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CRISIS IN THE COCKPIT? THE ROLE OF MARKET FORCES IN PROMOTING AIR TRAVEL SAFETY*

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I. Introduction

This article examines the brand-name effect of airline crashes. These disasters raise several financial issues. A crash represents the loss of a plane, the loss of lives (which the airline indemnifies), the loss of scheduling capacity, higher insurance costs, and the potential loss of consumer goodwill. This article focuses on the last of these. Are consumers reluctant to fly with airlines that have poor safety records or do they treat crashes merely as random events that bear no reflection on the quality of the airline?

The theory of brand names implies the former. Not all crashes affect consumer behavior but some crashes will. Some disasters—and we argue that these are the ones where the carrier is at fault—cause consumers to revise their expectations about the probability of accident. This change in probability will cause travelers to revise their consumption patterns and cause the goodwill value of the carrier to decline.

To test this theory, we examine the abnormal stock market performance of airlines immediately following a crash. Stock market event analysis is useful in studying airline disasters because these accidents can be pinpointed in time, with the effect of the catastrophe incorporated into stock prices at that point. We examine fifty-six crashes between 1964 and 1987. We break the crashes into two groups—those caused by pilot error

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and those in which the carrier was judged by the press or by the Federal Aviation Administration (FAA) not to be at fault. We find that, for crashes caused by pilot error, the carrier experienced significantly negative stock returns but that in the case of other crashes there was no stock market reaction.

The fact that there is no stock market reaction in the case of no-fault crashes suggests that airlines are fully insured against this peril. The cause of the stock market reaction to at-fault crashes must then be due to one or both of the following: the loss of consumer goodwill or increases in the cost of insurance. In fact, if the theory of brand names is correct, an increase in insurance costs should *cause* a loss in consumer goodwill. This is because an increase in insurance costs reflects a change in the probability of accident that will also be taken into account by consumers.

We report an insurance rate function that shows insurance costs do increase consequent to pilot-error crashes and not to disasters caused by forces arguably outside the control of the carrier. And, consistent with the theory, this insurance cost increase adds up to only around 38 percent of the stock market decline. Hence, we conclude that a strong brand name effect is operating in the airline industry to insure quality performance.

This result raises the question, What is the value of regulation in this industry? We could not find any evidence that deregulation caused a change in the stock market response to crashes. Even though more work is warranted, this result interests us because it suggests that regulation had virtually no air-safety effects, a point much in contention today.

II. Airplane Crashes and Brand Name Reputation

In most markets, consumers possess insufficient information about some attributes of products they want to purchase. Acquiring information concerning the intrinsic quality of products prior to purchase is costly. It is commonly believed that in the absence of a government to enforce contracts and sanction stealing, market exchange would be impossible. This is not necessarily true. Brand names and reputations may be enough to prevent cheating by fraudulent firms.

The idea of brand names or reputations as quality assuring devices has formally emerged in the last decade. Klein and Leffler, following the arguments by Klein, Crawford, and Alchian, develop a model in which the presence of firm-specific sunk capital investments, such as those incurred in establishing a brand name, provide a mechanism for assuring contractual performance.[1] Empirical evidence by Jarrell and Peltzman;

[1] Benjamin Klein & Keith Leffler, The Role of Market Forces in Assuring Contractual Performance, 21 J. Pol. Econ. 615 (1981); and Benjamin Klein, Robert G. Crawford, &

Chalk; Mitchell; and Benjamin and Mitchell have recently been accumulated in support of this theory.[2] These studies document wealth losses—in excess of out-of-pocket costs—associated with reduction in product quality.

Air transportation is an industry where almost all companies have well-known brand names. American, Delta, Pan Am, and United are household names. An airline's brand name can be devalued in many ways—delayed or cancelled flights, lost baggage, and unpleasant flight attendants. Arguably, the event most damaging to the brand name capital of an airline is a fatal crash caused by negligence.

Consumers have an expectation about the likelihood of crashes; some crashes will cause consumers to escalate this expectation. When this happens, the theory predicts, consumers will reduce their assessment of the amount of resources the airline devotes to safety. Consumer demand will shift to the left with adverse profit effects. The capital market will recognize this and devalue the goodwill assets of the company.

Airline crashes are caused by a variety of factors including pilot error, improper maintenance, manufacturer error, air traffic control error, and hazardous weather conditions. Theoretically, crashes due to pilot error and improper maintenance are cases where consumers are most likely to reassess the probability of future crashes on that airline. These cases represent a failure to monitor effectively situations directly controllable by the company. Indeed, because airlines are expected to control malfeasance in these important areas, they invariably hire and train their own pilots and maintenance crews, as opposed to subcontracting for these services as they do for meal preparation. Crashes due to causes under the immediate control of an airline will be more likely to affect consumers' expectations about the quality of the airline than are crashes due to what is judged to be bad luck. Consequently, a negligent airline is more likely to suffer a loss in brand name capital than is a nonnegligent carrier in the event of a crash.[3]

Armen A. Alchian, Vertical Integration, Appropriable Rents, and the Competitive Contracting Process, 21 J. Law & Econ. 297 (1978), discuss the notion of a price premium as a bonding device in contract enforcement.

[2] Gregg Jarrell & Sam Peltzman, The Impact of Product Recalls on the Wealth of Sellers, 93 J. Pol. Econ. 512 (1985); Andrew Chalk, Market Forces and Aircraft Safety: The Case of the DC-10, 24 Econ. Inq. 43 (1986), and Market Forces in Commercial Aircraft Safety, 36 J. Indus. Econ. 61 (1987); Mark L. Mitchell, The Impact of External Parties on Brand-Name Capital: The 1982 Tylenol Poisonings and Subsequent Cases, Econ. Inq. (in press); and Daniel Benjamin & Mark L. Mitchell, Quality-Assuring Price Premium: Classic Evidence from the Real Thing (Working paper, U.S. SEC 1989).

[3] Consumers do not have perfect information about the cause of any crash and consumers recognize that the company has an incentive to make itself appear innocent. There is an old

Events that do not change the expectations of future crashes do not affect consumer behavior. In such cases, the stock market reacts only to the airline's out-of-pocket losses. The value of the plane is almost always fully insured, and the liability insurance carried by most airlines would cover the worst imaginable crash: two 747s colliding over New York City. Thus, the only out-of-pocket losses are higher insurance costs, and these should only increase if the probability of future accidents increases, which should also elicit a consumer response.

In other words, a stock market effect attributable to a loss of brand name capital can only occur if there is a revision in the probability of product failure. The experiment reported here tests whether airplane crashes are, on average, associated with a revision of the probability of a crash.[4] Some crashes will change consumer expectations; some will not. But the effect of a crash is asymmetric. We argue that a crash will never cause consumers to lower their expectation of the likelihood of future crashes. Hence, we seek to find a significant effect of those that do change expectations among the noise of those that do not.

Other researchers have approached this problem differently and sometimes, in our opinion, incorrectly. We look for a stock market effect and then examine the other costs in search of a net brand name effect. Others have sought to find a *quantity* effect as a consequence of the stock market reaction.[5] The problem with this approach is that the theory says nothing about quantity. It speaks to price. When a firm depreciates its brand name, the predicted effect is that it must lower price. When it lowers price, because it is offering a lower-quality good, who is to say what happens to quantity? For instance, it is certainly the case that more pieces of cheap jewelry are sold at K-Mart than there are expensive items sold at Tiffany & Co. When a carrier unexpectedly crashes a plane, it moves from the Tiffany class to the K-Mart category.

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saying, "Sorry don't feed the dog." Hence, consumers may revise upward the probability of crashing even when the news accounts say that the airline was blameless. We argue that the more an airline is judged to have been at fault, the more likely consumers are to reduce their demand.

[4] It is in this sense that we reconcile the results reported in this article with other findings presented in Mitchell, note 2 *supra*. There it is reported that Johnson & Johnson suffered a brand name loss consequent to the 1982 Tylenol poisonings even though that catastrophe was not directly the fault of Johnson & Johnson. We argue that consumers hold companies responsible for all events, but that they have an expectation about performance. When that expectation changes, there will be a stock market reaction that can be used to gauge the brand name value of a company. That the Tylenol disaster represented a revision of consumer expectations is an issue addressed by Mitchell.

[5] Severin Borenstein & Martin B. Zimmerman, Market Incentives for Safe Commercial Airline Operation, 78 Am. Econ. Rev. 913 (1987), approach the problem from this perspective. They conclude that because the consumer response to crashes is quite small in quantity terms, the stock market losses do not reflect a brand name effect.

Interesting evidence on this point has been amassed by Benjamin and Mitchell.[6] They examine the Coca-Cola fiasco with New Coke. They find that Coca-Cola suffered a substantial brand name loss but no market share decline. They then show that both of these results are explainable based on substantial wholesale price cuts by Coca-Cola to its bottlers following the New Coke episode.[7]

Today, direct price cutting in the airline industry is commonplace; however, much of our sample covers the era of airline regulation when price cutting was possible but cumbersome. Even so, we argue that airlines can do many things to fill the price gap created by the loss of consumer goodwill. They can be on time, schedule more flights, offer better food and snacks, provide more numerous and more courteous attendants, and so forth. They can increase the level of maintenance, supervision, and training. They can also increase the commission rate and incentives paid to travel agencies, increase the number of sales representatives calling on these people, increase the number of their own ticketing agents, and increase advertising in general. All of these benefits to consumers can result from depreciated brand name and yet there will be no sign of their effect in the quantity dimension.

III. Airplane Disasters

To examine this theory, we constructed a crash data set. It consists of all fatal airline crashes involving U.S. airlines over the period 1964–87. These crashes meet two criteria. First, the airline must have been registered on either the New York Stock Exchange or the American Stock Exchange at the time of the crash. Second, at least one passenger must have been killed in the crash.[8] The data set contains fifty-six crashes.

We assigned each of the fifty-six crashes to one of two categories: *pilot error* (thirty-four) and *manufacturer error and miscellaneous causes* (twenty-two). Information from the *Brief of Fatal Accidents* and from articles in *Aviation Week and Space Technology* (*AWST*) and the *Wall Street Journal* (*WSJ*) provided the basis for classification.[9] Pilot error

[6] Note 2 *supra*.

[7] Similarly, Mitchell, note 2 *supra*, finds that Johnson & Johnson regained Tylenol's market share within a year following the 1982 cyanide poisonings, but largely at the expense of large price cuts relative to other pain relievers.

[8] Many of the fatal accidents involving U.S. airlines were not crash related. Examples include running over trespassers on the runway, company agents walking into the propeller, and so on. Incidents of this nature are not the focus of this study and hence are excluded.

[9] The crashes are summarized in Briefs of Fatal Accidents, which is compiled from the final reports by the National Transportation Safety Board (NTSB).

represents our at-fault category and manufacturer error and miscellaneous causes represent the no-fault group.[10]

A fortuitous characteristic of the data is that the articles in *AWST* and *WSJ* are rarely in conflict with the information contained in the *Briefs of Fatal Accidents*. This point is essential for the purpose of this study. Many of the articles in *AWST* and *WSJ* were written immediately following the crash, while the National Transportation Safety Board (NTSB) does not typically issue a final report until several months after the crash. If the cause of the crash were not known within a few days after the crash, financial market analysis would be suspect because it would be difficult to determine exactly when the cause of the crash became known to investors. For instance, information about the NTSB investigation could leak out slowly and be spread in trivial proportion across the stock returns of several months. However, since the initial reports from the *AWST* and *WSJ* articles generally prove to be consistent with the *Briefs of Fatal Accidents*, we assume that the cause of the crash was known within a few days after the crash, and on many occasions it was known on the day of or the day after the crash.

The pilot-error category contains those crashes where the pilot (or crew) was the major contributor to the cause of the crash. Thirty-four of the fifty-six crashes belong to this category and are described in Panel A of Table 1. As evident from the "story" column, most of these crashes were due solely to pilot error. For a few of the crashes in Panel A of Table 1, however, a contributing factor may have been hazardous weather conditions, plane malfunctions, or air traffic controller mistakes. Even for those crashes in Panel A of Table 1, the pilot was largely at fault. For example, in the United Airlines crash on December 28, 1978, the plane crashed upon running out of fuel, a crisis that went unnoticed due to the crew's preoccupation with a landing gear malfunction. Undoubtedly, the landing gear malfunction was due either to manufacturer or maintenance error. A plane can make an emergency landing without landing gear, however; consequently, it was the crew's forgetfulness to check the fuel status that led to the crash and eight passenger deaths.[11]

[10] Chalk 1987, note 2 *supra*, uses a similar taxonomy to analyze the effect on the stock price of aircraft manufacturers as a consequence of crashes. He looks at seventy-six crashes, 1966–81. For twenty-three crashes, aircraft design may have been the cause.

[11] According to excerpts from the final report by the NTSB, "the probable cause was the failure of the captain to monitor properly the aircraft's fuel state and to properly respond to the low fuel state and the crew member's advisories regarding fuel state. His inattention resulted from preoccupation with a landing gear malfunction and preparation for a possible emergency landing. Contributing to the accident was the failure of the other two crew members either to fully comprehend the criticality of the fuel state or to successfully communicate their concern to the captain." See Aviation Week and Space Technology, Novem-

Eight of the fifty-six crashes were primarily due to manufacturer error; they are described in Panel B of Table 1. In the well-known American Airlines crash of a McDonnell-Douglas DC-10 in Chicago on May 25, 1979, initial press coverage placed the blame on the manufacturer even though the final NTSB report found the carrier at fault due to improper maintenance procedures. We classify the crash as manufacturer error based on other research.[12] The second part of this category given in Panel B of Table 1 contains fourteen miscellaneous crashes. Six of the crashes had undetermined causes. The remaining eight crashes resulted from a combination of air traffic control error, unavoidable weather conditions (such as wind shear), pilot of another plane at fault, and in one instance, the accident was caused by a bomb in the cargo. Obviously, the carrier could have taken precautions to prevent all of these crashes as well as those attributable to pilot error. We base our argument on the assumption that the costs of reducing the likelihood of pilot-error crashes are lower and that a pilot-error crash is therefore more likey to affect consumers' expectations about future crashes.

IV. Stock Market Event Analysis

There are several methods available to evaluate the stock market effect of an event.[13] The method used in this study estimates the normal market model across the pooled returns of the air carriers involved in each category of crash. The regression includes a dummy variable for the crash event:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma D_t + \epsilon_{it}.$$

ber 5, 1979. A similar incident initiated the Eastern Airlines crash on December 29, 1972. The gear lock indicator failed to come on during the landing approach and the crew tried to determine visually whether the landing gear was extending properly. In their preoccupation with the landing gear, none of the crew monitored any of the flight instruments during the final four minutes preceding the crash, failing to detect an uninterrupted descent that led to the crash.

[12] Chalk 1986, note 2 *supra*, estimates the losses suffered by McDonnell-Douglas as a result of the crash. His study shows tht McDonnell-Douglas suffered large losses contemporaneous with the crash, even though the company was eventually cleared by the NTSB.

[13] For a discussion of some of the many choices, see Steve Cantrell, Mark L. Mitchell, & Michael T. Maloney, On Estimating the Variance of Abnormal Stock Market Performance (working paper, U.S. SEC 1989). John Binder, On the Use of the Multivariate Regression Model in Event Studies, 23 J. Acct. Res. 370 (1985); and Michael R. Gibbons, Multivariate Tests of Financial Models: A New Approach, 10 J. Fin. Econ. 3 (1982), discuss an approach very similar to ours. Our approach differs in that we use a pooled estimate of the variance of the residual even though we allow for firm-specific estimates of α and β. We have replicated our results using Binder's model as well as the techniques discussed in Cantrell *et al.* The results we present here are robust.

TABLE 1

DESCRIPTION OF FIFTY-SIX FATAL AIRLINE CRASHES DURING 1964–87 INVOLVING NEW YORK STOCK EXCHANGE OR AMERICAN STOCK EXCHANGE CARRIERS

A: THIRTY-FOUR CRASHES DUE TO PILOT ERROR

Date of Crash	Location	Airline	Aircraft	Passengers Killed	Story
February 8, 1965	Long Island, New York	Eastern	Douglas DC-7	79	Illusion prompted evasive action to avoid collision, placing the plane in an altitude from which it did not recover
September 17, 1965	Monteserrat, British West Indies	Pan Am	Boeing 707	21	Descended too low due to navigational error
November 8, 1965	Constance, Kentucky	American	Boeing 727	53	Failed to arrest an excessive descent rate during landing
November 11, 1965	Salt Lake City, Utah	United	Boeing 727	43	Undershot runway
December 4, 1965	Carmel, New York	Eastern	Lockheed 1049	3	Hit other plane due to misjudgment of altitude separation
August 6, 1966	Falls City, Nebraska	Braniff	British AC	38	Flew too close to avoidable hazardous weather
March 9, 1967	Urbana, Ohio	Trans World	Douglas DC-9	21	Hit other plane due to excessive speed during approach
November 20, 1967	Constance, Kentucky	Trans World	Convair 880	64	Attempted to land without instrument assistance
May 3, 1968	Dawson, Texas	Braniff	Lockheed 188	80	Pilot overloaded wing stress; weather a contributing factor
June 12, 1968	Calcutta, India	Pan Am	Boeing 707	5	Hit trees due to misuse of instruments
October 25, 1968	Hanover, New Hampshire	Northeast	Fairchild 227	30	Premature descent due to misuse of instruments
December 24, 1968	Bradford, Pennsylvania	Allegheny (U.S. Air)	Convair 580	18	Hit trees due to misuse of instruments
November 19, 1969	Glens Falls, New York	Mohawk	Fairchild 227	11	Hit mountain due to misuse of instruments

June 7, 1971	New Haven, Connecticut	Allegheny (U.S. Air)	Convair 580	26	Struck power line due to misuse of instruments
September 4, 1971	Juneau, Alaska	Alaska	Boeing 727	104	Hit mountain due to misuse of instruments
December 8, 1972	Chicago, Illinois	United	Boeing 737	40	Stalled plane in landing; failed to exercise proper flight management
December 29, 1972	Miami, Florida	Eastern	Lockheed 1011	94	Uninterrupted descent; several deviations from normal operation procedures
July 23, 1973	St. Louis, Missouri	Ozark	Fairchild 227	37	Flew into avoidable thunderstorm
July 31, 1973	Boston, Massachusetts	Delta	McDonnell-Douglas DC-9	82	Hit seawall; failed to note altitude; weather a contributing factor
January 31, 1974	Pago Pago, Samoa	Pan Am	Boeing 707	86	Hit trees due to excessive rate of speed that was uncorrectable
April 22, 1974	Bali, Indonesia	Pan Am	Boeing 707	96	Improper landing; misuse of instruments
September 11, 1974	Charlotte, North Carolina	Eastern	McDonnell-Douglas DC-9	69	Improper landing; lack of altitude awareness due to not following prescribed procedures
December 1, 1974	Berryville, Virginia	Trans World	Boeing 727	85	Hit hill; failed to control an excessive rate of descent; air traffic control procedures partly at fault
April 5, 1976	Ketchikan, Alaska	Alaska	Boeing 727	1	Ran into ditch; misjudged distance necessary to stop on icy runway
April 27, 1976	St. Thomas, Virgin Islands	American	Boeing 727	35	Ran off runway; deviated from prescribed landing techniques
March 27, 1977	Tenerife, Canary Islands	KLM Royal Dutch	Boeing 747	234	Hit other plane; takeoff without clearance
May 8, 1978	Pensacola, Florida	National	Boeing 727	3	Failed to monitor descent rate and altitude
September 25, 1978	San Diego, California	Pacific Southwest	Boeing 727	128	Collided with small plane; failed to comply with a visual separation clearance
December 28, 1978	Portland, Oregon	United	McDonnell-Douglas DC-8	8	Ran out of fuel during preoccupation with a landing gear malfunction
February 12, 1979	Clarksburg, West Virginia	U.S. Air	Frakes M298	1	Failed to deice
October 31, 1979	Mexico City, Mexico	Western	McDonnell-Douglas DC-10	61	Tried to land on closed runway; failed to gain positive visual contact with the open runway

TABLE 1 (*Continued*)

Date of Crash	Location	Airline	Aircraft	Passengers Killed	Story
August 2, 1985	Dallas, Texas	Delta	Lockheed 1011	135	Initiated and continued approach into cloud observed to contain lighting; wind shear also cited
August 16, 1987	Detroit, Michigan	Northwest	McDonnell-Douglas MD80	156	Failed to extend wing flaps in proper position for takeoff
November 15, 1987	Denver, Colorado	Continental	McDonnell-Douglas DC-9	27	Failed to deice after extended wait

B: Twenty-two Crashes in Which Carrier Was Not at Fault

Date of Crash	Location	Airline	Aircraft	Passengers Killed	Story
Manufacturer error:					
February 25, 1964	New Orleans, Louisiana	Eastern	Douglas DC-8	51	Uncontrolled descent due to horizontal stabilization malfunction
November 23, 1964	Rome, Italy	Trans World	Boeing 707	43	Aborted takeoff; power lost on two engines
June 23, 1967	Blossburg, Pennsylvania	Mohawk	British AC 1-11	30	Material failure caused fire in flight
January 18, 1969	Los Angeles, California	United	Boeing 727	32	Inflight electrical failure; weather a contributing factor
March 3, 1972	Albany, New York	Mohawk	Fairchild 227	14	Malfunction of cruise pitch lock system
August 28, 1973	Los Angeles, California	Trans World	Boeing 707	1	Plane porpoised; design defect in control system
March 1, 1978	Los Angeles, California	Continental	McDonnell-Douglas DC-10	2	Skipped off runway; sequential failure of two tires on one landing gear
May 25, 1979	Chicago, Illinois	American	McDonnell-Douglas DC-10	258	Engine fell off on takeoff
Miscellaneous causes:					
July 9, 1964	Parrotsville, Tennessee	United	Viscount 745	35	Exploded in midair; fire in cabin; cause undetermined

August 16, 1965	Lake Michigan, Illinois	United	Boeing 727	24	Crashed in Lake Michigan; cause undetermined
November 6, 1967	Erlanger, Kentucky	Trans World	Boeing 707	1	Aborted takeoff to avoid other plane that lied to tower
December 12, 1968	Caracas, Venezuela	Pan Am	Boeing 707	42	Cause undetermined; possible visual illusion caused by town lights
January 6, 1969	Bradford, Pennsylvania	Allegheny (U.S. Air)	Convair 440	9	Cause undetermined
September 9, 1969	Fairland, Indiana	Allegheny (U.S. Air)	McDonnell-Douglas DC-9	78	Collision with small plane; air traffic control system at fault
July 23, 1973	Papeete, Tahiti	Pan Am	Boeing 707	68	Cause undetermined
September 8, 1974	Cephalomia, Greece	Trans World	Boeing 707	79	Exploded in midair; bomb in cargo
June 24, 1975	Jamaica, New York	Eastern	Boeing 727	106	Wind stream; air traffic control did not advise
March 27, 1977	Tenerife, Canary Islands	Pan Am	Boeing 747	317	Hit by other plane that was taking off without clearance
January 23, 1982	Boston, Massachusetts	World	McDonnell-Douglas DC-10	2	Insufficient information provided by ground control as to runway conditions
July 9, 1982	New Orleans, Louisiana	Pan Am	Boeing 727	153	Wind shear
January 1, 1985	Bolivia	Eastern	Boeing 727	29	Cause undetermined
December 7, 1987	Los Angeles, California	Pacific Southwest	British Aerospace BAe-146	43	Passenger shot crew

The term R_{it} is the return at time t for the ith carrier, R_{mt} is the market return at that date, and the slope and intercept parameters of the market model are allowed to vary for each airline. The dummy variable, D_t, takes a value of one during the event window for each crash in the sample and zero the rest of the time. It directly tests the effects of the event on the stock returns of all companies experiencing this type of crash. In this way, γ is the expected stock market reaction to a crash of this type by any airline.[14]

The window of time used to capture the stock market reaction to the crash is arbitrary. The first day of the crash event window will either be the day of the crash or the day thereafter, depending on whether the stock market was open at the time of the crash.[15] Recall from the previous section that in examining the *Briefs of Fatal Accidents,* which summarizes the NTSB's final reports, and the articles from *AWST* and *WSJ*—many of which were written immediately following the crashes—there was conflict between the initial news accounts and the final reports in only one case. It seems likely that for most of the crashes, the probable cause is known immediately after the crash and, therefore, a short event window should accurately measure the full effect of the crashes. For all models in this article, we present crash event windows ranging from one to ten trading days. Ten trading days (two weeks) should allow more than enough time for investors to accurately forecast the effect of the crashes.

A. *Pilot Error*

We first estimated variations of the pooled, modified market model for the pilot-error category. The estimation periods are 50, 100, and 150 trading days, respectively, and the event window ranges from one to ten trading days.[16] Rather than reporting the estimates of (α_i, β_i) for each

[14] When an airline has more than one crash of a given type, we estimated different sets of $\{\alpha_i, \beta_i\}$ for each crash. In some cases the groupings overlap. Our technique for handling this is discussed in note 19 *infra*.

[15] For crashes that occurred while the stock market was open, the day of the crash is counted as the first day of the crash event window even though the stock market might have been open only thirty minutes after the crash. The first trading day after the crash is used as the first day of the crash event window if the stock market was closed when the crash occurred.

[16] In the pilot-error category, Pan American Airlines had a crash on January 31, 1974, followed by another crash on April 22 during the same year. There are only fifty-five trading days separating the two crashes. The problem here is that if the estimation period is 100 trading days (preceding the crash) for the crash that occurred in April, then the estimation period for that crash would include the crash event window from the January crash and hence bias the estimates. To solve this problem, the first day of the estimation period for the April crash will be the eleventh trading day following the January crash, that is, the first day after the longest crash event window (ten trading days) that will be tested later in this

TABLE 2

ESTIMATES OF γ WHERE D IS {0,1} IN THIRTY-FOUR CRASHES DUE TO PILOT ERROR
MODEL: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma D_t + \epsilon_{it}$

CRASH EVENT WINDOW (Trading Days)	ESTIMATION PERIOD		
	50 Trading Days	100 Trading Days	150 Trading Days
1	−.01566	−.01626	−.01679
	(−3.45)***	(−3.63)***	(−3.80)***
2	−.01101	−.01144	−.01160
	(−3.39)**	(3.58)***	(−3.69)***
3	−.00811	−.00859	−.00864
	(−3.03)**	(−3.28)***	−3.35)***
4	−.00561	−.00625	−.00631
	(−2.40)**	(−2.74)***	(−2.81)***
5	−.00453	−.00522	−.00527
	(−2.14)**	(−2.56)***	(−2.62)***
6	−.00253	−.00312	−.00314
	(−1.30)	(−1.66)*	(−1.71)*
7	−.00150	−.00192	−.00194
	(−.83)	(−1.10)	(−1.14)
8	−.00095	−.00134	−.00131
	(−.55)	(−.82)	(−.81)
9	−.00151	−.00183	−.00174
	(−.92)	(−1.18)	(−1.15)
10	−.00172	−.00203	−.00191
	(−1.10)	(−1.37)	(−1.32)

NOTE.—t-statistics are in parentheses.
* $p \leq .10$.
** $p \leq .05$.
*** $p \leq .01$.

model, we report only the coefficient and t-statistic for the crash dummy variable.[17] The estimates, presented in Table 2, show that crashes caused by pilot error have a negative effect on the stock returns of the respective airlines. Regardless of the estimation period used (50, 100, or 150 trading days), the coefficient for the crash dummy variable is statistically significant at the 1 percent level for the event windows from one to five trading days with only two exceptions: the crash dummy-variable coefficient for the event windows of four and five trading days associated with the fifty trading days estimation period is statistically significant at the 5 percent level.

section. As discussed earlier, it is not likely that any new information concerning the crashes should develop after ten trading days (two weeks) following the crash. Adopting this procedure, the estimation period for the April 22, 1974, crash will be forty-five trading days, but will be 100 trading days for the other thirty crashes in the pilot-error category. Deleting the second Pan Am crash does not affect the results we report.

[17] The estimates of all the parameters are available upon request.

TABLE 3

% Negative Cumulative Abnormal Returns in Thirty-four Crashes due to Pilot Error

Crash Event Window (Trading Days)	Estimation Period		
	50 Trading Days	100 Trading Days	150 Trading Days
1	1.57	1.63	1.68
2	2.20	2.29	2.32
3	2.43	2.58	2.59
4	2.24	2.50	2.52
5	2.27	2.61	2.64

For the most part, the coefficients for the crash dummy variable in Table 2 decline as the event window lengthens, but the estimated effect of the crash stays approximately constant. To calculate the cumulative abnormal return, multiply the coefficient for the crash dummy variable by the number of trading days in the event window. Table 3 contains the cumulative abnormal returns corresponding to the dummy variable coefficients from Table 2 for the first five trading days.

For the crash event window of one trading day (the day of the crash if the market was open at the time of the crash), the negative abnormal returns average 1.63 percent. They increase for the two-day event window to 2.27 percent and are 2.53, 2.42,and 2.51 percent for the event windows of three, four, and five trading days, respectively. By all appearances, an airline suffers a negative abnormal return of approximately 2.5 percent due to crashes caused by pilot error.

B. *Manufacturer Error and Miscellaneous Causes*

In this section, we report the pooled, modified market model for those crashes in which passengers were killed but the airline was not directly at fault. These crashes should have a smaller effect on the respective airlines' brand names than those crashes, discussed in the previous section, that are directly the responsibility of the airline.

The pooled, modified market model was estimated for the twenty-two crashes in this category. The coefficient and t-statistic for the crash dummy variable from each model (estimation period—50, 100, and 150 trading days; event window—one to ten trading days) are shown in Table 4.

Unlike the results from the pilot-error category, it does not appear that crashes for which the airline is not directly responsible have much of an effect on the stock returns of the respective airlines. None of the crash

TABLE 4

ESTIMATES OF γ WHERE D IS {0,1} IN TWENTY-TWO CRASHES DUE TO MANUFACTURER ERROR AND MISCELLANEOUS CAUSES
MODEL: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma D_t + \epsilon_{it}$

CRASH EVENT WINDOW (Trading Days)	ESTIMATION PERIOD 50 Trading Days	100 Trading Days	150 Trading Days
1	−.00602	−.00459	−.00406
	(−.86)	(−.70)	(−.64)
2	−.00631	−.00561	−.00523
	(−1.26)	(−1.20)	(−1.17)
3	−.00231	−.00196	−.00152
	(−.56)	(−.51)	(−.41)
4	−.00288	−.00291	−.00250
	(−.81)	(−.88)	(−.78)
5	−.00231	−.00246	−.00215
	(−.79)	(−.83)	(−.75)
6	−.00091	−.00116	−.00090
	(−.31)	(−.42)	(−.34)
7	−.00281	−.00294	−.00268
	(−1.02)	(−1.16)	(−1.10)
8	−.00295	−.00312	−.00299
	(−1.14)	(−1.31)	(−1.32)
9	−.00172	−.00184	−.00185
	(−.70)	(−.82)	(−.86)
10	−.00042	−.00062	−.00060
	(−.18)	(−.29)	(−.29)

NOTE.—*t*-statistics are in parentheses.

dummy coefficients is statistically significant at conventional levels. This evidence suggests that airlines suffer negative abnormal returns due to crashes for which they are largely responsible but are generally immune to other types of crashes.[18]

C. Death Rate

One problem posed by the {0,1} dummy-variable technique is that it treats all crashes the same. This creates two inaccuracies: crashes differ in terms of the number of people killed and in terms of the size of the

[18] We tested one additional category that consisted of seven crashes; six occurred on training flights, the seventh on a ferry flight. The plane was destroyed in all seven crashes and in only one did any of the crew survive. None of the crash coefficients is statistically significant and the point estimates are positive.

We also estimated the pooled, modified market model for the manufacturer error and miscellaneous crash categories separately. Results from these models are not unlike those shown in Table 4 and are available on request as are any other results mentioned but not reported.

airline involved. The more people killed in an at-fault crash, the more the airline will likely suffer. That is, when the pilot misjudges the runway and goes into a ditch killing one passenger, consumers will revise their estimate of a future crash less than when the pilot takes off without clearance, hits another plane, and kills 234 people. On the other hand, the larger the airline, the more likely it is to have a crash due to any cause and the less effect an at-fault crash should have on its rate of return.

To rectify both of these shortcomings, we defined a *death-rate* variable. We modified the dummy variable to let the nonzero values become the square root of the number of passengers killed in each crash divided by the number of passengers served by the airline in the year of the crash.[19]

Employing this new crash variable, we reestimated the regressions shown in Table 2. Table 5 displays the results. In each case, the coefficients have the negative sign predicted by the theory, and the significance levels are substantially higher than the results found using the {0,1} dummy. All but eleven of the thirty coefficients are statistically significant at the 1 percent level and those eleven are significant at either the 5 percent or 10 percent level.[20] These results indicate that, when the number of people killed and the size of the airline involved are accounted for, the negative stock market performance of the negligent carriers is even more pronounced.

We also estimated death-rate model for the combined *manufacturer-error and miscellaneous causes* crash category consisting of twenty-two crashes. Results are shown in Table 6. For the first trading day event window, the estimated effect is negative and statistically significant in all specifications. However, none of the remaining death-rate dummy variable coefficients is significantly different from zero. The statistical significance of the first day is probably due to imperfect information about the cause of the crash. We interpret these results, like those shown in Table 4,

[19] Other deflators for airline size could be used. For instance, revenue-passenger-miles is a common metric in the airline business. However, because most crashes occur during the takeoff and landing phases of the flight, distance weighting seems inappropriate. In all events, we tried several deflators, including the equity value of the airline. The results are very close in every case to those found using deaths per passenger served. Similarly, employing a square root transformation of deaths per passenger served is arbitrary; this transformation maximized the goodness of fit, but the results using untransformed deaths per passenger served or higher roots of this variable are nearly identical to those reported here and are available upon request. See Table 1, Panels A and B, for the number of passenger deaths per crash. Annual passenger data comes from Airport Activity Statistics of Certified Route Air Carriers, prepared jointly by the Civil Aeronautics Board (CAB) and the FAA.

[20] All of the coefficients for the events ranging from one to six trading days are statistically significant at the 1 percent level.

TABLE 5

ESTIMATES OF γ WHERE D IS DEATH RATE IN THIRTY-FOUR CRASHES DUE TO PILOT ERROR
MODEL: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma D_t + \epsilon_{it}$

CRASH EVENT WINDOW (Trading Days)	ESTIMATED PERIOD		
	50 Trading Days	100 Trading Days	150 Trading Days
1	−6.30881	−6.23988	−6.26241
	(−5.24)***	(−5.19)***	(−5.27)***
2	−3.73167	−3.66816	−3.67762
	(−4.33)***	(−4.30)***	(−4.37)***
3	−2.93351	−2.86842	−2.84801
	(−4.14)***	(−4.09)***	(−4.13)***
4	−2.05363	−2.00388	−2.00635
	(−3.30)***	(−3.28)***	(−3.34)***
5	−1.86909	−1.83025	−1.79398
	(−3.33)***	(−3.34)***	(−3.33)***
6	−1.53917	−1.47420	−1.43356
	(−2.98)***	(−2.93)***	(−2.91)***
7	−1.26338	−1.17413	−1.07514
	(−2.62)***	(−2.51)**	(−2.34)**
8	−.90006	−.80399	−.72771
	(−1.97)**	(−1.82)*	(−1.69)*
9	−1.01744	−.91887	−.87177
	(−2.34)**	(−2.20)**	(−2.01)**
10	−.89674	−.76918	−.74794
	(−2.15)**	(−2.00)**	(−1.65)*

NOTE.—t-statistics are in parentheses.
* $p \leq .10$.
** $p \leq .05$.
*** $p \leq .01$.

to mean that carriers endure no losses as a consequence of airline crashes where the carrier is not at fault.[21]

D. *Deregulation*

To test for the effect of deregulation, we split the sample into two parts. More precisely, we included a deregulation dummy variable (zero prior to 1976 and one thereafter) interacted with the crash variable. This deregulation dummy variable is insignificant in both the at-fault and no-fault re-

[21] Borenstein & Zimmerman, *supra* note 5, at 915 n.4, take exception to this conclusion, saying that the coefficients are not statistically different. The argument is problematic. Clearly the coefficients in the at-fault regressions are statistically significant and those in the no-fault regressions are insignificant. We have already argued that the sampling errors in the no-fault category should be large and the point estimates negative because consumers will hold carriers responsible for some of these crashes. Add to this the results reported in note 18 *supra*. We stand by our conclusion.

TABLE 6

ESTIMATES OF γ WHERE D IS DEATH RATE IN TWENTY-TWO CRASHES DUE TO MANUFACTURER ERROR AND MISCELLANEOUS CAUSES
MODEL: $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma D_t + \epsilon_{it}$

CRASH EVENT WINDOW (Trading Days)	ESTIMATION PERIOD 50 Trading Days	100 Trading Days	150 Trading Days
1	−5.30527	−4.57396	−4.41457
	(−2.02)**	(−1.85)*	(−1.86)*
2	−2.76623	−2.44749	−2.40820
	(−1.48)	(−1.39)	(−1.43)
3	−.94753	−.67739	−.55591
	(−.61)	(−.47)	(−.40)
4	−.79363	−.69778	−.56756
	(−.59)	(−.56)	(−.47)
5	−.72113	−.76665	−.67540
	(−.60)	(−.68)	(−.63)
6	−.06889	−.13051	−.05458
	(−.06)	(−.13)	(−.06)
7	−1.05332	−1.07047	−.98692
	(−1.02)	(−1.12)	(−1.08)
8	−1.20830	−1.23018	−1.18930
	(−1.24)	(−1.37)	(−1.39)
9	−.76621	−.79487	−.79161
	(−.83)	(−.94)	(−.98)
10	−.44926	−.49273	−.49139
	(−.50)	(−.61)	(−.63)

NOTE.—t-statistics are in parentheses.
* $p \leq .10$.
** $p \leq .05$.

gressions. We ran some sensitivity tests with respect to the date (1977 and 1978 were tried) and with respect to the model specification, but we uncovered no sign of a change in the pattern of stock market reactions to crashes as a result of the change in the regulatory regime.

V. INSURANCE RATING

The reaction of the stock market in the case of at-fault crashes compared to bad-luck crashes differs markedly. In the case of pilot-error crashes, airlines experience significantly negative stock market returns, whereas in crashes that are the fault of other carriers, government employees, or bad luck, no stock market effect is observed. Yet, in both cases, airplanes are destroyed and passengers are killed.[22] Since there is

[22] The average number of passengers killed is fifty-seven in at-fault crashes and sixty-four in no-fault crashes.

no evidence that liability claims for the loss of passenger lives differ between these two categories of crashes,[23] we are left with only two explanations of the difference in the stock market reaction. The stock market losses in the case of pilot-error crashes are due to a brand name effect and/or to insurance rate adjustments. The question is one of assessing the relative magnitudes.

Airlines are required by the federal government to carry liability insurance; they are required to report the amount paid for both liability and hull insurance to the U.S. Department of Transportation. In this section, we report estimates of the insurance rating formula. Our interest is in knowing if the occurrence of a crash has an effect on insurance rates. We have data on total liability and total hull insurance premiums paid annually by the airlines in our sample. The insurance data for each carrier start at least five years before its first crash and extend at least five years after its last crash, with a few exceptions.[24] The data set contains 301 observations on passenger-liability insurance and 300 observations on hull insurance. We calculate the two insurance rates by dividing total liability and total hull insurance premiums paid by each airline in each year by the revenue-passenger-miles served by the airline in that year.[25]

We hypothesize that insurance rates are a function of several things. First, there may be economies of scale. Just as two-car families typically receive lower rates than a one-car insuree, we expect big airlines to get lower rates than small airlines. Two-car families receive lower rates because the average miles driven per car declines. Bigger airlines get lower rates because they fly longer flights. Most crashes occur during takeoffs and landings. The probability of a crash declines the more the airline is engaged in the cruising phase of flight.

[23] We searched the WSJ, Business Insurance, and the aviation trade publications on this point and found no evidence of differences in settlements systematically related to the cause of the crash. Settlements appear to differ by crash based on the amount of the publicity associated with the disaster, which may or may not be related to fault on the part of the carrier.

[24] No insurance data are available for KLM because it is a foreign carrier and not required to file CAB Form 41. Pacific Southwest (PSA) was not required to file Form 41 because it operated only in California. Mohawk Airlines was purchased two years after a pilot-error crash and hence the insurance data end at that point. Insurance data for World Airlines was not consistently available due to bankruptcy.

[25] Liability insurance rates are typically expressed in this fashion. For instance, Texas Air paid fifty cents per 1,000 revenue-passenger-miles flown in 1987, whereas Frontier paid 72 cents, as reported in Texas Air Picks Hall as Aviation Broker, Bus. Ins. 1 (November 3, 1986). Hull insurance rates, on the other hand, are typically expressed as cents per $100 of insured value. The hull rate we construct approximates the industry standard in that revenue-passenger-miles are highly correlated with the value of the fleet. That is, more passengers implies more planes and longer flights means bigger planes. The data on revenue-passenger-miles were obtained from CAB Air Carrier Traffic Statistics.

Second, we expect that insurance rates for one airline are a function of the rates charged to other airlines. Obviously, there are industry-wide phenomena at play. The air traffic controllers' strike, terrorists' attacks, and general congestion are all industry-wide conditions that should affect rates.[26] Using the average rate paid by all other carriers is a convenient way to capture industry effects when estimating the rate paid by each individual carrier.

Lastly, the safety record of the carrier itself should, in an efficiently functioning insurance market, affect the rate paid by the carrier.[27] The safety record that we examine is the frequency of both at-fault and no-fault crashes. It is possible that no-fault crashes could cause insurance rates to rise; however, the absence of a significant stock market reaction reduces the probability of this.

In order to estimate the rating formula, we first regressed the liability insurance rate for each carrier in each year on the carrier's revenue-passenger-miles in that year, the average liability rates paid by all other carriers in that year, and the crash variable for both at-fault and no-fault crashes. The crash variable definition is the same as that used in the stock market analysis: using the dummy variable approach, it takes the value of one in the year of the crash and zero otherwise; similarly, the death-rate crash variable is positive in the year of the crash and zero otherwise. If there are two crashes in a year, the death rates are summed and the dummy variable takes a value of two.

We include the current value and five lags of the crash variable. This specification captures directly the continuing, but decaying, effect of idiosyncratic adjustments in the rates paid by each carrier. For instance, if a carrier is at fault in a crash, then its rates should go up and should remain high for some time thereafter. Again, like automobile insurance, the rate increases occasioned by an at-fault crash should be forgiven over time.

[26] Acording to several articles in Business Insurance, rates generally increase for all airlines following an above-normal series of crashes, such as in 1985. See Record Aviation Losses to Hike Rates for Airlines, Bus. Ins. 1 (August 19, 1985) and, likewise, following four terrorist attacks on airlines in 1985 and 1986, insurers added a "terrorist surcharge" to international carriers. See Terrorist Surcharge Adds to Growing Cost of Airlines' Coverage, Bus. Ins. 1 (June 23, 1986).

[27] For example, in 1983, while most airlines received rate reductions from 2 to 10 percent, Pan American Airlines was expected to be hit with a rate increase of about 20 percent. The rate increase for Pan Am was due to a July 1982 crash in New Orleans that killed all 146 passengers aboard and eight people on the ground. In September of 1983, Pan Am experienced another accident when one of its Boeing 747s skidded off the runway in Pakistan, resulting in several million dollars of damages. Both of these crashes combined contributed to a 90 percent rate increase from 1982 to 1984. See Increased Competition Cuts Most Aviation Rates, and Pan Am Can't Avoid Increase, Bus. Ins. 3 (July 11, 1983); Losses Force Pan Am to Take Special $10 Million Deductible, Bus. Ins. 1 (July 30, 1984).

Even though insurance rates do not necessarily formally change in the year of the crash, airlines that do not experience a crash receive a rebate.[28] Hence, a crash affects our measure of insurance rates in the calendar year of the crash. In the years after the crash, the actual rates are expected to adjust. Also, the policy date can vary through the calendar year. We estimated the insurance equations using specifications of the crash variable accounting for this effect. We weighted the crash variable based on the proportion of the calendar year remaining after the crash.

Table 7 displays the results of the liability rate estimates. All variables perform as expected. The dependent and independent variables, except for the crash variable, are in natural logs. Revenue-passenger-miles is the economy-of-scale variable and shows a small, but significant, negative effect.[29] The industry effect is similarly significant and carries the expected positive sign.

For both specifications of the crash variable (zero, one, and death-rate), the coefficients show a decaying pattern after an at-fault crash. In the dummy variable model, the coefficients represent the percentage increase in insurance premiums after the crash over what they would have been in the absence of a crash. For instance, insurance premiums are 34 percent higher in the year of a crash, 19 percent higher in the year after, 17 percent higher two years later, and so on. The total effect of a crash is the sum of these coefficients. The significance level of this sum can be investigated using a standard F-test. In both specifications, the significance of the sum is .007 for at-fault crashes.

In the dummy variable model, the sum of the coefficients for at-fault crashes is .88; this says that, all told, an at-fault crash causes premium increases spread over the following years that total to almost 90 percent of the premium paid in the year before the crash. In the death-rate specification, these coefficients must be multiplied by the value of this crash variable for each disaster to assess the effect of the crash on insurance premiums. We compute the discounted average dollar effect for all specifications in the next section.

There is some evidence in the liability insurance regressions that no-fault crashes have insurance rate effects. In the dummy variable model, the no-fault crash coefficients taken together are significant at the .06

[28] The airline forfeits a profit commission (as high as 20 percent of the premium paid), which it receives if no crash occurs. See American Airlines Gets Reduced Rates, Bus. Ins. 19 (September 19, 1983).

[29] We tried estimating the equation in levels and included a squared term for this variable. A U-shaped function results, but the minimum is found at the upper boundary of the data on the independent variable.

TABLE 7

PASSENGER LIABILITY INSURANCE RATES

Crash Variable Specification	{0,1}	Death Rate
Intercept	5.897	5.376
	(14.972)***	(13.419)***
Revenue-passenger-miles	−.451	−.413
	(−17.128)***	(−15.777)***
Industry liability rate	.277	.295
	(11.008)***	(11.759)***
At-fault crash$_t$	.341	105.595
	(2.616)***	(2.729)***
At-fault crash$_{t-1}$	.193	51.134
	(1.465)	(1.286)
At-fault crash$_{t-2}$	.174	44.596
	(1.274)	(1.106)
At-fault crash$_{t-3}$	.071	17.219
	(.493)	(.413)
At-fault crash$_{t-4}$	.056	3.995
	(.394)	(.096)
At-fault crash$_{t-5}$	.055	−.948
	(.139)	(−.023)
No-fault crash$_t$	.306	66.045
	(1.754)**	(.947)
No-fault crash$_{t-1}$	.067	27.944
	(.351)	(.374)
No-fault crash$_{t-2}$	.199	68.771
	(.983)	(.849)
No-fault crash$_{t-3}$	.064	22.974
	(.314)	(.289)
No-fault crash$_{t-4}$	.073	3.950
	(.369)	(.050)
No-fault crash$_{t-5}$	−.025	−5.345
	(−.130)	(−.069)
F-test on the sum of coefficients on:		
At-fault crash	7.209***	7.223***
No-fault crash	3.507*	1.853
R^2	.702	.694
Degrees of freedom for error	286	286

NOTE.—*t*-statistics are in parentheses; dependent variable, Passenger liability insurance rates, Revenue-passenger-miles, and Industry liability rate are expressed in logarithms.

* $p \leq .10$.

** $p \leq .05$.

*** $p \leq .01$.

level. However, the coefficients do not show the smooth decay pattern found in the at-fault category. Using the death-rate model, the sum of the coefficients is insignificant at conventional levels.

Essentially the same model is used for hull insurance rates with the substitution of industry-wide average hull rates for industry-wide liability rates. Since hull insurance covers the plane itself and not the passesngers, we substitute total miles flown instead of revenue-passenger-miles for the economy-of-scale variable. The results from the hull insurance equation, shown in Table 8, parallel those found in liability insurance. None of the dummy variable crash coefficients is significant, but the at-fault coefficients on the death-rate variable are. Their sum is significant at the .05 level. The no-fault death-rate coefficients are insignificant. The industry and economy-of-scale effects are both shown to operate in the predicted fashion.

VI. Net Brand Name Effects

The insurance results indicate that at least some of the declines in stock market value consequent to at-fault crashes can be attributed to the positive effect these crashes have on the insurance premiums paid by the airlines. In this section we compare the insurance premium adjustments to the stock market losses. To the extent that the stock market losses are greater than can be explained by the insurance adjustments, the residual can be interpreted as a brand-name loss suffered by the airlines due to at-fault crashes.

In order to compare the two effects, we first need a measure of the capitalized stock market losses resulting from at-fault crashes. For each crash we multiply the average abnormal return (-2.31 percent) on the crash variable for the five-day event window in the stock market analysis times the value of the variable (one in the dummy variable specification and the square root of deaths per passenger served in the death-rate specification) and then this times the equity value of the airline at the end of the day prior to the crash. This value is shown in Table 9 for the two specifications. Using the dummy variable model, the average value across all pilot-error crashes in 1987 dollars is \$27.3 million.[30] Accounting for the number killed and the size of the airline in each crash, the estimated average stock market losses from at-fault crashes are \$19.1 million.

[30] We inflated the dollar value of the lost equity to 1987 terms using the Consumer Price Index. The appropriateness of inflating equity values by the inflation rate is problematic. It measures the current purchasing power of the stock market losses. We inflated the insurance cost increases similarly.

TABLE 8

HULL INSURANCE RATES

Crash Variable Specification	{0,1}	Death Rate
Intercept	−.993	−1.135
	(−10.578)***	(−12.971)***
Revenue miles	−.713	−.740
	(−8.234)***	(−8.561)***
Industry liability rate	.337	.326
	(9.600)***	(9.422)***
At-fault crash$_t$	.055	126.636
	(.292)	(2.339)***
At-fault crash$_{t-1}$	.062	71.287
	(.324)	(1.277)
At-fault crash$_{t-2}$	−.064	33.409
	(−.323)	(.590)
At-fault crash$_{t-3}$	−.177	3.159
	(−.862)	(.053)
At-fault crash$_{t-4}$	−.196	5.817
	(−.967)	(.100)
At-fault crash$_{t-5}$	−.278	−12.152
	(−1.394)	(−.216)
No-fault crash$_t$	.222	163.932
	(.884)	(1.669)*
No-fault crash$_{t-1}$	−.030	−3.165
	(−.110)	(−.030)
No-fault crash$_{t-2}$	.248	142.162
	(.854)	(1.245)
No-fault crash$_{t-3}$	−.244	−92.627
	(−.840)	(−.830)
No-fault crash$_{t-4}$	.015	5.048
	(.054)	(.045)
No-fault crash$_{t-5}$	−.286	−116.212
	(−1.057)	(−1.078)
F-test on the sum of coefficients on:		
At-fault crash	1.597	4.022***
No-fault crash	.020	.267
R^2	.456	.465
Degrees of freedom for error	285	285

NOTE.—t-statistics are in parentheses; dependent variable, Revenue miles, and Industry liability rate are expressed in logarithms.

* $p \leq .10$.

*** $p \leq .01$.

TABLE 9

CAPITALIZED VALUE OF STOCK MARKET LOSSES, INSURANCE LOSSES, AND BRAND NAME LOSSES

Crash Variable Specification	{0,1}	Death Rate
Insurance cost increases ($)	8,940,097	8,055,210
Stock market losses ($)	27,275,068	19,103,226
Brand name loss ($)	18,334,971	11,048,016
% brand name loss/ stock market losses	67.0	57.8

The insurance losses are capitalized in the following fashion. The insurance premium increases occasioned by each crash are projected using the coefficients on the current and lagged values of the crash variable. Negative coefficients are set equal to zero. The projected premium percentage increases from each model are discounted back to the point of the crash.[31] In the death-rate specifications, the premium increases are found by multiplying the estimated coefficients by the square root of deaths per passenger served. The sum of these coefficients times the total insurance premium paid in the year prior to the crash gives the present value of the increase in insurance costs at the time of the crash. Hull and liability premium increases are summed, and this value is inflated to 1987 dollars and compared to the stock market losses. Table 9 reports the results. The total insurance cost increases are $8.94 million and $8.05 million for the two models.

Comparing the insurance and stock market losses yields estimates of a brand name loss of $18.3 million and $11 million. In percentage terms, the brand name loss is 67 percent in the dummy variable model and 57.8 percent using the death-rate specification.

Both specifications yield consistent results. By and large, at-fault crashes show negative abnormal stock market returns, positive insurance cost increases, and a net brand name loss. No-fault crashes produce no systematic stock market or insurance reaction. Using death-rates, there is an initial stock market blip that then recedes and there is no insurance effect following no-fault crashes. Using the dummy variable model, there

[31] To obtain a discount rate, we average the rate of return on equity for all airlines over the period 1965–86 using monthly stock market returns. This gives an estimate of the nominal discount rate. We adjust this by the inflation rate computed from the Consumer Price Index to obtain a real discount rate. The nominal return was 14.15 (in annual terms); the inflation rate was 5.95; this gives a real rate of 8.2.

is no stock market reaction and a small, erratic insurance effect. Taken together, we dismiss the no-fault effects.

VII. Conclusions

All told, the results are straightforward and support the notion that airline crashes cause consumers to reduce their demand for the services provided by negligent carriers, which is the prediction of the theory that brand names are a quality assuring mechanism. To summarize the results, in those instances where there is the greatest likelihood that the air carrier is at fault, there is a significantly negative stock market reaction to the event. However, in cases where there is less reason to suspect that the airline shirked its safety responsibilities, there is no adverse stock performance.

Together these results imply that the negative returns in the first case are not attributable to the loss of the plane or the passenger liability claims that result from the crash. In both of the categories that we have contrasted here, planes were lost and liability claims ensued. Our examination of the industry reports of liability claims for passenger deaths yields no suggestion that the awards are larger in the case of at-fault crashes as opposed to, say, cases where weather is the causal factor. Thus, the absence of stock market reaction to crashes in which the carrier is not at fault suggests that airlines purchase insurance against these perils in an amount sufficient to offset virtually all of the losses. The decline in stock market value associated with at-fault crashes must, then, represent a decline in the brand name value of the company or an expected increase in insurance rates.

To examine the magnitude of insurance rate adjustments, we estimated an insurance rating equation for both liability and hull insurance. We find that insurance rates do respond to the safety record of the airline as measured by the incidence and severity of crashes due to pilot error. The fact that insurance rates adjust as a result of these crashes implies that there is a revision of the probability of a crash. This is a necessary condition for there to be a brand name effect. When we compare the magnitude of the insurance rate increases to the stock market losses we find that, at most, 42 percent of the stock market losses can be explained by insurance cost increases. The rest, then, must be due to declines in the value of brand name.

The insurance effects, in conjunction with the analysis of brand names, provide an interesting twist in the discussion of liability claims against airlines. Consider the implication of a finding that says there is no brand name effect in at-fault airline crashes. This would mean that consumers did not care how careful the airline was and presumably this would stem from the fact that they were being overindemnified. That is, such a result would mean consumers were at least indifferent between the settlement value available to their heirs when they ride on risky airlines and the reduced probability of death when they choose a safe carrier. On the other hand, the results we have presented here suggest that consumers do, indeed, avoid risky airlines, which suggests that consumers are not overindemnified by liability awards. This, in turn, raises the question of why there appears to be no extra compensation in the liability settlements for at-fault crashes.

Finally, we find no evidence of deregulation in the pattern of brand name effects. This raises the question of whether or not we can expect deregulation to have any safety effect. Indeed, since our results suggest the market is quite efficient at punishing airlines for at-fault crashes, the need for increased airline safety regulation is not apparent.

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