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Post-crash airline pricing: A case study of Alaska Airlines Flight 261

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ABSTRACT

This paper examines the impact of the crash of Alaska Airlines Flight 261 on the domestic fares of the crash carrier, using a difference-in-difference approach. The results show that the crash reduced fares of Alaska Airlines relative to those of its competitors only in the months right after the crash, indicating that the financial ramifications are not persistent.

1. Introduction

Though rare, the crash of an airline flight is a disastrous event that brings with it significant economic and emotional consequences. The few major commercial airline crashes that have occurred have received wide media attention, despite the high safety standards of the airline industry and its low fatality rate when compared to other sources of risk. The isolated air crashes, from what is considered the safest mode of transportation, may impose financial ramifications on the carrier involved and the entire aviation industry.

Much of the research regarding the impact of airline crashes has investigated the stock prices of airlines. But no research has previously been conducted on changes in fares following a crash, a significant omission in the literature. Since stock value is derived from profits, which are established by fares and passenger count, this paper can offer a detailed explanation for the stock price effect by examining its determinants.

The paper estimates the impact of one crash, that of Alaska Airlines flight 261, on the carrier's fares on its domestic routes, with a goal of determining how much the accident decreased the fares and passenger count of the crash airline in the months following the event. It could be expected that after a fatal airline disaster, people would be wary of flying, and this fear would either reduce the frequency of their airline use (which would cause traffic for all carriers to drop), or that they would switch to a competing carrier. In both scenarios, the drop in demand would negatively impact Alaska Airlines and could force its fares to decrease following the crash in order to retain business.

Currently, all research agrees that crash airlines lose market value post-crash. Ho et al. (2013) study the consequences of a crash for stock prices as the number of fatalities is varied. They show that, if fatalities are few, crash airlines suffer immediately and non-crash airlines benefit consistently due to the effect of passengers switching away from the crash airline. If fatalities are high, all airlines suffer due to a contagion effect, which results in a drop in the firms' equity values due to heightened fears about the safety of air travel. This outcome is likely due to the media attention large disasters receive, which creates panic among the public.

Bosch et al. (1998) provide additional evidence on the switching and contagion effects. Their results show that as crash airlines lose value, non-crash airlines with greater market overlap with the crash airlines benefit due to the switching effect, while airlines with less or no overlap with the crash airline lose value due to the contagion effect, where overlap is defined as shared routes between airlines.

Similarly to this paper, Nethercutt and Pruitt (1997) also study the effects of a single crash. As in the other papers, their focus is the stock value of airlines, particularly those of rival airlines when the crash airline is a low-cost carrier (LCC). They examine the crash of ValuJet Flight 592, after which the airline was shut down for several months. Analysis showed that the contagion effect of this LCC crash overshadows the switching effect for other low-cost airlines, driving down the stock values of both crash and non-crash LCCs, while owners of major airline stocks gain from the tragedy.

The financial impact of a crash has additionally been studied through factors other than stock prices. Rose (1992) found a negative correlation between profit margins and a carrier's safety performance. Barnett et al. (1992) and Borenstein and Zimmerman (1988) analyzed the effect of a crash on passenger traffic.

The present study differs from the prior work by being the first to look at air fares as opposed to stock prices, as well as focusing on only one

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crash event. The change of fares and passenger counts post-crash directly lead to an impact on airline profits, and thus, stock value, drawing a link to previous studies. The empirical model controls for typical fluctuations in airline markets in order to observe the effects on fares of Alaska Airlines exclusively due to the crash of its Flight 261. A difference-in-difference approach is used to isolate the fare effects.

The paper is organized as follows. The crash of Flight 261 is described in Section 2. Section 3 presents the data and variables that are used in the empirical model. The results of the regression are provided in Section 4. Section 5 summarizes the conclusions.

2. Crash

Flight 261 was scheduled for January 31, 2000, from Puerto Vallarta, Mexico, to Seattle, Washington, with a layover in San Francisco, California. During the flight, the tail jackscrew, which adjusts the position of the tail control surfaces, separated from the acme nut holding it in place, causing the pilots to lose pitch control of the aircraft. With the aircraft no longer able to maintain horizontal stability, it nosedived into the ocean. All 88 passengers and crew on board died from blunt-force impact trauma.

An investigation by the National Aviation Safety Board determined that the crash resulted from poor maintenance (National Transportation Safety Board, 2002). The jackscrew was excessively worn due to poor lubrication, a lapse that was not caught earlier because the FAA allowed Alaska Airlines to extend the time intervals between maintenance events. Another cause of the crash was the absence on the aircraft, the McDonnell Douglas MD-80, of a fail-safe mechanism to prevent the effects of total acme nut thread loss. Altogether, the crash was due to poor maintenance on the airline's part and a manufacturing defect.

3. Model

The data are collected from the DB1B database, a 10 percent quarterly sample of all domestic airline tickets provided by the U.S. Department of Transportation. In order to observe the change in prices on the routes of the crash airline, only airport-pairs served by Alaska Airlines are used in the analysis. The sample spans eight quarters: the second quarter of 1999 to the first quarter of 2001. As the Alaska Airlines crash took place in January of 2000, the sample considers ticket prices before and after the crash.[2] Only round-trip flights are included. Itineraries with more than 4 ticket coupons (flight segments) are excluded, as are those with fares of zero. Fares are divided in half so as to count each direction of round-trip itineraries separately. Additionally, directionality is suppressed, with each observation recorded as a one-way trip within an airport-pair (i.e., a flight from San Francisco to Los Angeles is considered to be in the same market as a flight from Los Angeles to San Francisco). Both direct and connecting flights are included, using a dummy variable *connect* to represent a connecting flight. After aggregating and filtering for unusable data, 31,553 observations remain.[3]

The data set provides the number of passengers who paid the same fare for a specific market and carrier during a given quarter. Therefore, different fares on the same flight will generate separate observations. The fares are aggregated for each market i, carrier c, quarter t, also separating non-stop and connecting flights, with the fares weighted by the number of associated passengers. The log of the resulting passenger-weighted average fare is denoted *lfare*.

To separate the ramifications of the crash on fares from market variations unrelated to the accident, three variables to distinguish market characteristics are created. The first is population, collected from the 2000 U.S. Census. The variable, denoted pop_i, is calculated as the geometric mean of the populations of the endpoint cities in each market. Higher demand on a route may raise fares but it may also tend to reduce them via economies of traffic density (which reduces airline costs as traffic rises).

The second control variable is distance for the market, denoted $dist_i$, which is also provided by the DB1B data bank. The variable takes the same value for all direct flights, but may vary across connecting flights, based on location of the layover. Therefore, a passenger-weighted average value is computed for connecting flights when the data is aggregated to the market-carrier-quarter-connect level. As distance increases, passengers are faced with fewer substitutes to flying, which could raise fares. Higher airline costs for longer flights would have the same effect.

A third characteristic is the market temperature differential ($temp_i$), representing the absolute value of the difference between the average January temperatures at the endpoints of the market. Since a large value signifies a leisure market, where consumers would travel to a location whose temperature is different from their origin, a negative fare effect of $temp_i$ is expected.

Competition variables capture how many other carriers are offering service in the market each quarter. The variables capture two types of competition: nonstop competition ($nscomp_{it}$) and connecting competition ($concomp_{it}$). The goal is to provide more insight into which kind of competition has a larger effect on fares. An increase in the number of competitors is expected to decrease prices.

Quarter dummies, denoted δ_t, are included to capture temporal effects, one for each of the eight quarters in the sample. $Post_{1t}$ is a dummy that accounts for the crash. It is activated post crash, being assigned a value of 0 in the pre-crash quarter (quarters 2 through 4 of 1999), $\frac{2}{3}$ during the crash quarter, and 1 in the post-crash quarter. The reasoning for the $\frac{2}{3}$ value during the crash quarter is that the crash occurred $\frac{1}{3}$ of the way into this quarter, so two-thirds of the ticket data are from after the crash. Since, as mentioned earlier, the ticket data are provided quarterly, there is no way to separate tickets into those right before or right after the crash.[4]

A drawback of using this data set is it does not provide the ticket purchase date. It is therefore unknown how far in advance passengers purchased their tickets, so that whether the purchase date is during the quarter of the scheduled flight or in the previous quarter is unclear. This lack of information means that some tickets used during the last part of the first quarter or during the second quarter of 2000 could have been purchased prior to the crash. Nevertheless, using the dummy $post_t$ is the best way to capture the effect of the crash, given the available data.

The dummy variable AS_c indicates that the reporting carrier is Alaska Airlines. Multiplying AS_c and the variable $post_{1t}$ creates an interaction variable that captures the change in fares of Alaska Airlines following its crash, and it is the variable of interest in this study. The resulting framework thus embodies a difference-in-difference approach.

In addition to the way of defining the variable $post_{1t}$ described above, the paper considers four modifications of that variable. The first approach creates a second variable $post_{2t}$ that equals two-thirds for observations in the crash quarter (the first quarter of 2000), and 0 otherwise. Under this approach, fare impacts are expected only during the crash quarter, dissipating in the following quarter. Another approach creates a third variable $post_{3t}$ that equals 1 for observations in the second quarter of 2000 (the quarter after the crash), and 0 otherwise. This approach assumes that, with advance purchase of tickets, fare effects would not materialize in the weeks following the crash, showing up only in the subsequent quarter. The remaining adaptations of the variable test for extended effects. $Post_{4t}$ and $post_{5t}$ are activated in the third and fourth quarters of 2000, respectively. The values of the variations of the *post*

[2] Previous research on the effect on stock prices suggests that a market reaction to a crash is not prolonged.

[3] The dataset initially contained 37,930,172 observations.

[4] Since the crash could affect fares for only $\frac{2}{3}$ of the quarter, failure to use $\frac{2}{3}$ rather than 1 as the dummy value would lead to a coefficient that misstates the percentage fare impact on post-crash fares.