statistically significant at the 1 percent level.[27] The percentage of firms experiencing

eliminated the smaller crash from the sample. In both cases, the accident eliminated resulted in only one fatality. In all but one case of less than complete overlap between two accidents by the same airline, the fact of the overlap was ignored. Essentially, this procedure overestimates the demand impact of accidents by attributing the joint effect of two crashes to each of the accidents. In the one such case that exists in the deregulation period, two Pan Am crashes in July and August 1982, the latter accident, involving a bomb explosion that killed one person, was eliminated from the demand studies. Because we found no significant demand effect in the regulation period, we did not explore further corrections for the 4 overlap cases that occurred during this period.

[23]The DPFI was a wide-ranging investigation into airline prices that ran from 1971 to 1974. It resulted in the imposition of new and stricter policies on discount fares and route entry.

[24]The United Airlines crash on 12/18/77 is included in the deregulation period.

[25]Months in which a carrier experienced a labor strike were not considered full-operation periods.

[26]Because there is little indication of an equity value effect after the first day and because the event window can be so confidently specified, we have not done corrections for the interdependence of daily abnormal return estimates that may bias cumulative abnormal return estimates over long event windows. See Michael Salinger, 1988.

[27]This proportional loss is in line with the first-day effect that Chance and Ferris found, −1.18 percent, and that Mitchell and Maloney, 1988, found −1.19 percent. The differences are explained mostly by differences in the sample. Ours extends back to include earlier accidents that either of the other works, but not forward past 1985. Eighteen accidents in our sample do

TABLE 4—FINANCIAL RETURNS ASSOCIATED WITH ACCIDENTS

Day	AR	CAR	Percent Negative	T	T-CAR	Z	Z-CAR
−2	−.00009		52.703	−0.28		−.708	
−1	.00104		52.703	.314		−0.22	
0	−.00940	−.00940	64.865	−2.818	−2.818	−3.087	−3.087
1	−.00031	−.00971	52.703	−.093	−2.059	−.108	−2.259
2	.00098	−.00873	51.351	.295	−1.511	.199	−1.730
3	−.00102	−.00975	56.757	−.309	−1.463	−.024	−1.510
4	−.00302	−.01277	62.162	−.910	−1.715	−1.086	−1.837
5	.00090	−.01187	48.649	.271	−1.455	.069	−1.648
6	.00089	−.01098	54.054	.267	−1.246	.434	−1.362
7	.00348	−.00750	50.000	1.050	−.795	.756	−1.007
8	.00075	−.00675	54.054	.227	−.674	−.244	−1.031
9	−.00100	−.00775	52.703	−.302	−.735	−.300	−1.073
10	.00541	−.00234	45.946	1.618	−.213	1.846	−.466
11	−.00240	−.00474	55.405	−.716	−.410	−.874	−.699
12	−.00031	−.00505	55.405	−.092	−.420	.016	−.667
13	.00075	−.00429	48.649	.226	−.344	.544	−.497
14	−.00170	−.00600	54.054	−.510	−.464	−.513	−.613

Notes: AR = Abnormal return; CAR = Cumulative abnormal return; %NEG = percent of firms with negative abnormal returns; T = t-statistic as described in text; T-CAR = The t-statistic for the significance test on the cumulative abnormal returns; Z = z-statistic as described in text; Z-CAR = The z-statistic for the significance test on the cumulative abnormal returns.

negative abnormal returns is high, 65 percent, which is statistically different from 50 percent at the 5 percent level. It also appears that the information is, on average, totally absorbed in the stock price on the first trading day after the accident. Abnormal returns are small and mostly insignificant after that date. Of course, new information on particular crashes often becomes available as the National Transportation Safety Board conducts its investigation. The average result means that the market forms an unbiased estimate of significant negative consequences as soon as the crash becomes known.

Analysis in terms of the proportional change in equity value could be misleading, however, since debt/equity ratios vary substantially across airlines and many firms have large holdings in non-airline industries. If most of the losses are direct costs from the accident, such as insurance deductibles or co-payments, then the absolute loss of firm value is likely to be more systematically related to crashes than the proportional loss. The average value loss on the first day information about a crash reaches the market is \$3.67 million.[28] The estimated standard error of this mean is \$3.60 million, producing a t-statistic of -1.03.[29] The cumulative two-day loss averages \$4.50 million, with a standard error of \$4.49 million and a t-statistic of -1.01. The range over these two days is much larger, however, going from a loss of \$169 million to a gain of \$138 million. Clearly, in some cases news about the crash

not appear in Mitchell and Maloney's, while 4 in their sample are not included in ours. The sample used by Chance and Ferris is a subset of ours, but omits 25 accidents that we include.

[28]This is in 1985 constant dollars, as are all monetary figures in this paper. These figures include only changes in the value of common stock. If the value of either preferred stock or bonds displayed systematic abnormal returns following accidents, these figures could underestimate the total change in firm value. A large bias seems unlikely, however, because very few of these accidents posed any real threat to the long-term survival of the airline.

[29]The z-statistic that results when each value change on the day of an accident is adjusted for the standard error in value change is the same as the z-statistic for the proportional change in Table 4, -3.087.

coincides with other new information that has a positive effect on the valuation of the firm.

Of the 74 accidents for which equity value data were available, 12 were crew-only accidents. These are accidents of major carriers, for example, Pan Am and United, but it is possible that they attract less attention from potential passengers and from the FAA, if that agency is guided to some extent by public and congressional pressure. Eliminating these from the sample increases the averages substantially, as the average equity value effect of the 12 crashes removed is positive, though not significant. For the 62 accidents that had passengers on board, the average equity value loss on the first day is -1.29 percent (t-stat: -3.58, z-stat: -4.01), or $-\$6.58$ million (t-stat: -2.03). The average cumulative two-day loss is -1.48 percent (t-stat: -2.97, z-stat: -3.41), or $-\$9.97$ million (t-stat: -2.30). These average equity losses, calculated with or without the crew-only accidents, are small relative to the social losses of the airline accidents. The average death toll in these accidents is more than 40 and in most cases the aircraft destroyed was worth more than $10 million (1985 constant dollars).

B. *The Average Effect of Accidents on Demand*

The results of the four sets of demand regressions are summarized in Table 5. Since 15 to 20 demand regressions were run for each time period (one for each carrier with enough data for estimation within the period) and each included more than 15 right-hand side variables, the results have been summarized in order to make the presentation manageable. The constant terms, trend terms, and seasonal dummy variables are not shown. The firm constants vary as one would expect; larger firms have larger constants. The trend terms vary by airline, but most are positive, particularly in the early periods. As expected, since the omitted month in the seasonal dummy variables is February, the trough in industry demand, most of the carriers show greater demand in every other month and the highest in the summer months. Some north–south carriers, for example, Eastern and National, consistently show a winter peak and lower demand in the summer months.

Though the price and income parameters differ for each carrier, only the weighted averages of these estimates are presented (where the weights are the inverse of the variance of each parameter estimate) along with their standard errors.[30] In the pre-deregulation periods, nearly all price elasticity parameters are negative and the few positive estimates are insignificant. The average elasticities correspond roughly with previous estimates, though they indicate less price-elastic demand than earlier work.[31] The estimated pre-deregulation income elasticity parameters are consistent with previous studies.

Using an industry cost-index as an instrument to identify the effect of price on quantity in the deregulation period, demand functions were estimated for 19 firms. Though the weighted average price elasticity is -0.50, it was positive in 6 estimates, none statistically significant. The weighted average price elasticity estimate when the deregulation period demand functions are estimated by OLS is -0.62, with only one positive (and quite insignificant) estimate. To further check the sensitivity of the results to the price elasticity parameter, the demand functions were re-estimated restricting all firms' price elasticities to be alternatively -0.5 and -2. The results are changed only slightly, as discussed in footnote 35 below.

The primary focus of Table 5 is the deviation from expected demand during the months following a crash. Due to the variation among firms in the precision of the estimates, particularly in the two-stage least squares estimates of the deregulation period, we present both the unweighted average ef-

[30] This weighted average approach is identical to estimating the mean by running OLS on a constant and adjusting the regression for heteroskedasticity.

[31] See Richard Ippolito, 1981; Severin Borenstein, 1983; David Graham, Daniel Kaplan, and David Sibley, 1983; and Steven Morrison and Clifford Winston, 1986.

TABLE 5—ESTIMATED IMPACT OF ACCIDENTS ON AIRLINE'S DEMAND

1960–65: 31 Observations	1st month	2nd month	3rd month	4th month	Total
Weighted Mean (in Percents)	−0.9	−1.1	−1.0	−1.3	−4.3
Mean	−0.6	0.4	3.0	7.0	9.8
(t-statistic)	(−0.48)	(−0.07)	(0.68)	(1.57)	(0.68)
[z-statistic]	[−0.56]	[−0.44]	[−0.08]	[0.35]	[−0.41]
Weighted Average Elasticities (Standard Error)—Price: −0.16 (0.04)—Income: 1.09 (0.23)					
1966–71: 26 Observations	**1st month**	**2nd month**	**3rd month**	**4th month**	**Total**
Weighted Mean (in Percents)	−0.1	−2.5	0.0	1.3	−1.4
Mean (in Percents)	−1.5	−3.1	0.3	1.0	−3.5
(t-statistic)	(−1.01)	(−1.60)	(0.03)	(0.35)	(−0.85)
[z-statistic]	[−0.52]	[−1.70]	[0.03]	[0.81]	[−0.72]
Weighted Average Elasticities (Standard Error)—Price: −0.59 (0.07) —Income: 1.96 (0.26)					
1972–77: 21 Observations	**1st month**	**2nd month**	**3rd month**	**4th month**	**Total**
Weighted Mean (in Percents)	0.1	0.6	1.1	−0.2	1.7
Mean (in Percents)	−0.3	−0.2	−.04	−1.3	−2.1
(t-statistic)	(−0.33)	(−0.35)	(−0.47)	(−0.85)	(−0.75)
[z-statistic]	[0.00]	[0.11]	[0.34]	[−0.42]	[−0.36]
Weighted Average Elasticities (Standard Error)—Price: −0.29 (0.05)—Income: 0.70 (0.11)					
1960–77: 78 Observations	**1st month**	**2nd month**	**3rd month**	**4th month**	**Total**
Weighted Mean (in Percents)	−0.4	−1.0	−0.1	−0.2	−1.8
Mean (in Percents)	−0.8	−0.9	1.1	2.8	2.2
(t-statistic)	(−1.00)	(−1.00)	(0.39)	(1.15)	(−0.14)
[z-statistic]	[−0.65]	[−1.20]	[0.14]	[0.47]	[−0.86]
1978–85: 13 Observations (OLS)	**1st Month**	**2nd month**	**3rd month**	**4th month**	**Total**
Weighted mean (in Percents)	−1.4	−5.2	−4.7	−3.9	−15.3
Mean (in Percents)	−1.6	−3.1	−1.6	−1.0	−7.4
(t-statistic)	(−0.56)	(−0.86)	(−0.45)	(−0.35)	(−0.86)
[z-statistic]	[−0.80]	[−1.63]	[−1.26]	[−1.05]	[−1.77]
Weighted Average Elasticities (Standard Error)—Price: −0.63 (0.04)—Income: 0.46 (0.16)					
1978–85: 13 Observations (2SLS)	**1st month**	**2nd month**	**3rd month**	**4th month**	**Total**
Weighted Mean (in Percents)	−1.0	−4.8	−4.7	−0.3	−10.7
Mean (in Percents)	−1.3	−4.9	−1.0	5.3	−1.8
(t-statistic)	(−0.09)	(−0.18)	(−0.06)	(0.02)	(−0.06)
[z-statistic]	[−0.36]	[−0.93]	[−0.88]	[−0.21]	[−0.64]
Weighted Average Elasticities (Standard Error)—Price: −0.50 (0.20)—Income: 1.38 (0.37)					

fects and the weighted average where the weights are again the inverse of the variance of each estimated effect. The latter approach seems to yield more reasonable results.[32]

The results are consistent throughout the pre-deregulation period. Accidents, even the most catastrophic ones, appear to have very

[32]The weighted and unweighted average percentage demand deviations are obtained by taking the exponential of the δ parameter estimates. The t- and z-statistics are calculated directly from the δ estimates. They are changed only slightly when they are calculated from the variances of the transformed estimates approximated from a first-order Taylor series.

small average effects on the demand that the airline faces.[33] None of these estimates is statistically different from zero. Even the most negative estimates are quite small relative to the fluctuation caused by other factors. As a point of comparison, the peak-to-trough seasonal variation in demand (with February being the trough and July or August the peak for most carriers) is estimated to average more than 30 percent during these periods. Furthermore, the standard errors of these demand regressions, which represent the random demand component, range from 3 to 31 percent and average 9 percent. It seems clear that prior to deregulation, the effect of a crash on demand was quite small and was very difficult to distinguish from other factors that cause demand fluctuations.

Since deregulation, consumers' responses to crashes appear to have increased. These results must be qualified, however, because they are based on only 13 accidents, a small sample that may not be representative of the "typical" crash. Though the estimated effects are generally not significant at conventional levels, the results indicate a pattern of negative response to crashes that tapers off after approximately two months.[34] The total loss of demand over the four-month period due to an accident is estimated to (weighted) average 10.7 percent of one month's traffic when estimated by two-stage least squares. When the deregulation period demand regressions are estimated by OLS, assuming that price is exogenous, the estimated (weighted) average quantity effect of a crash is 15.3 percent of one month's demand. The t-statistics for these estimates are not significant, due in part to the large variance in demand for a few carriers. The z-statistics for the 2SLS and OLS estimates are -0.64 and -1.77, respectively, the latter being significantly different from zero at the 10 percent level, using a one-tailed test.[35]

The danger of inferring a systematic demand response from these 13 observations is highlighted by a closer look at the accident of Air Florida in January, 1982. For many reasons, this crash of a Boeing 737 in Washington, D.C., that killed 74 of the 79 people on-board seems to be among the most likely candidates for significant adverse consumer reaction. Air Florida was a new airline without an established safety record. The accident was quickly and conclusively deemed to be the result of pilot error. Furthermore, the error was probably related to inadequate pilot training by the airline regarding flight procedures in subfreezing temperatures. Due in part to its location and the heroic rescues that took place, the crash received extensive media coverage, including mention during the President's state of the union address two weeks later. Finally, most of Air Florida's traffic was carried on the highly competitive routes between northeastern cities and Florida, so travelers could fairly easily switch airlines. Still, the cumulative abnormal demand in January through April of 1982 is estimated to be *positive*, though not significantly so. Despite a slumping economy and virtually the same prices as a year earlier, Air Florida carried 30 percent more passengers in the first quarter of 1982 than in the first quarter of 1981.[36]

[33]The results are similar when the analysis includes only accidents in which there were 30 or more fatalities, as well as when the crew-only accidents are excluded.

[34]Though the 1979 American Airlines DC-10 crash is in this group, it does not dominate the analysis. The estimated demand loss for that accident is about equal to the average for the sample of 13.

[35]Due to the question of the effectiveness of the cost index as an instrument in the 2SLS estimation, the demand equations were also estimated restricting the price elasticities to be alternatively, -0.5 and -2.0 and using the actual price as the right-hand side variable. The results are:

Price Elasticity	Weighted Total	Total	t-statistic	z-statistic
-0.5	-12.0 percent	-1.2 percent	-0.25	-0.96
-2.0	-23.2 percent	-16.0 percent	-1.49	-2.32

Total Effect is as a proportion of one-month demand.

[36]Air Florida did have lower-load factors in the first quarter of 1982 than a year earlier, but this appears to be due to an expansion of capacity that occurred at the end of 1981. The load factor for February and March 1982 was above that for December 1981, before the

TABLE 6—ANALYSIS OF THE CAUSES OF DEMAND CHANGE

Descriptive Statistics

Variable	N	Mean	Standard Deviation	Minimum	Maximum
δ_0	91	−0.0155	0.118	−0.500	0.294
δ_1	91	−0.0237	0.137	−0.766	0.348
δ_2	91	−0.0004	0.133	−0.483	0.538
δ_3	91	0.0170	0.152	−0.273	0.924
FATAL	91	46.0659	53.155	1.000	327.000
ART	91	5.3846	6.555	0.000	38.000
PAGE1	91	0.9890	1.111	0.000	7.000
RPMLAG (billion)	91	0.7420	0.794	0.003	3.206
DATE	91	15.7582	9.294	1.000	31.000
FATSUM	91	201.1319	108.998	0.000	454.000
FATSUMOWN	91	11.3297	28.542	0.000	177.000
FAULT	74	0.7703	0.424	0.000	1.000

Observations: 91

Dependent Variable:	δ_0	δ_1	δ_2	δ_3	($\times 1000$)
INTERCEPT	−4.176	20.885	24.174	5.791	
	(28.340)	(33.600)	(31.529)	(30.164)	
FATAL	−0.088	0.039	−0.183	−0.259	
	(0.252)	(0.300)	(0.280)	(0.266)	
ART	1.694	3.154	5.903[a]	2.246	
	(2.372)	(2.833)	(2.646)	(2.503)	
PAGE1	−8.146	16.656	−23.162	6.969	
	(11.967)	(14.823)	(13.877)	(13.063)	
RPMLAG	11.386	−15.072	−13.121	−10.627	
	(13.534)	(16.064)	(15.0661)	(14.589)	
DATE	0.097	−0.332	0.683	0.936	
	(0.852)	(1.004)	(0.940)	(0.905)	
FATSUM	−0.038	−0.084	−0.133	−0.107	
	(0.090)	(0.106)	(0.099)	(0.094)	
FATSUMOWN	0.323	0.043	−0.042	0.130	
	(0.325)	(0.362)	(0.328)	(0.308)	
R-Squared	0.0285	0.0422	0.1100	0.0716	
Adjusted R-Squared	−0.0534	−0.0386	0.0350	−0.0067	
$F(8,83)$	0.348	0.522	1.466	0.915	
P-value	0.9287	0.8167	0.1901	0.5003	

[a] Significantly different from zero at the 10 percent level.

C. *Explaining the Change in Demand*

The regressions of (log) proportional abnormal demand on factors that plausibly affect the magnitude of the crash effect are reported in Table 6.[37] The only statistically significant estimate, the effect of the number of articles on δ_2, is of the "wrong" sign, indicating that greater news coverage damp-

crash and historically a month of high demand for north–south travel. January load factor was 1 percent below December. Industry output in the first quarter of 1982 was also suppressed somewhat by the flight restrictions that followed the strike and eventual firing of more than half of the nation's air traffic controllers. It is unclear how much this affected Air Florida's routes.

[37]These regressions are corrected for heteroskedasticity by dividing all variables by the standard error of the estimated δ_k, which is the dependent variable. The results are equally insignificant when this correction is omitted.

ens the negative impact of an accident on demand. This seems to be an aberration, however, and *ART* is not significantly correlated with δ_2. In fact, none of the explanatory variables is significantly correlated with the total (proportional) demand effect of crashes.[38]

The *FAULT* variable is not included in the Table 6 regressions, because we were able to reliably classify only 74 of the 91 accidents as being the airline's fault or not. When the regressions are run with only these 74 accidents and *FAULT* is included, the estimates of its effect are positive—indicating smaller demand reactions when the carrier is at fault—but the associated t-statistics are all less than 1.

As discussed in Section II, significant updating of prior beliefs may be much more likely to result from multiple accidents by the same airline than from a single accident. Yet, neither *FATSUM* nor *FATSUMOWN* are significant in the regressions.[39] These variables indicate a run of accidents for the industry and the firm, respectively.[40]

These insignificant results are not surprising for the pre-deregulation crashes, since there appears to be virtually no demand reaction in the first place. The 13 observations in the post-deregulation period alone are too few to get meaningful results from a regression with eight right-hand side variables. For these 13 observations, however, none of the potential explanatory variables is significantly correlated with any of the δ_k's.

Greater demand losses since deregulation are consistent with the more competitive environment that now exists. Prior to deregulation, carriers faced less actual competition and virtually no potential competition. In the 1978–85 period, consumers had more airlines to choose from than in earlier years and could respond more easily to a crash by switching carriers. Such a substitution effect, if it existed, would manifest itself as a positive change in the demand for competing carriers. Our analysis of the traffic of other carriers following a crash gives weak indication of such an effect, as discussed in Section V, Part E below. Such a substitution effect might become apparent from a more detailed route-by-route study. Nevertheless, our estimates suggest that the revenue implications of such a route-specific response would probably be small relative to the size of a major airline.

D. *Explaining the Change in Shareholder Wealth*

Table 7 presents an attempt to relate the loss in firm value to variables expected to influence the magnitude of that loss. *VALCH1* is the change in the total value of outstanding stock on the first day of the event. *VALCH12* is the cumulative change for the first and second day.[41]

Direct costs—uninsured tort liability, lost equipment value, and expected changes in future insurance rates—are represented by the variable *INJ*, which is the total number of people killed or seriously injured in the accident. The number of passengers seriously injured is included based on the observation that a tort settlement or award for a permanently injured person is often as high or higher than for a wrongful death suit.[42]

[38]The insignificant F-statistics for each of the regression in Table 6 further indicate that the insignificant t-statistics are not due to multicollinearity. Though fatalities, articles, and page 1 coverage are highly correlated with one another, none is consistently significant if the regression is run omitting the other two.

[39]Nor is either variable correlated with the proportional change in demands.

[40]Actually, these variables are the cumulative number of fatalities for the industry and the firm in the 365 days preceding the accident. Substitution of the cumulative number of fatal accidents also yields insignificant results.

[41]These variables are constructed by multiplying the percentage change in the firm's stock price on the day of the accident (or the next trading day, if the accident occurred after 3 P.M. New York time or on a day on which the stock exchanges were closed) and the succeeding day by the value of all of a firm's outstanding common stock on the day before the accident.

[42]The capacity of the aircraft, *CAP*, was included as well in early specifications of the regression. *CAP* was intended to reflect the cost, direct and through experience rated insurance, of losing the aircraft. The capacity, however, added very little to the explanatory power of the regression and, because of its high correlation

TABLE 7—ANALYSIS OF THE CAUSES OF FIRM VALUE CHANGE

Descriptive Statistics

Variable	N	Mean	Standard Deviation	Minimum	Maximum
VALCH1 (\$mil)	67	−5.78	27.08	−103.81	61.45
VALCH12 (\$mil)	67	−6.54	36.53	−168.91	86.67
REVCHACT (\$mil)	67	−18.04	132.66	−732.97	458.42
REVCHFIT (\$mil)	67	−12.02	53.10	−243.58	126.81
INJ	67	55.52	63.70	1	382

Observations: 67 Dependent Variable:	*VALCH1*	*VALCH1*	*VALCH12*	*VALCH12*
INTERCEPT	0.200	0.205	0.560	0.585
	(0.419)	(0.417)	(0.651)	(0.647)
INJ	−0.038[a]	−0.038[a]	−0.037[a]	−0.037[a]
	(0.011)	(0.011)	(0.017)	(0.017)
REVCHACT	−0.001		0.018	
	(0.016)		(0.025)	
REVCHFIT		0.020		0.062
		(0.036)		(0.056)
R-Squared	0.1500	0.1539	0.0757	0.0858
Adjusted R-Squared	0.1234	0.1274	0.0468	0.0572
$F(3,64)$	5.647[a]	5.819[a]	2.621[b]	3.003[b]
P-value	0.0055	0.0048	0.0806	0.0567

Correlation Matrix

	VALCH1	*VALCH12*	*INJ*	*REVCHACT*	*REVCHFIT*
VALCH1	1.00000	0.82781[a]	−0.21830[b]	−0.01945	0.02186
VALCH12		1.00000	−0.22258[b]	−0.01894	0.04276
INJ			1.00000	0.03043	0.05051
REVCHACT				1.00000	0.43743[a]

[a]Significantly different from zero at the 5 percent level.
[b]Significantly different from zero at the 10 percent level.

An estimate of indirect costs, that is, lost revenue, was derived from the estimated abnormal demand that the airline experienced in the months following the crash. If, in fact, airlines adapt to lost demand in the short run, by canceling some flights for instance, then the revenue loss will overstate the lost profits due to demand loss. On the other hand, if the effect were to persist beyond the three- to four-month period that is posited here, the revenue loss in this period may understate lost profits. Still, one would expect the coefficient on *REVCH* to be in the neighborhood of 1, a \$1 drop in revenue from a short-run demand loss will generate roughly a \$1 loss in profits.

The change in firm value was regressed on the estimated lost future revenue and the number of fatalities plus serious injuries.[43]

with *INJ*, increased the standard error of the coefficient estimate on *INJ* substantially. Therefore, the regressions presented here exclude *CAP*. The estimated effect of *INJ* should be interpreted as the impact of both tort liability and lost equipment, as well as the changes in the cost of future insurance against these losses. The multicollinearity in this relatively small sample does not allow one to separate these effects.

[43]Because the volatility of airline stocks differs quite a bit among airlines, the residuals in such a regression would be expected to be heteroskedastic. The variables

The sample for these regressions includes 67 accidents, the intersection of the observations used in the estimation of demand changes, and the observations available from the *CRSP* data base for equity value changes. Because the regressions of demand impact on causal factors exhibit very poor fits, we tried using alternatively the "actual predicted" revenue impact of each crash (*REVCHACT*), based on δ_{jlk}, as well as the "fitted predicted" revenue impact of each crash (*REVCHFIT*), based on $\hat{\delta}_{jlk}$, in the regressions to explain changes in the equity value of firms due to accidents.

Table 7 shows that neither *REVCHACT* nor *REVCHFIT* is significantly related to the change in firm value. Though the parameter estimates are mostly positive, they are very small—indicating a decrease of between zero and six cents in profits for every decrease of $1 in revenue—and statistically insignificant.[44] The simple correlation between each of these variables and the change in equity value is also small and not significantly different from zero. The number of fatalities plus serious injuries, *INJ*, does appear to be a significant cause of the change in equity value. The parameter estimate in each of the *VALCH1* regressions is significant at the 1 percent level. The parameter estimates for this variable indicates an equity loss of about $38,000 per life.[45]

E. *Externality Effects on Other Airlines*

One airline's accident could affect other airlines through many different transmission mechanisms. The public could react to an airline's crash by deciding that all air travel is less safe, or they could view the information as firm-specific and switch to other carriers. In response to an accident, the FAA could make a change in regulations that would increase production costs for all airlines, or it could redeploy its limited monitoring resources to scrutinize one airline more closely, thereby lessening surveillance of other carriers. The direct costs of a crash could increase the probability that an airline will go out of business, thereby increasing future sales for other carriers.

In both the pre- and post-deregulation periods, Table 8 shows very little evidence that the demand faced by one airline is affected by another carrier's accident. For 1960–77, the average estimated abnormal demand for other carriers after an accident is just slightly negative in the month of a crash and the following month. Neither estimate is significantly different from zero and a 95 percent confidence interval for each estimate of demand change as a fraction of monthly demand is wholly contained within (−2 percent, +2 percent). The results are similarly small in the post-deregulation period, though somewhat less tightly estimated, probably because the sample contains only 13 accidents. Isolation of the eight accidents in which 100 or more people were killed yields weak evidence of a small positive externality during the month of the accident, though it appears to be offset somewhat in the following month.

When one isolates the ten cases in which crashes were estimated to have had the largest proportional own-firm demand effects, however, the average effect on other firms is significant and negative, −1.4 percent in the month of the crash and −0.5

for each observation are divided by the square root of the product of the mean squared error from the stock market model regressions (equation (1)) and the value of firm's outstanding equity on the day before the accident. This is not an exact correction. The true standard error of the predicted values includes terms of order 1/N that are ignored in this adjustment.

[44] The descriptive statistics in Table 7 indicate an average *REVCHACT* of −$18 million. This reasonably large negative mean results entirely from the deregulation-era accidents. The mean *REVCHACT* for all of the 78 pre-deregulation accidents for which demand effects were estimated is +$0.3 million, while the mean for the 13 post-deregulation crashes is −$91.1 million. Still, *REVCHACT* is uncorrelated with the value change in the deregulation era. All *REVCH* values for the post-deregulation accidents are calculated using the δ_k values from the 2SLS estimation of the demand functions.

[45] The financial regressions were also run eliminating "crew-only" accidents. The results were not altered qualitatively. The effect of *INJ* on *VALCH1* is estimated to be about $37,000 and significant, while the *REVCH* variables are estimated to have a positive, but insignificant effect.

TABLE 8—ESTIMATED IMPACT OF ACCIDENTS ON OTHER AIRLINES' DEMANDS

1960–77: 78 Accidents, 1116 Observations	1st month	2nd month
Weighted Mean Effect (in Percent)	−0.380	−0.235
Mean External Demand Effect (in Percent)	0.012	0.350
(t-statistic)	(−0.874)	(0.412)
[z-statistic]	[−1.369]	[−0.372]
1978–85: 13 Accidents, 168 Observations	1st month	2nd month
Weighted Mean Effect (in Percent)	−0.809	−1.370
Mean External Demand Effect (in Percent)	1.860	2.748
(t-statistic)	(−0.319)	(0.023)
[z-statistic]	[−0.789]	[−1.005]
8 Accidents with More Than 100 Fatalities, 140 Observations	1st month	2nd month
Weighted Mean Effect (in Percent)	0.827	−0.656
Mean External Demand Effect (in Percent)	1.578	−0.452
(t-statistic)	(0.866)	(−0.359)
[z-statistic]	[1.531]	[−1.032]
10 Accidents with Largest Own-Demand Effects, 176 Observations	1st month	2nd month
Weighted Mean Effect (in Percent)	−1.440	−0.507
Mean External Demand Effect (in Percent)	0.692	2.951
(t-statistic)	(−0.913)	(0.854)
[z-statistic]	[−2.262][a]	[0.747]

Note: Effect of accidents during 1978–85 calculated from two-stage least squares regressions.
[a]Significantly different from zero at the 5 percent level.
[b]Significantly different from zero at the 10 percent level.

percent in the following month.[46] One explanation for this result is that the crashes that have large own-firm effects also impose significant negative externalities on all other firms. An alternative explanation, however, is that both the own-firm and other-firm estimates of demand effects are being influenced by external factors unrelated to the accident that our demand regressions have not fully accounted for.[47] Without including such variables in the demand regressions, which would be quite difficult, it is not possible to distinguish between these hypotheses from the demand data alone. Some information is provided, however, by examination of stock price behavior on crash days of uninvolved airlines.

These ten events produce 160 observations on the movement of other airlines' stock prices. On the first trading day associated with the accident the average equity value change of the other carriers is -0.61 percent with a t-statistic of -1.70, a z-statistic of -2.29, and 63.1 percent negative stock movements. The average second-day movement for other carriers is positive, $+0.44$ percent, with a t-statistic of 1.24, a 1.48 z-statistic, and 43.8 percent negative.[48]

[46]These 10 cases represent 11 crashes, because in one of these cases 2 crashes occurred in the same month.

[47]These could include supply restrictions such as might be due to fuel rationing, a shortage of air traffic controllers, or limited short-run availability of aircraft. External demand factors, such as the prices of alternative modes of transportation or the presence or absence of demand stimulating incentives, for example, frequent flyer programs, could also have such industrywide effects.

[48]By contrast, the own-firm effects for these 10 events were

Day of Event:	AR −1.29 percent t-stat −1.44 z-stat −1.44 70 percent neg.
Day after event:	AR 0.11 percent t-stat 0.12 z-stat 0.53 40 percent neg.

Though the first-day movements suggest some spillover effects, the second day appears to offset this effect. Further, if there are spillover effects, they are not associated with the largest crashes. For the eight events with 100 or more fatalities, the movement of other airlines' stocks averages virtually zero: $+0.05$ percent on the day of the event, -0.06 percent on the day following the event, neither figure at all significant.

VI. Conclusion

This paper has examined the losses suffered by airlines in connection with a crash. On average, crashes are associated with a statistically significant loss in equity value of 1 percent or $4.5 million. Since most crashes in the sample involve total destruction of the aircraft and an average of more than 40 fatalities, the average firm loss appears to be below the total social costs of the accident. This is consistent with the practice of carrying insurance against the direct costs of major crashes, and indicates that the insurance cost is only partially dependent on an airline's own experience.

The investigation of consumer response found that before deregulation, travelers did not respond to crashes to an extent that is statistically discernible. In the period since deregulation, the consumer response appears to have increased. The reaction to the 13 post-deregulation crashes that we studied is weakly significant. Still, the sample of crashes in this period is quite small and may be idiosyncratic.[49]

Previous work has speculated that the wealth losses associated with accidents or product recalls result from adverse consumer reaction. In the case of airline accidents, our direct estimation of consumer response does not support this hypothesis. The on-site airline safety supervision by the government may explain why the effects found here are quite a bit smaller than the effects due to prescription drug recalls found by Jarrell and Peltzman (1985). Alternatively, the greater consumer familiarity with airline travel, as compared to new drugs, may explain why consumers seem to infer much more information from drug recalls than from an airline crash.

Chalk's work suggests that air carriers may infer more information about aircraft manufacturers from aircraft-related crashes than consumers derive about airlines from their accidents. Two factors may explain this difference. First, airlines are experts in the purchase of aircraft and thus may be better equipped than consumers to process the information from an accident. Second, there may be more information in aircraft-related accidents about other aircraft from the same manufacturer than there is in airline accidents in general (or even those deemed to be the carrier's fault) about other flights by the same airline. That is, accidents not caused by aircraft failure may be more idiosyncratic.

It must be stressed that our results and conclusions are conditional upon the level of FAA monitoring and the outstanding safety record that the industry maintains. The relatively small demand effects observed, whether due to very limited updating of prior beliefs or to a low *marginal* valuation of safety, would probably increase if accident records deteriorated substantially.

[49] Recent press reports support a skeptical view of the post-deregulation results. Delta Airlines suffered few cancellations following a spate of near accidents in 1987, almost all of which were due to errors by flight crews or maintenance personnel. See *New York Times*, July 25, 1987. Vocal dissatisfaction with an airline due to poor performance in other areas also does not seem to indicate much avoidance of the carrier. See *Wall Street Journal*, November 19, 1987.

DATA APPENDIX

The following data series were used in the statistical calculations (All monetary variables are expressed in January 1985 constant dollars.):

Revenue Passenger-Miles—monthly, by carrier, (a) domestic scheduled service, (b) international scheduled service, *Source:* Air Carrier Traffic Statistics, 1957–1985, CAB.

Revenue Passenger-Miles—monthly, industry total, scheduled plus nonscheduled services. *Source:* Air Carrier Traffic Statistics, 1957–1985, CAB.

Available Ton-Miles—monthly, total certificated carriers, (a) domestic scheduled services, (b) international scheduled services. *Source:* Air Carrier Traffic Statistics, 1957–1985, CAB.

Total Revenues—quarterly, by carrier, (a) domestic scheduled service, (b) international scheduled service.

Source: Air Carrier Financial Statistics, 1957–1985, CAB.

Yield—monthly, by carrier, (a) domestic scheduled services, (b) international scheduled services. **Construction:** Total Revenues divided by Revenue Passenger-Miles, which have been aggregated to be quarterly data. This produces quarterly yield. Monthly yield is the produced through linear interpolation. Each yield number is assumed to correctly reflect the second month in each quarter. The yield for the first month of quarter i is then $= 0.667 * yield_i + 0.333 * yield_{i-1}$, where the subscripts indicate quarters. The yield for the third month of quarter i is then $= 0.667 * yield_i + 0.333 * yield_{i+1}$.

Industry Cost Index—monthly, total certificated carriers, (a) domestic scheduled services, (b) international scheduled services. *Source:* Air Carrier Financial Statistics, 1957–1985, CAB. Air Carrier Traffic Statistics, 1957–1985, CAB. **Construction:** Total Expenses = line 29–line 26–line 23–line 21 all from quarterly air carrier financial stats. Available Ton Miles = line 5 of air carrier traffic stats aggregated for the 3 months in each quarter. This produces a quarterly index, which is then smoothed to monthly using linear interpolation, as with yields above.

Firm Fatalities—by carrier. *Source: Briefs of Accidents: U.S. Civil Aviation*, 1958–85.

Total Industry Fatalities. *Source: Briefs of Accidents: U.S. Civil Aviation*, 1958–85.

Cause of Accident. *Source: Briefs of Accidents: U.S. Civil Aviation*, 1958–85.

News Coverage, Total Articles—by accident. Total number of articles. *Source: New York Times* and *Chicago Tribune* Index of Articles, 1959–1985.

News Coverage, Total Days of Page-One Exposure—by accident. Total number of articles. *Source: New York Times* and *Chicago Tribune* Index of Articles, 1959–1985.

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