Gettysburg Economic Review

Volume 10 Article 6

2017

The Effects of Airline Behavior on Aircraft Accidents

Anneliese S. Soderberg
Gettysburg College
Class of 2017

The Effects of Airline Behavior on Aircraft Accidents

Abstract

The purpose of this paper is to study the effects of specific airline business decisions on aircraft accident propensity. Airline safety affects everyone and has large regulatory and policy implications. Existing research has focused largely on three areas: airline financial health, safety and the resulting effects of accidents. I use both Poisson and Negative Binomial models to study two different airline features: low-cost carriers and flight length, and how they relate to the probability of an aircraft accident. Based on results using a Generalized Negative Binomial model, I find statistically significant evidence at the 99% confidence level that a 1-unit increase in the flight length leads to a 0.11% decrease in the number of accidents. I also find statistically significant evidence at the 99% confidence level that when an airline is classified as a low-cost carrier, the number of accidents decreases by 79.16%. These results indicate that a homogenous safety regulation framework is not appropriate for the airline industry with regard to flight length and cost structure.

Keywords

airline business, aircraft accident propensity, airline safety, aviation regulations, poisson binomial model, negative binomial model

The Effects of Airline Behavior on Aircraft Accidents

Anneliese S. Brown
Gettysburg College
Browan03@gettysburg.edu

April 17, 2017

Abstract:

The purpose of this paper is to study the effects of specific airline business decisions on aircraft accident propensity. Airline safety affects everyone and has large regulatory and policy implications. Existing research has focused largely on three areas: airline financial health, safety and the resulting effects of accidents. I use both Poisson and Negative Binomial models to study two different airline features: low-cost carriers and flight length, and how they relate to the probability of an aircraft accident. Based on results using a Generalized Negative Binomial model, I find statistically significant evidence at the 99% confidence level that a 1-unit increase in the flight length leads to a 0.11% decrease in the number of accidents. I also find statistically significant evidence at the 99% confidence level that when an airline is classified as a low-cost carrier, the number of accidents decreases by 79.16%. These results indicate that a homogenous safety regulation framework is not appropriate for the airline industry with regard to flight length and cost structure.

I. Introduction

This paper investigates the following two questions: Do budget or low-cost airlines have more aircraft accidents than their counterparts of legacy carriers? Do airlines that provide longer average flight routes have more airplane accidents than their counterparts?

Intuitively, it may be expected that budget airlines only take the minimum safety precautions in order to provide the same services as their counterparts for a lower cost. Thus, an airline classified as a budget airline may have more accidents than a non-budget airline as a result of less investment in safety. Alternately, budget airlines may spend more on safety in order to preserve their reputation and thus experience fewer accidents than their counterparts. A longer flight length may cause an increase in the number of accidents because the more time an aircraft is in the air, the more time there is for an accident to occur. Conversely, if the probability of an accident occurring is greatest during taxiing, takeoff and landing, operators who service short-haul flights may experience more accidents as they rely on quick turnaround times and incur a larger number of takeoffs and landings.

Existing research relating to these topics focuses on the subsequent effects of airplane accidents, the effect of an airline company's financial health on safety and the ways in which airlines make business decisions. The Poisson model for discrete independent variables is used consistently throughout the research related to accident rates. Using this model, existing research has found contradicting evidence on the statistical significance between financial health and safety (Wang, Hofer and Dresner, 2013; Rose, 1990; Golbe, 1986).

This paper closes the gap in existing research between business decisions and safety as I investigate the effect of business decisions, specifically whether or not the airline is a budget airline and flight routes, on accident rates. I make use of count models, specifically Poisson and

Negative Binomial, to answer my questions of interest because my dependent variable, number of accidents, is a positive count variable. While there is an abundant amount of existing research which uses the Poisson model and number of accidents as a dependent variable, no other research has combined these things with independent variables which relate specifically to deliberate business decisions such as flight length and whether or not an airline is a budget airline. Applying the Generalized Negative Binomial model closes a gap in existing research while also generalizing my conclusions by eliminating the assumption that the variance of my dependent variable is linear and equal to the mean.

This topic is important because it relates to issues of safety, transportation routes and business efficiency. Understanding the connection between a firm's decision making incentives and the frequency of accidents can help to prevent airplane accidents in the future through more effective regulation and improved business efficiency. Airlines adapt to changing economic environments while continuously aiming to maximize profits. Recognizing these decisions in relation to accident frequency may help businesses to understand the results of their actions and thus, change them accordingly to increase safety.

These research questions address issues of public policy and customer awareness, both nationally and internationally. The potential risks associated with flying are large and affect many more individuals than just those who fly. It is important for both consumers and the public to recognize the risks associated with flying, particularly if the risk is not uniform across airlines or flight routes. The results might help to determine if a universal regulatory framework for all types of airlines is the best form of safety-related policy.

The paper is organized as follows: In section II, I review related literature, important variables and common models used to answer similar questions. In section III, I outline the

Poisson and Negative Binomial models, my hypotheses and describe my research method. In section IV, I discuss the data and define each variable. In section V, I present the empirical results of my research. In section VI, I conclude my analysis with the implications and applicability of my results.

II. Literature Review

Existing research related to the effects of airline business decisions on aircraft accidents falls into two categories. A first line of this research focuses on safety as it relates to profits, financial health, investment and demand. A second line of this research studies business decisions as they relate to both topics of low cost competition and flight routes. My research provides a link between the existing yet isolated research on business decisions and safety.

First I discuss existing research relating to safety, and accidents in particular. A useful study is conducted by Golbe (1986), who examines the relationship between profits and safety precautions taken by an individual airline. She implements both cross-sectional and time-series techniques on data of U.S. airlines aggregated at the industry level from 1952 – 1972. Golbe (1986) emphasizes key variables of number of departures, load factors and net income, as a measure of profitability. Golbe (1986) uses airline accident experience as a measure of safety and models both accident experience and net income as dependent variables. Her research concludes that there is no significant relationship between profits and safety (Golbe 1986).

Bornstein and Zimmerman (1988) investigate the effect of an aircraft accident on flight demand using time series data for U.S. air carriers from 1960 - 1985, modeling revenue per passenger as a function of elapsed time since an accident, seasonal dummies, and firm and time fixed effects. They conclude that although an accident results in a significant \$4.5 million loss for a firm, there is not a significant relationship between accidents and flight demand before deregulation of the industry and only weak evidence of an effect on demand after deregulation (Bornstein and Zimmerman 1988).

Rose (1990) studies the effect of an airlines' financial health on accident rates using panel data across thirty-five U.S. airlines from 1957 - 1986. She measures safety as a risk distribution, gathering data on both safety investment and physical conditions in which firms operate their aircraft. Similar to Wang, Hofer and Dresner (2013), Rose (1990) uses the Poisson probability distribution to model the dependent variable of accident rate. Using fixed effects, Rose (1990) separately models both total accidents and fatal accidents as an effect of departures (system departures in thousands), average stage length (thousands of miles), carrier type, foreign flights, size of firm, airline operating experience (billions of miles) and time variant characteristics of technology. While I use some of the same variables, all of my models use only total accidents as the dependent variable. She concludes that an increase in operator profit leads to a statistically significant decrease in accident rates (Rose 1990).

Wang, Hofer and Dresner (2013) measure the effect of safety investment on accident propensity and financial health. They use panel data on airlines from the National Transportation Safety Board (NTSB) and the U.S. Department of Transportation (DOT) from 1991 – 2008. Due to the entry and exit of airlines within the industry, they treat their panel dataset as unbalance. These authors model Poisson functions of number of accidents as I will do in this paper. Further, they create a variable for average accidents per departure, substituting this as the dependent variable in their reduced form model. They conclude that safety investment reduces accident propensity and find no relationship between financial condition and accident propensity nor financial condition and safety investment (Wang, Hofer and Dresner 2013).

Other pertinent research emphasizes airline business decisions in relation to budget airlines and flight routes. Fischer and Kamerschen (2003) examine the relationship between low-cost operator presence at airports and average airfare. They use the DOT's form 41 for Air Carrier Traffic Statistics to crease a time-series data consisting of the four quarters of 1996. They use a cross section regression model in which the dependent variable is average yield (price/distance) with independent variables including total passengers, distances (stage length) and ValueJet. They measure ValueJet as a binary variable valued at 1 if the airline ValueJet services a particular airport and 0 otherwise; this variable accounts for the presence of low cost carriers at any given airport. Fischer and Kamerschen (2003) conclude that the presence of low-cost competition for a particular route has a statistically significant negative effect on revenue.

Garrow, Holte and Mumbower (2012) study the phenomenon of product de-bundling as it relates to the emergence of low-cost carriers. They collect airline data from individual airline websites regarding baggage fees, cancelation fees, seat fees and ticket change fees. They find statistically significant evidence that low-cost carriers are the most likely carriers to charge additional fees.

Gillen and Hazledine (2015) study the effect of regional route fluctuations on firm pricing strategy. They use data from a total of six regions on various flight routes and use the Hirschman-Herfindahl index to account for airline concentration. They find no significant relationship between supply of seats and route length but find a significant difference in airfares across regions (Gillen and Hazledine 2015).

The limitation of prior research addressed in this paper is the lack of research examining the cause of accidents as related to business decisions. Although there is abundant research on airline safety and business decisions relating to budget airlines and flight routes, these topics have only been studied in isolation from each other. Current research focuses on the effects of accidents but little has been examined regarding the cause of the accidents. My research utilizes many of the same variables, models and tests as those introduced above but I investigate the link between these industry characteristics and accidents to determine the effect of both flight length and budget airlines on accidents.

III. Model and Methodology

I test whether budget airlines have more accidents than their counterparts and whether an increase in flight length leads to an increase in the number of aircraft accidents using a unified model. I hypothesize that budget airlines have more accidents than their counterparts as budget airlines may cut safety costs in order to provide cheaper fares than legacy or non-budget airlines. I expect an increase in flight length to cause a decrease in the number of accidents as I suspect that operators who provide long-haul flights invest more in safety and experience fewer takeoffs and landings, which are most damaging to the engines and aircraft, than operators who provide more frequent short-haul services.

I use a unified Negative Binomial model to answer my two questions of interest because of the similarity in potential control variables. I have included control variables which intuitively affect aircraft accidents without being directly related to flight length or whether or not an airline is a budget airline.

Similar to previous research such as that of Wang, Hofer and Dresner (2013) and Rose (1990), I begin by using the Poisson model to estimate the relationship between flight distance, budget airlines and accidents. The Poisson model is applicable to this data set because the dependent variable, aircraft accidents, is a count variable. This model requires the dependent variable to be a discrete, non-negative value including zero, which is true of aircraft accidents.

As the number of accidents may equal zero for any given year, we cannot take the log of the dependent variable. Instead, I use the following exponential function:

$$E(y|x_1, x_2, \ldots, x_k) = \exp(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k) = \exp(X_{it}\beta) \quad (1)$$

Where x_{it} represents various independent or control variables for airline i at time t while β represents corresponding estimated coefficients. However, with the Poisson model, equation 1 can be simplified because the distribution is determined by the mean; in fact, the mean and variance of Y are equal in the Poisson model. This is represented in the following equation:

$$P(Y_{it}) = (\exp[-\exp(x_{it}\beta)][\exp(x_{it}\beta)^{Y_{it}}] / Y! \quad (2)$$

Where $P(Y_{it})$ is the probability of Y accidents for airline i at time t, $\exp(x_{it}\beta)$ is the expected number of accidents for airline i at time t or the average accident rate per departure and Y = 0, 1, 2, …, $\exp(x_{it}\beta) > 0$.

Further, in the Poisson model, the mean and the variance are equal. This is represented in the following equation:

$$E(Y_{it}) = \exp(x_{it}\beta) = Var(Y_{it}) \quad (3)$$

However due to the nature of accident rates, there may be more or less variation in the data than expected under Poisson. Thus, the Negative Binomial model may provide a better fit for the relationship of interest as the Poisson model may produce biased coefficient estimates in the presence of over- or under-dispersion (Shankar, Mannering and Barfield, 1995).[8] As shown

[8] As stated by Shankar, Mannering and Barfield (1995), "It is well known, based on the finding of many previous research efforts, that accident frequency data tend to be over-dispersed, with the variance being significantly greater than the mean" (Shankar, Mannering and Barfield, 1995).

by Shankar, Mannering and Barfield (1995), who study the effect of roadway accidents using the Negative Binomial model, equation 3 can be altered to represent the relationship with a Negative Binomial model in the following way:

$$Var(Y_{it}) = E(Y_{it})[1+ \alpha E(Y_{it})] \qquad (4)$$

From the above equation, the variance is no longer equal to the mean when using the Negative Binomial model due to the existence of the term $[1 + \alpha E(Y)]$, when $\alpha E(Y) \neq 0$. When α is equal to 0, Var(Y) = E(Y) and I am left with variance which is represented in the Poisson model. However, when α is not equal to zero, there is evidence of either over - or under-dispersion. It is important to note that the Negative Binomial model is only applicable in the presence of over-dispersion using the Poisson distribution, in which the variance is greater than the mean; when there is under-dispersion using the Poisson distribution, the Negative Binomial model is not valid (Shankar, Mannering and Barfield, 1995). As used by Shankar, Mannering and Barfield (1995), the following equation represents the probability distribution using the Negative Binomial model:

$$P(Y_{it}) = \frac{\Gamma(\theta + Y_{it})}{\Gamma(\theta) Y_{it}!} (u_{it}{}^{\theta})(Y_{it})(1 - u_{it}) \qquad (5)$$

Where $u_{it} = \theta/(\theta + \exp(x_{it}\beta))$, $\theta = 1/\alpha$ and $\Gamma()$ represents a function of gamma (Shankar, Mannering and Barfield, 1995).

I will also implement the Generalized Negative Binomial model in which the form of the variance is not assumed to be linear, as it is in the Negative Binomial model. Thus, the Generalized Negative Binomial model makes my results more precise as the form of the variance is not assumed to be linear.

In my regression, I specify the following model:

$$E(Accidents_{it}) = Departures_{it} * \exp(\beta_0 + \beta_1 Budget\ Airline_{it} + \beta_2 Average\ Stage \qquad (6)$$

$\text{Length}_{it} + u_{it})$

Consistent with existing research, the expected number of accidents is the number of departures multiplied by the average accident rate per departure because of the stochastic or random nature of accident data (Wang, Hofer and Dresner, 2013; Rose, 1990).

Based on equation 6, my hypothesis that budget airlines are less safe is supported when $\beta_1 > 0$. When an airline is considered to be a budget airline and β_1 is positive, there is a positive effect on the expected value of accidents and thus my hypothesis is supported. My hypothesis that an increase in average flight length leads to a decrease in accidents is supported when $\beta_2 < 0$, as an increase in the average stage length should be negatively related to the number of accidents, according to my prediction.

IV. Data

I use data from the National Transportation Safety Board (NTSB), Federal Aviation Administration (FAA) and the Bureau of Transportation Statistics (BTS) as has been used in previous research. To minimize measurement errors, I make use of a consolidated data set from the Airline Data Project at Massachusetts Institute of Technology (MIT) which contains data from the BTS form 41 which gathers quarterly billing data and monthly airline data. Using these data sources, I construct a panel data set which varies across fifteen U.S. airlines over twenty-one years, from 1995 through 2015. Data on all fifteen airlines in the MIT project is included; a list of these airlines along with the years for which data is available for each airline can be found in table 1 of section VIII.

Due to mergers and acquisitions within the industry, there is no data for all twenty-one years for all fifteen airlines. It is important to note that while this is considered “missing data” in terms of the raw data, the data is not in fact missing as the airlines simply were not in existence or operating during the years in which I do not have data. I have verified with individual airline websites that the years in which there is "missing data" align with mergers, acquisitions, entries or closings within the industry. Because of these gaps in the data, together with the fact that my panel is relatively narrow in the sense that I only include data on fifteen airlines, I continue my analysis by treating my panel data set as cross sectional data as done by Golbe (1986).[9]

I use a dependent variable of aircraft accidents as used by Golbe (1986) Borenstein and Zimmerman (1988), and Rose (1990) and Wang, Hofer and Dresner (2013). I have gathered the information from the FAA which has the NTSB's Accident and Incident Database. According to the FAA Aviation Safety Information Analysis and Sharing (ASIAS), an aircraft accident is defined as "an occurrence associated with the operation of an aircraft which takes place between the time any person boards the aircraft with the intention of flight and all such persons have disembarked, and in which any person suffers death or serious injury, or in which the aircraft receives substantial damage" (ASIAS). I have included all U.S. aircraft accidents, including fatal and non-fatal, from January 1995 through December 2015 for all fifteen airlines used in my dataset. Due to the nature of aircraft accidents, this variable is a non-continuous, discrete count variable.

In order to answer my question regarding the effect of flight length on accident propensity, my primary independent variable of interest is average stage length which is used by Golbe (1986), Rose (1990) and Wang, Hofer and Dresner (2012). This variable is available in the consolidated MIT study, which pulls data from the BTS form 41, and measures the total number

[9] I report results using fixed effects in tables 9 and 10 of section VIII. While the signs of the average stage length and budget airline variable coefficients are the same when implementing cross sectional data methods, neither coefficient is statistically significant at even the 10% significance level.

of miles flown divided by the total number of departures. Thus, the average stage length represents average flight length of each departure, measured in miles.

In order to answer my question regarding the effect of being a budget airline on accident propensity, I have investigated three potential independent variables including a dummy variable, total baggage fee and total cancelation fee. Based on the research of Garrow, Holte and Mumbower (2011), who study the phenomena of product de-bundling in the airline industry, I have created a binary variable valued at 1, which is attributed to a budget or low-cost carrier and 0, which is attributed to a non-budget or legacy airline. Their research includes a total of eleven U.S. airlines, ten of which I also include in my data set. Although Garrow, Holte and Mumbower (2011) do not precisely define budget or legacy carriers, they state that the legacy carriers "participate in well-established alliances that enable them to further increase the number of destinations they can serve; these major carriers also tend to have a moderate number of other airline partners that further enhance their networks" (Garrow, Holte and Mumbower, 2011). Based on their classification of low cost carriers, I identify the following same four budget airlines: Southwest, AirTran, JetBlue and Frontier.[10] I classify the remaining eleven airlines in my data set as legacy or non-budget airlines, six of which are also considered to be legacy carriers by Garrow, Holte and Mumbower (2011). Thus, I assume that the five airlines included in my data set, but not included in the specific reference literature, are also legacy carriers.

I have also included total baggage fees and total cancelation fees as potential key independent variables to account for budget airlines. I have gathered both fee variables from the consolidated MIT study, both of which are measured in thousands of U.S. dollars. I use the

[10] In conducting further company research, I find both Allegiant Air and Sprit to be considered budget airlines. While I do not include these classifications in my primary results, tables 11 and 12 in section VIII show the results of my research with additionally categorizing both Allegiant Air and Spirt as budget airlines.

conclusion of Garrow, Holte and Mumbower's (2011) research that budget airlines are the most likely to charge additional ancillary fees. Thus, I use the fee variables, interchangeably, as proxy variables to represent an airline behaving "more like a budget airline." I assume that a 1-unit increase in either fee variable indicates an airline behaving more like a budget airline. However, due to structural breaks and variation across low-cost carriers, as mentioned by Garrow, Holte and Mumbower (2011), there is potential bias in the way these fee variables may represent budget airlines. Due to the difficulty in defining a budget airline precisely, as shown in previous research, I include all three variables (baggage fee, cancelation fee, budget airline) to interchangeably account for budget airlines.

I use the number of incidents reported for each airline in each year, from the FAA ASIAS as done by Rose (1990). An incident is defined as "an occurrence other than an accident, associated with the operation of an aircraft, which affects or could affect the safety of operations" (ASIAS). Due to the nature of aircraft incidents, this variable is a non-continuous, discrete count variable. As I have not been able to include the average age of the aircraft, I presume that incidents will work to control for age of aircraft-related characteristics, which may affect accidents as an increase in incidents intuitively leads to an increase in the probability of an accident.

The following control variables that I mention are all gathered from the MIT project and thus the BTS form 41. I control for size of aircraft by dividing average seat miles (ASM) by the total number of miles flown. ASM is an industry standard measurement of utilization and airline output and measures the total number of available seats per departure multiplied by the total number of miles traveled. However, because ASM includes mileage, there is potential for collinearity with my independent variable of interest, average stage length. Thus, I divide ASM by miles and am left with the average number of seats per departure.

I control for airline size by including the number of functioning aircraft and total operating revenue measured in billions of U.S. dollars. I include the average salary of both pilots and co-pilots, measured in U.S. dollars, to control for pilot experience and skill level. I include maintenance per aircraft in which I divide the total maintenance expenditure, measured in thousands of U.S. dollars, by the total number of aircraft in the fleet to account for maintenance cost per aircraft. Summary statistics of all variables can be found in table 2 of section VIII.

While I attempt to create a robust data set including industry standard, intuitively sound and previously used variables, I have not been able to collect data on average aircraft age and airline profitability. Aircraft incidents may serve as a proxy variable for aircraft age while total revenue may serve as a proxy variable for profitability, although neither fully capture the effect of the absent variables.

V. Results

I present my basic Poisson regressions in table 3 of section VIII. In running the most simplified regression presented in column 1, the sign of the coefficient of interest in positive and statistically significant at the 99% level. When I include control variables to the same model, as seen in columns 2 and 3 of table 3, the estimated coefficient of the average stage length variable becomes negative while remaining statistically significant. The results in column 1 indicate that a 1-unit increase in flight length leads to a 0.059% increase in the number of accidents while the results in columns 2 and 3 indicate that a 1-unit increase in average stage length leads to a 0.10% decrease in the number of accidents, which are all statistically significant at the 99% confidence level. Further, seen in the regressions in columns 2 and 3 of table 3, when an airline is a budget airline the number of accidents decreases by 61.74% and 61.41%, respectively.[11]

Based on the regression represented in column 3 of table 3 in section VIII, I run both Deviance and Pearson goodness-of-fit tests. With P-values of 0.0017 and 0.0005, respectively, I reject the null hypothesis that the Poisson model fits my relationship of interest well.

The regressions in table 5 utilize the Negative Binomial model. The basic regression in column 1 indicates that a 1-unit increase in the average flight length leads to a 0.07% increase in the number of accidents which is statistically significant at the 5% significance level. This positive sign of the coefficient is similar to that of the basic regression using the Poisson model shown in column 1 of table 3. When I implement the Negative Binomial model and run the LR test of alpha = 0, I get a P-value of 0.000. Thus, I reject the null hypothesis that alpha is equal to zero and conclude the Negative Binomial model to be a good fit for my data as I find over-dispersion and cannot assume the variance of accidents to be equal to the mean or for alpha to be equal to 0.[12]

When I include control variables to the basic Negative Binomial model, as seen in columns 2-5 of table 5, the estimated coefficient of the average stage length variable becomes negative. The difference between the regressions represented in columns 2-4 is the variable in which I use to account for budget airline. In column 2 of table 5, I include the baggage fee variable while in column 3 of table 5, I include the cancelation fee variable. Intuitively I expect an increase in baggage or cancelation fees to lead to an increase in the number of accidents, as I assume that airlines that charge higher fees behave more similarly to budget airlines. From the

[11] The output in table 4 of section VIII represents the marginal effect interpretations associated with the Poisson regressions represented in table 3.
[12] Further, because the mean of accidents is 1.28 while the variance is 3.43, I can simply identify the presence of over-dispersion within my data.

regression output seen in columns 2 and 3, neither estimated coefficient of the baggage nor cancelation fee variable is statistically significant at even the 90% confidence level. Due to the insignificance of the estimated coefficients, structural breaks and potential measurement error, I conclude that neither baggage nor cancelation fees accurately represent budget airlines.[13]

The regressions represented in columns 4 and 5 of table 5 include a binary budget airline variable as opposed to a fee variable to account for budget airlines. Both regressions show that a 1-unit increase in the average stage length leads to 0.11% decrease in the number of accidents, which is statistically significant at the 1% significance level. The estimated coefficients of the budget airline variable are large in magnitude and statistically significant at the 99% level; I find that when an airline is a budget airline, the number of accidents decreases by 71.84% and 79.16%. It is worth noting the changes in significance of the estimated coefficients of the average stage length, maintenance per aircraft, number of seats and incidents variables from column 3 to column 4.[14] The large magnitude of the budget airline coefficients in columns 4 and 5 may be explained by the measurement error in the variable and thus I am not confident in these conclusions drawn to answer my question regarding the effect of budget airlines on accident propensity.

The regressions represented in table 7 are the same as those presented in table 5, although they implement the Generalized Negative Binomial model as opposed to the Negative Binomial model. The results are almost identical to those of the Negative Binomial model but because the generalized model even further loosens the assumptions of the variance structure, I have decided

[13] The output in table 6 of section VIII represents the marginal effect interpretations associated with the Negative Binomial regressions represented in table 5.
[14] In line with previous literature, I also run these regressions with an added time trend variable in order to account for advances in technology over time which may decrease accident propensity. However, because the estimated coefficient of the time trend variable is consistently statistically insignificant, I do not include it in my final results.

to treat the regression in column 5 of table 7 as my final regression. As some of the estimated coefficients in the regression represented in column 4 of table 7 are not statistically significant at even the 90% confidence level, I run the regression in column 5 of table 7 in order to more accurately estimate the coefficients of interest.

From the regression output represented in column 5 of table 7, I have statistically significant evidence at the 1% significance level that a 1-unit increase in average stage length leads to a 0.11% decrease in the number of accidents while I have statistically significant evidence at the 1% significance level that when an airline is classified as being a budget airline, the number of accidents decreases by 79.16%. All of the signs of the estimated coefficients align with intuition.[15]

The negative and statistically significant coefficient of the average stage length variable does not align with the research of Wang, Hofer and Dresner (2013) nor Rose (1990), who both find statistically significant positive coefficient estimates.[16] However, the negative sign of the average stage length coefficient does align with the findings of Golbe (1986) though she does not find the negative average stage length coefficients to be statistically significant at any level.

VI. Conclusion

From the previous section, I conclude that there is statistically significant evidence at the 1% significance level that a 1-unit increase in average stage length leads to a 0.11% decrease in

[15] The output in table 8 of section VIII represents the marginal effect interpretations associated with the Negative Binomial regressions represented in table 7. Column 5 of table 8 in section VIII represents the marginal effects corresponding to my final regression in which a 1-unit increase in average flight length is associated with 0.00093 fewer accidents and an airline being a budget carrier is associated with 0.57 fewer accidents.

[16] Wang, Hofer and Dresner (2013) find statistically significant evidence at the 1% level that "longer stage lengths are associated with a higher accident propensity" (Wang, Hofer and Dresner, 2013).

the number of aircraft accident. I have statistically significant evidence at the 1% significance level that when an airline is a budget airline, the expected value of an accident decreases by 79.16%.

As stated in section III, I hypothesize that an increase in the average stage length leads to a decrease in the number of accidents as operators who provide short-haul services incur more takeoffs and landings, which put the engines and aircraft under the most stress. Based on the negative sign of the coefficient of the average stage length variable, this hypothesis is supported. I also hypothesize the number of accidents increases when an airline is a budget airline as budget airlines may spend less on safety in order to provide comparable services to non-budget airlines. However, due to the negative sign of the estimated coefficient of the binary budget airline variable, my hypothesis relating to budget airlines is not supported.

Intuitively the negative and statistically significant, at the 99% level, coefficients of both independent variables of interest may be explained by airline business decisions. Based on my results, an increase in average flight length leads to a decrease in the number of accidents. This may mean that carriers that provide longer flights put more resources toward flight safety as opposed to carriers which provide flights with shorter average stage lengths.[17] After further investigating the specific position of each accident during the flight, I find that 30.58% of accidents occur while the aircraft is on the ground, 16.25% of accidents occur while at cruising level, 44.35% occur during either takeoff or landing and 8.82% of accidents occur with an "other" or undefined reason. Thus, it makes sense that short-haul carriers, that experience a larger number of takeoffs and landings, have more accidents as 44.35% of accidents occur at

[17] In testing the effect of average stage length on maintenance expenditure per aircraft, I find statistically significant evidence that a 1-unit increase in flight length leads to an increase in maintenance expenditure per aircraft. Thus I conclude that longer-haul carriers have higher expenditure on maintenance per aircraft than that of their counterparts.

takeoff and landing. Conversely, it makes sense that airlines that provide longer flight lengths have fewer takeoffs and landings than their short-haul provider counterparts and thus incur a smaller number of accidents. These results indicate that airlines that provides longer-haul flights have inherently different operating methods and flight safety structures than those of shorter-haul carriers.

Based on the results, when an airline is a budget airline, the number of accidents decreases by an extremely large magnitude. Although these results may support the idea that budget airlines may be sensitive to an unsafe reputation and thus may allocate more resources toward safety than that of their counterparts in order to maintain strong reputations of safety, after further investigation I find, this is not the case.[18] While these results indicate that budget airlines have different safety structures than that of non-budget or legacy airlines I am not confident in my results regarding the budget airline variable. The unrealistically large coefficient signifies an error within the application. I suspect measurement error of the budget airline variable to be a large potential issue within my model which leaves me with little confidence in my results associated to the budget airline variable.[19]

Ultimately these results indicate that a homogenous airline regulation framework is not appropriate for budget nor long-haul airlines. With statistically significant evidence that both an increase in average flight length and an airline being a budget airline lead to a decrease in the number of aircraft accidents, it is apparent that not all airlines should be held to identical

[18] In further investigation, I find statistically significant evidence at the 1% level that budget airlines spend less on maintenance per aircraft than non-budget airlines.

[19] It is worth noting that in testing the difference between accident rates of budget and non-budget airlines, I find the mean of accidents for budget airlines to be .8133 while that of non-budget airlines is 1.45. Thus my regression results and conclusions align with the variable within my data set; thus I assume there to me measurement error within the variable and an “outside” factor affecting the large decrease in accident rate of budget airlines.

benchmarks. Airline business decisions have shown to significantly affect aircraft accident rates; thus airlines should be regulated and upheld to specific standards based on these decisions.

VII. References

Works Cited

Bornstein, Severin, and Martin Zimmerman. "Market Incentives for Safe Commercial Airline Operation." *American Economic Review* 78.5 (1988): 913-35.

Cameron, Adrian Colin, and Pravin K. Trivedi. *Microeconometrics Using Stata*. College Station, Texas: Stata, 2010.

FAA Accident and Incident Data System (AIDS). N.d. Raw data. U.S. Department of Transportation Federal Aviation Administration, Washington, DC.

Fischer, Thorsten, and David R. Kamerschen. "Measuring Competition in the U.S. Airline Industry Using the Rosse-Panzar Test and Cross-Sectional Regression Analysis." *Journal of Applied Economics* 6.1 (2003): 73-93.

Garrow, Laurie A., Susan Hotle, and Stacey Mumbower. "Assessment of Product Debundling Trends in the US Airline Industry: Customer Service and Public Policy Implications." *Transportation Research Part A: Policy and Practice* 46.2 (2012): 255-68.

Gillen, David, and Tim Hazledine. "The Economics and Geography of Regional Airline Services in Six Countries." *Journal of Transport Geography* 46 (2015): 129-36.

Golbe, Devra L. "Safety and Profits in the Airline Industry." *The Journal of Industrial Economics* 34.3 (1986): 305-18.

Greene, William H. *Econometric Analysis*. 2nd ed. New York, NY: Maxwell Macmillan International Group, 1993.

Gujarati, Damodar N. *Basic Econometrics*. New York: McGraw-Hill/Irwin, 2003. Print.

NTSB Aviation Accident and Incident Data System (NTSB). N.d. Raw data. U.S. Department of Transportation Federal Aviation Administration, Washington, DC.

Rose, Nancy L. "Profitability and Product Quality: Economic Determinants of Airline Safety Performance." *Journal of Political Economy* 98.5 (1990): 944-64.

Shankar, Venkataraman, Fred Mannering, and Woodrow Barfield. "Effect of Roadway Geometrics and Environmental Factors on Rural Freeway Accident Frequencies." *Accident Analysis & Prevention* 27.3 (1995): 371-389.

Swelbar, William S., and Peter P. Belobaba. Global Airline Industry Program; Airline Data Project. N.d. Raw data. Massachusetts Institute of Technology, Cambridge, MA.

Wang, Zuozheng, Christian Hofer, and Martin Dresner E. "Financial Condition, Safety Investment and Accident Propensity in the US Airline Industry: A Structural Analysis." *Transportation Research Part E: Logistics and Transportation Review* 49.1 (2013): 24-32.

Wooldridge, Jeffrey M. *Introductory Econometrics: A Modern Approach*. 5th ed. Mason: Cengage Learning, 2013.

Wooldridge, Jeffrey M. *Introductory Econometrics: A Modern Approach*. 6th ed. Boston: Cengage Learning, 2016.

VIII. Supporting Tables

Table 1: Airlines included in the Analysis and Available Observations for Each Airline

Airline	Available Data (Inclusive)
AirTran Airways	1995 - 2011
Alaska Airlines	1995 - 2015
Allegiant Air	2000 - 2015
America West Airlines	1995 - 2007
American Airlines	1995 - 2015
Continental Airlines	1995 - 2011
Delta Air Lines	1995 - 2015
Frontier Airlines	1995 - 2015
Hawaiian Airlines	1995 - 2015
JetBlue Airways	2000 - 2015
Northwest Airlines	1995 - 2009
Southwest Airlines	1995 - 2015
Spirit Airlines	1995 - 2015
United Airlines	1995 - 2015
US Airways	1995 - 2014

Table 2: Summary Statistics

Airline	Units	Observations	Mean	Standard Deviation	Minimum	Maximum
Number of Accidents	Count	283	1.282686	1.852146	0	9
Average Stage Length	Total Miles Flown / Aircraft Departures	282	935.0396	278.6823	256.0417	1720.326
Budget Airline	Binary	282	.2659574	.4426272	0	1
Baggage Fee	Thousand U.S. $	252	108026.3	198955.6	20.54	1125846
Cancelation Fee	Thousand U.S. $	237	267122.2	460147.5	2690.4	3117848
Number of Aircraft in Fleet	Count	282	265.3815	235.9029	.9863014	971.8904
Pilot and Co-Pilot Average Salary	U.S. $	260	130379.8	113164.9	16694.64	1859096
Maintenance Per Aircraft	Maintenance Expenditure ($1,000)/ Fleet Size	264	2420.938	996.9043	428.5007	5586.672
Total Revenue	Billion U.S. $	274	8.340641	9.127099	.0536117	41.08443
Number of Incidents	Count	287	8.355401	10.39193	0	58
Number of Seats	ASM / Miles	282	160.6285	32.88094	93.34768	265.6832

Table 3: Poisson Regressions
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)
Average Stage Length	.0005898 (.0001858)***	-.0010085 (.0003297)***	-.001009 (.0002927)***
Budget Airline		-.6174235 (.2218317)***	-.6140813 (.1752401)***
Maintenance / Aircraft		-.0002912 (.0001192)**	-.0003702 (.000085)***
Fleet Size		.0041103 (.0006356)***	.0042339 (.0003065)***
Pilot Salary		-9.72e-07 (1.41e-06)	
Number of Seats		-.0036111 (.0041183)	
Number of Incidents		.0033688 (.0055896)	
Total Revenue		.0030551 (.0154579)	
Intercept	-.3181392 (.1898117)*	1.181443 (.7035263)*	.6731913 (.2754536)**
Robust Standard Errors?	No	Yes	Yes
Pseudo R^2	0.0095	0.3019	0.3031
Chi Squared	9.96	222.40	216.34
Number of Observations	282	260	264

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 4: Poisson Regression Interpretations (Marginal Effects)
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)
Average Stage Length	.0007448 (.00023)***	-.0008845 (.00029)***	-.0008721 (.00025)***
Budget		-.4748103 (.1541)***	-.4656173 (.12154)***
Maintenance / Aircraft		-.0002553 (.0001)**	-.00032 (.00007)***
Fleet Size		.0036048 (.00055)***	.0036592 (.00023)***
Pilot Salary		-8.53e-07 (.00000)	
Number of Seats		-.003167 (.0036)	
Number of Incidents		.0029544 (.0049)	
Total Revenue		.0026794 (.01355)	

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 5: Negative Binomial Regressions
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	.0007184 (.0003591)**	-.0005928 (.0002924)**	-.0006922 (.0003893)*	-.0011078 (.000349)***	-.0011111 (.0003296)***
Budget Airline				-.7184402 (.2333835)***	-.7916491 (.2245004)***
Baggage Fee		7.40e-07 (7.01e-07)			
Cancelation Fee			3.28e-07 (2.61e-07)		
Maintenance / Aircraft		-.0002036 (.000133)	-.0000663 (.0001418)	-.0002223 (.0001257)*	-.0002559 (.0001094)**
Fleet Size		.0044434 (.0009075)***	.0042938 (.0010027)***	.0042367 (.0006174)***	.0044162 (.0002986)***
Pilot Salary		-1.80e-06 (2.05e-06)	-3.28e-06 (2.90e-06)	-9.61e-07 (1.14e-06)	
Number of Seats		-.0018323 (.0040688)	-.0036962 (.0043345)	-.0064759 (.0043613)*	-.0060738 (.0040212)
Number of Incidents		.0132486 (.0059269)***	.018139 (.0079114)***	.0037346 (.0058818)	
Total Revenue		-.0226676 (.0324717)	-.0210113 (.0333182)	.0033395 (.0155194)	
Intercept	-.441502 (.353355)	.2237119 (.6562952)	.4707563 (.663461)	1.538596 (.7558503)*	1.450162 (.6742874)**
Robust Standard Errors?	No	Yes	Yes	Yes	Yes
Pseudo R^2	0.0046	0.1718	0.1676	0.1864	0.1865
Chi Squared	4.00	225.76	225.04	254.70	237.78
Number of Observations	282	244	230	260	264

Notes: Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 6: Negative Binomial Regression Interpretations (Marginal Effects)
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	.0009044 (.00045)**	-.00056 (.00028)**	-.0005847 (.00033)*	-.0009521 (.0003)***	-.0009337 (.00027)***
Budget Airline				-.5315556 (.15305)***	-.5652535 (.1409)***
Baggage Fee		6.99e-07 (.00000)			
Cancelation Fee			2.77e-07 (.00000)		
Maintenance / Aircraft		-.0001924 (.00012)	-.000056 (.00012)	-.0001911 (.00011)*	-.0002151 (.00009)**
Fleet Size		.0041975 (.00086)***	.0036268 (.00083)***	.0036416 (.00054)***	.0037113 (.00024)***
Pilot Salary		-1.70e-06 (.00000)	-2.77e-06 (.00000)	-8.26e-07 (.00000)	
Number of Seats		-.0017309 (.00385)	-.0031221 (.00365)	-.0055662 (.00374)	-.0051043 (.00338)
Number of Incidents		.0125155 (.00569)**	.0153216 (.00691)**	.00321 (.00505)	
Total Revenue		-.0214132 (.03074)	-.0177477 (.02811)	.0028704 (.01333)	

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 7: Generalized Negative Binomial Regressions
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	.0007184 (.0003591)**	-.0005928 (.0002924)**	-.0006922 (.0003893)*	-.0011078 (.000349)***	-.0011111 (.0003296)***
Budget Airline				-.7184398 (.2333834)***	-.791649 (.2245004)***
Baggage Fee		7.40e-07 (7.01e-07)			
Cancelation Fee			3.28e-07 (2.61e-07)		
Maintenance / Aircraft		-.0002036 (.000133)	-.0000663 (.0001418)	-.0002223 (.0001257)*	-.0002559 (.0001094)**
Fleet Size		.0044434 (.0009075)***	.0042938 (.0010027)***	.0042367 (.0006174)***	.0044162 (.0002986)***
Pilot Salary		-1.80e-06 (2.05e-06)	-3.28e-06 (2.90e-06)	-9.61e-07 (1.14e-06)	
Number of Seats		-.0018323 (.0040688)	-.0036962 (.0043345)	-.0064759 (.0043613)	-.0060738 (.0040212)
Number of Incidents		.0132486 (.0059269)***	.018139 (.0079114)***	.0037346 (.0058818)	
Total Revenue		-.0226676 (.0324717)	-.0210113 (.0333182)	.0033396 (.0155194)	
Intercept	-.441502 (.353355)	.2237118 (.6562952)	.4707563 (.6634611)	1.538595 (.7558502)**	1.450162 (.6742874)**
Robust Standard Errors?	No	Yes	Yes	Yes	Yes
Pseudo R^2	0.0046	0.1718	0.1676	0.1864	0.1865
Chi Squared	4.00	225.76	225.04	254.70	237.78
Number of Observations	282	244	230	260	264

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 8: Generalized Negative Binomial Regression Interpretations (Marginal Effects)
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	.0009044 (.00045)**	-.00056 (.00028)**	-.0005847 (.00033)*	-.0009521 (.0003)***	-.0009337 (.00027)***
Budget Airline				-.5315554 (.15305)***	-.5652534 (.1409)***
Baggage Fee		6.99e-07 (.00000)			
Cancelation Fee			2.77e-07 (.00000)		
Maintenance / Aircraft		-.0001924 (.00012)	-.000056 (.00012)	-.0001911 (.00011)*	-.0002151 (.00009)**
Fleet Size		.0041975 (.00086)***	.0036268 (.00083)***	.0036416 (.00054)***	.0037113 (.00024)***
Pilot Salary		-1.70e-06 (.00000)	-2.77e-06 (.00000)	-8.26e-07 (.00000)	
Number of Seats		-.0017309 (.00385)	-.0031221 (.00365)	-.0055662 (.00374)	-.0051043 (.00338)
Number of Incidents		.0125155 (.00569)**	.0153216 (.00691)**	.00321 (.00505)	
Total Revenue		-.0214132 (.03074)	-.0177477 (.02811)	.0028704 (.01333)	

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 9: Fixed Effects Negative Binomial Regressions
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	-.0007067 (.0003892)*	-.0003581 (.0007181)	-.0004855 (.0008489)	-.0003422 (.0007117)	-.0003761 (.0005644)
Budget Airline				-1.015469 (1.756771)	-.9040006 (1.641604)
Baggage Fee		-8.00e-08 (5.60e-07)			
Cancelation Fee			1.46e-08 (2.23e-07)		
Maintenance / Aircraft		-.0000784 (.0001749)	-.0000348 (.0001956)	-.0000821 (.0001694)	
Fleet Size		.0037966 (.0012328)***	.003085 (.0014513)**	.0037115 (.0012205)***	.0037001 (.0010353)***
Pilot Salary		-3.46e-06 (3.21e-06)	-3.85e-06 (3.42e-06)	-3.75e-06 (3.15e-06)	-3.70e-06 (2.96e-06)
Number of Seats		.0020996 (.0116373)	-.0105001 (.0135941)	-.0006037 (.0114217)	
Number of Incidents		-.0015042 (.0092532)	-.0022328 (.0127798)	-.0025023 (.0092082)	
Total Revenue		-.0198427 (.0286438)	-.007008 (.0293961)	-.0216388 (.019868)	-.0233521 (.0160176)
Intercept	2.718387 (.7503188)***	1.644222 (1.989476)	3.955269 (2.439316)	2.48019 (2.208632)	2.162544 (1.235409)*
Chi Squared	3.30	18.97	15.87	19.70	19.52
Number of Observations	282	238	230	260	260

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 10: Fixed Effects Negative Binomial Regression Interpretations (Marginal Effects)
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	-.0007067 (.00039)*	-.0003581 (.00072)	-.0004855 (.00085)	-.0003422 (.00071)	-.0003761 (.00056)
Budget Airline				-1.015469 (1.75677)	-.9040006 (1.6416)
Baggage Fee		-8.00e-08 (.00000)			
Cancelation Fee			1.46e-08 (.00000)		
Maintenance / Aircraft		-.0000784 (.00017)	-.0000348 (.0002)	-.0000821 (.00017)	
Fleet Size		.0037966 (.00123)***	.003085 (.00145)**	.0037115 (.00122)***	.0037001 (.00104)***
Pilot Salary		-3.46e-06 (.00000)	-3.85e-06 (.00000)	-3.75e-06 (.00000)	-3.70e-06 (.00000)
Number of Seats		.0020996 (.01164)	-.0105001 (.01359)	-.0006037 (.01142)	
Number of Incidents		-.0015042 (.00925)	-.0022328 (.01278)	-.0025023 (.00921)	
Total Revenue		-.0198427 (.02864)	-.007008 (.0294)	-.0216388 (.01987)	-.0233521 (.01602)

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table 11: Re-defined Budget Variable Regressions
Dependent Variable: Number of Aircraft Accidents

Regressor	(1)	(2)	(3)	(4)	(5)
Average Stage Length	-.0011291 (.0003257)***	-.0011291 (.0003257)***	-.0010107 (.0003017)***	-.0003294 (.0007111)	-.0003649 (.000564)
Budget Airline	-.9677346 (.2219163)***	-.9677344 (.2219163)***	-.955858 (.2032952)***	-.8518152 (1.811383)	-.7464848 (1.708464)
Maintenance / Aircraft	-.0003749 (.0001323)***	-.0003749 (.0001323)***	-.0003526 (.0001056)***	-.0000837 (.0001694)	
Fleet Size	.0041583 (.0006001)***	.0041583 (.0006001)***	.0041529 (.0003086)***	.0037185 (.0012219)***	.0037109 (.0010365)***
Pilot Salary	-1.23e-06 (1.47e-06)	-1.23e-06 (1.47e-06)		-3.71e-06 (3.15e-06)	-3.68e-06 (2.96e-06)
Number of Seats	-.0054923 (.0040084)	-.0054923 (.0040084)	-.0057792 (.0036146)	-.0003993 (.0114145)	
Number of Incidents	-.0027056 (.0062859)	-.0027056 (.0062859)		-.0023595 (.0092196)	
Total Revenue	.0050343 (.0151806)	.0050343 (.0151806)		-.0217331 (.0198984)	-.023557 (.0160326)
Intercept	1.987853 (.7174252)***	1.987852 (.7174251)***	1.717778 (.6175659)***	2.392866 (2.194456)	2.113079 (1.220386)*
Type of Regression	Negative Binomial	Generalized Negative Binomial	Generalized Negative Binomial	Fixed Effects Negative Binomial	Fixed Effects Negative Binomial
Robust Standard Errors?	Yes	Yes	Yes	No	No
Pseudo R^2	0.1974	0.1974	0.1984		
Chi Squared	265.39	265.39	263.31	19.53	19.39
Number of Observations	260	260	264	260	260

Notes: Standard Errors are given in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level