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| University of Maryland Baltimore County |
| Merger to Delays? |
| An Analysis of the Relationship between the US Airways & American Airlines merger and Delayed Flights |

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This paper examines the effects of the recent merger of US Airways and American

Airlines. Specifically, the analysis is focused on the patterns of flight delays at

selected airports before and after the merger. An ordinal logit model is used to analyze

a dataset of 29032 flights. The analytical method presented here leads to inconclusive

results regarding the impact of the merger on flight delays. A brief discussion of the antitrust

case which led to the merger as well as some public policy solutions to the problem of

flight delays accompany the empirical analysis.

**Introduction**

October 24th, 2018 will be the 40th anniversary of the signing of the Airline Deregulation Act which unwound the power of the Civil Aeronautics Board while opening the U.S. airline industry to an unprecedented level of competition and innovation. During the 20 years which followed the market for air transportation grew as a mélange of new airlines entered the market and then quickly exited. Concurrently, the advent of low cost carriers (LCCs) and further development of the hub-and-spoke air-service model challenged the efficiency and profitability of traditional airline business models. For these and several other reasons, some of the most iconic names in commercial aviation faded away through mergers or bankruptcies.

In the twenty-year period from 1998 to the present the U.S. airline industry has experienced further consolidation, especially among the firms – henceforth referred to as legacy carriers – which were operating before de-regulation. Additionally, there has been considerable growth in the market shares of LCCs. In several ways these changes to the airline industry have enhanced consumer welfare. Inexpensive ticket prices, a large component of an airline passenger’s consumer utility, generate increasing levels of demand for more airline flights and airline services. For example, fluctuations in average airline ticket prices during the 1980s have become more stable and have since been slowly decreasing.[[1]](#footnote-1) Airfares had indeed remained well above $400 – on average – through the mid-2000s, but from then onward airfares have slowly decreased. The U.S. domestic average airfare in the second quarter of 2017 was $353.76 which is down from a first quarter 1998 airfare of $460.67 – in inflation adjusted dollars.[[2]](#footnote-2) Essentially, travelling by plane is no longer the option for business travelers and the proverbial “jet set” – people who have the leisure and income to pay for expensive airline tickets.

Airlines and the infrastructure supporting their operation have created a mode of travel without – in most cases – a viable substitute. A potential passenger can choose to use a train or automobile for long distance transportation, but those alternatives are not a practical substitute for these travelers in most regions of the country apart from of the northeast corridor along the Atlantic coast between Washington, DC and Boston, MA. The impracticality of ground transportation is also apparent in the amount of goods transported by passenger airlines. Near all of these airlines also have revenue from transporting cargo. Additionally, many airlines hold U.S. Postal Service contracts to convey mail. In general, passenger airlines, produce services which meet diverse demands for transportation.

Growth in the airline industry has enabled innovations that ease the impact on infrastructure. For example, the management at Dulles International Airport outside of Washington, DC plans to build a new 5th runway to enable more – and larger – aircraft operations while officials at Baltimore-Washington International Airport, which serves same region as Dulles, have organized construction of six additional aircraft gates on that airport’s international pier to support more aircrafts and passengers travelling overseas. In cities throughout the country airport authorities, the federal aviation administration (FAA), the national transportation safety board (NTSB), commercial airlines, and a variety of associated businesses are continually attempting to remove costs from infrastructure while making the air transportation system safer, more efficient, and more scalable to accommodate future growth.

Despite many improvements to the nation’s air traffic control system and associated airport systems which have all led to improvements in safety and efficiency passengers frequently encounter delays in reaching their destinations. A flight delay can result in considerable negative consequences for both airlines and passengers.

For example, airlines may face difficulty retaining passengers in the future if those passengers experience a particularly lengthy or uncomfortable delay. In some extreme cases passenger inconvenience and discomfort are violations of federal law.[[3]](#footnote-3) Airlines also incur costs related directly to delays because airlines often have to compensate displaced passengers, pay delay fines, and reallocate crews, gates, & aircraft. An executive for Delta airlines reported that these costs amount to at least $700 million in lost profit.[[4]](#footnote-4)

Passengers on the other hand face opportunity costs when experiencing a flight delay. These opportunity costs can be measured in dollars of lost work productivity, hours of lost leisure time, and many other ways. Every individual experiencing a delay has a unique value which he or she places on their lost time. An estimation of aggregate losses is shown in Graph 1 below. Here is a measurement of the collective time lost during flight delays at seven major airports from 2005 to 2016. This sample of flight delays equals $16,186,798 in gross wages.[[5]](#footnote-5)

Graph 1

What are the determinants of these delays? In this report I research flight delays. Specifically, I explore the relationship between the recent merger of American Airlines and US Airways and the resulting variation in flight delays. Here I limit the scope of my analysis to the routes between seven airports at which each of the merging airlines had substantial market shares.

Beginning in 2005 a pattern of consolidation began in the U.S. airline industry which has led to less competition amongst legacy carriers. Several of the most well-known airlines in the world have merged with other large airlines to form new mega airlines. In addition to these remaining airlines becoming much larger, several LCCs have either entered the market or expanded their operations. In some cases, like that of American Trans Air (ATA), merger nor bankruptcy could prevent their exit from the market. On the other hand, Sprit Airlines, JetBlue, and Southwest have all increased market shares in both domestic and international services. Table 1 shows the consolidation pattern of several major airlines during this 13-year period.

Passenger enplanements have also continued to grow throughout this period. How does increasing demand for air travel affect airline & airport operations while the industry consolidates? One could assume that increasing demand will be met by an efficient supply of available seats regardless of airline consolidation. However, this situation has been a major contributor to consolidation in the first place. For many years, the supply of airline seats has exceeded passenger demand.[[6]](#footnote-6) Basically, too many planes were flying with too few passengers. The industry metric “load factor” is used to measure these trends. Load factor is simply the ratio of passengers to available seats. When load factors are low - < 77%[[7]](#footnote-7) - a flight may operate at a loss especially when mail contracts and cargo shipments are also lower than aircraft capacity. Graph 2 shows average load factor trends over the last 13 years.

Graph 2

The evidence may seem counterintuitive. If enplanements are increasing without corresponding changes in available seats, then load factors will increase. Load factors are indeed increasing, but what is happening to the number of available seats and the number of flights? Fewer flights would lessen the demand for airport resources such as jet bridges, ground crews, taxiways & runways, etc. Fewer flights – thus fewer available seats - should result in fewer flight delays, yet the percent of flights delayed has remained steady without a significant drop between 2015 and 2017. Despite higher load factors, delayed flights are not steadily decreasing. In this report I will explore this phenomenon.

**Table 1**

**Consolidation of major U.S. airlines earning at least $20 million in revenue 2005 - 2017**

1 America West

2 US Airways

3 American 1

4 United 2

5 Continental

6 Delta 3

7 Northwest

8 AirTran\*

9 Southwest\* 4

10 ATA\* Exited Market

11 Hawaiian 5

12 Alaska 6

13 JetBlue\*  7

14 Frontier\* 8

15 Spirit\* 9

2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

\* Denotes Low Cost Carrier (LCC)

My research extends and augments previous research on flight delays performed by economists at Northwestern University Kellogg School of Management.[[8]](#footnote-8) From a sample of on-time performance data from the year 2000, researchers have determined several causal factors pertinent to the characteristics of several airports, airlines, and city-pairs. This research has led to additional lines of research that have resulted in similar findings.

I also use on-time performance data, but my approach compares 2015 data to 2017 data. Data from these two years are unique because they lie before and after the most recent merger between two legacy airlines.

U.S. airline consolidation in the 21st century has proceeded for many years without significant opposition from the U.S. Department of Justice Antitrust Division or the Federal Trade Commission; however, a merger proposal in 2013 was met with considerable resistance. The merger was eventually approved, and it was completed in 2015. Through analysis of data from March 2015 and August 2017 – the most recent data available – I am able to analyze of one of most significant airline mergers in the history of the airline industry and its effects on flight delays.

**Theory & Antitrust**

The significance of a flight delay begins by considering one of the most fundamental concepts in microeconomics, utility. Before the advent of websites such as Expedia, Flightaware, and those of individual airlines a consumer gained utility from flying, compared to that of vehicle or train travel, because, obviously, long distances are covered much quicker by aircraft. Essentially, consumer utility gain from flying is a utility gain based on time preferences. A consumer who is indifferent to time will value equally travelling by plane, train, or car. In such cases this consumer’s utility function would look like this.

*Utility = U(t­1, t2, t3­)*

In this basic utility function each tn represents time required for each of the three means of travel, and each of the three are equal substitutes of one another. In a more realistic situation, consumers will not be indifferent to time, so the means of travel that will be fastest will have more utility than the other two ceteris paribus.

Are there other preferences to consider amongst travelers whose time preferences favor air travel? Unless air travel is free – an unfulfilled dream of many – price is a logical next step. Consumer utility gains become a bit more complicated with consideration of price. Now the price and time of air travel determine consumer utility, and the resulting utility function looks like this.

*Utility = U(t, p)*

Here tradeoffs begin between time and price, and the highest gain in consumer utility goes to the mix of time and price that best suits the traveler’s preferences.[[9]](#footnote-9)

Airlines have used these tradeoff preferences for years as part of their ticket pricing strategies. For example, when the consumer is a business traveler more utility is gained from the speed of travel than the price, so an airline’s schedules – representing time in transit– are the most important component of the business traveler’s utility function. Business travelers in general have low price elasticity. In these cases, when an airline determines that the consumer is a business traveler it will likely charge high ticket prices. On the other hand, when an airline determines that the consumer is a leisure traveler with a price elasticity higher than that of the business traveler, it will likely charge low ticket prices. For much of the post-deregulation period airlines have engaged in this sort of price discrimination.

 Once air travel became available to the general public via the internet consumers were enabled to shop easily for flights meeting their budgets and schedules. The competition between airlines intensified as the consumer became better informed about prices and schedules. Concurrently, the U.S. Department of Transportation (DOT) began publishing a monthly summary *Air Travel Consumer Reports*. Additionally, the DOT established a database of on-time performance measures. Now a consumer can access this information, or, more easily, make a flight reservation online and view recent on-time performance of the flights on which they choose to travel. Now, a flight’s on-time performance has become a component of the consumer’s utility function, and these new utility functions look like this.

*Utility = U(t, p, d)*

Where *d* represents a delay. Previous research suggests that delays – from the passenger perspective – are recognized by the difference between a scheduled arrival and an actual arrival. That difference between schedule and arrival depends on congestion (C) both in the air and on the ground, random factors (X) such as overbooking that are under the control of the airline, and finally random factors (є) like the weather that the airline cannot control. A delay is a function of these three factors. Below is an example of the complete passenger utility function.[[10]](#footnote-10)

*Utility = U(t­n, pn,) + D(C,X,є)*

On-time performance is defined by flight delay. The standard measure used throughout the industry and the pertinent government agencies defines a flight as “delayed” if it departs more than 15 minutes later than its schedule. The 15-minute window allows flexibility into a schedule for any of the myriad reasons a flight may not depart or arrive exactly on-time. The 15-minute window is recorded after the departure, so 15 minutes total are automatically built into commercial flight schedules. It is important to note that this 15-minute period is the standard used throughout all the federal government’s aviation related agencies.

In addition to a general definition of flight delay and its role in the consumer utility function, we need additional explanation for the necessity of emphasizing one side of the flight delay over the other. For the balance of this report, the flight delay means delay of an arrival not a departure. A more detailed explanation will follow in the following section, but for now, I make the assumption that a flight that arrives late is more important to consumers than a flight that departs late. I believe, the rational consumer will not be dissatisfied with situations in which a flight departs late yet arrives on-time. The late arrival is paramount because it could lead to missed flight connections and post-flight late arrivals and inconveniences for many consumers. Furthermore, as will be shown, late departure data will still be included in the empirical analysis albeit indirectly.

In addition to consumer utility, the airlines also incur costs from flight delays. Recent estimates of these costs are $140.26 per minute (2017 dollars). This amount is the per-minute sum of aircraft operating costs, flight attendant costs, and the value of passenger’s time. The aircraft operating cost and flight attendant costs are obviously of no concern to a passenger, but they play an important role in an airline’s cost estimates. The important point is that airlines and passengers place different values on their time.

To examine the details of a delay as pertinent to the airline, we begin with the basic production and cost functions

*q = f(k,l) C = wl + vk*

These are the traditional producer functions indicating that output is a function of capital and labor and total cost is a function of the sum of two products: wages x labor and capital rents x capital. Total profit is then the product of output (*p*) and *q* minus the total costs, C.

 In this simple equation delay costs are associated with capital. The cost estimate of flight delays mentioned above will fluctuate by flight time. Flight time measures the use of capital. Airlines show great interest in estimates of flight time. A common definition of flight time is expressed by the equation written below.[[11]](#footnote-11)

*Time = M + S(C) + D(C,X,є)*

Here *Time* is flight time, M is the minimum travel time for a flight, S is a measure of excess time built into the airline schedule, C measures congestion, and delay is defined as it was previously in the passenger utility function. Note, these flight times are often manipulated by airlines in order to increase on-time performance reports. For example, airline A may add 10 minutes, S(C), to its minimum travel time, M, for a flight for which there is a low amount of congestion and delay. In more extreme cases longer times may be added to flights with expected congestion and delays, yet with the larger amount of S(C) the flight will not be considered delayed even though the overall flight time is increased. This practice is called “schedule padding.”

Flight delays are an important component to both airlines and passengers. If the consumer tolerates delays an airline will not lose market share to competitors. Cities in which there is no or little airline competition as well as no suitable substitute an airline has an incentive to not follow published schedules. Airlines may have an incentive to delay or cancel flights in which revenue from the load factor is less than the operating cost of the flight. In other words, an airline can incur losses by operating a flight with a small load factor that are larger than the losses incurred by delaying or cancelling a flight.

Small load factors have played a significant role in the airline industry especially since deregulation in 1978. Modern airlines realize the peril of operating flights with small load factors. When there are too many aircraft supplying too few passengers, cargo, and mail, load factors decrease. Airlines begin to lose money, and their consolidation can alleviate this problem. The higher the load factor the higher the likelihood an airline will maximize profits for an individual flight. This profit can be interpreted as a gain in overall economic efficiency. If fewer planes are flying with more passengers, cargo, and mail per plane there is less air traffic and less competition for airport resources, but, potentially, more flight delays and higher prices thus more loss of consumer utility.[[12]](#footnote-12)

From consumer utility and producer costs, I will now turn to a discussion of the US Airways & American Airlines merger as well as a brief summary of other mergers which have taken place over the past 13 years and the antitrust issues which have been part of each.

As indicated in Chart 1 from 2005 to 2017 the nine major U.S. airlines have consolidated to four firms. The first step in this consolidation was the 2005 America West Airlines purchase of US Airways. In this case the U.S. Department of Justice’s Antitrust Division (DOJ) cleared the merger of these two firms without challenge. America West Airlines provided service to cities predominantly within the western U.S. with hub operations in Phoenix and Las Vegas. On the other hand, US Airways provided service to cities predominantly within the east with hubs operations in Charlotte, Philadelphia, and Washington, DC – Reagan Airport. DOJ officials cited the lack of significant direct competition between the two firms as the primary reason for giving a summary approval of the merger without a full investigation into competitive impacts. Department officials also argued that another airline providing nationwide service would in fact promote competition within many city-pairs.[[13]](#footnote-13)

The next step was the 2010 merger of Delta Airlines and Northwest Airlines. Again, DOJ officials approved the merger without challenge; although, they investigated the proposal for 6 months in 2008. In the final assessment DOJ officials cite the overlap of Delta & Northwest route systems. Delta Airlines then as now maintained hubs in Atlanta, Cincinnati, and Salt Lake City while Northwest Airlines maintained hubs in Minneapolis, Detroit, and Memphis. These two airlines were directly competing with one another on many city-pairs, yet their merger was approved due to the competition each faced from many other airlines flying these routes. In this case DOJ documents cite other major airlines as well as several LCCs maintaining strong competition. In 2008 there was no concern about this merger causing harm to consumer welfare.[[14]](#footnote-14)

Two years later Continental Airlines and United Airlines proposed a merger. Their merger was more similar to that of America West & US Airways. DOJ officials did challenge the merger and completed a full investigation. At the completion of this investigation, in August, 2010, DOJ officials approved the merger, but they mandated a divestiture. Like the route networks of America West & US Airways, Continental & United provided services that did not compete directly with one another most of the time. United Airlines maintained hubs at Chicago, Cleveland, and Denver while Continental maintained hubs at Houston and Denver. The most significant exception to this complementarity was service out of Newark, NJ. Both Continental & United maintained hubs with a large number of flights, both domestic and international at Newark. The airport served as an east coast hub for Continental, and at the time of the merger it had 49.85% market share.[[15]](#footnote-15) This high concentration of market share at a large primary hub airport caused concern about consumer welfare losses post-merger. Nevertheless, DOJ officials approved the merger with the caveat that Continental & United had to divest landing and takeoff rights to Southwest Airlines in an attempt to promote LCC competition at EWR.[[16]](#footnote-16)

The fourth and most controversial merger was the 2015 merger of American Airlines and US Airways. Unlike the preceding three mergers, DOJ officials have given relative scrutiny to this most recent merger. American Airlines & US Airways competed with each other on many city-pairs throughout the country. Their merge would eliminate all of this competition while reducing the number of the large “legacy” airlines from four to three: United, Delta, & American + US Airways. DOJ officials as well as industry groups, politicians, other airlines, and airport authorities all expressed deep concern during the antitrust investigation over the resulting loss of competition.

Before discussing the details of the US Airways – American Airlines merger, I want to digress to explain the role of “slots” in airline – airport relationships. At four major airports, New York LaGuardia (LGA), New York John F. Kennedy (JFK), Ronald Reagan National Airport in Washington, DC (DCA), O’Hare International Airport in Chicago (ORD) take offs and landings are strictly controlled. Each take-off & landing, called a slot, is owned by one of the airlines serving the airport. This practice which began in 1969, is controlled by the FAA, and since that time it has led to many problems. Once an airline owns a slot it is reluctant to give it up to competition. The FAA has addressed this problem by issuing new slots at these airports to new airlines; furthermore, the FAA has developed a secondary market through which airlines can buy and sell slots.[[17]](#footnote-17) It is important to understand that the slots are only the right to land or take off at a designated time at one of these four airports. Usage of gates, air bridges, and ticket counters are different matters each with their own set of allocation problems. As we will see, the issue of slots will play a major role in the divestiture of the US Airways merger with American Airlines.

In November, 2013 the DOJ approved the merger of what would become a new larger American Airlines. The DOJ’s final judgement mandated an unprecedented divestiture of slots, gates, and other ground facilities at airports serving the following seven cities: New York City, Washington, DC, Boston, Chicago, Los Angeles, Miami, and Dallas. Additionally, the final judgement mandated the divestiture recipients be LCCs. Industry advocates and DOJ staff argued for an end to the anti-competitive nature of operational rights at the seven major airports. The anti-competitive practices had nearly shut out LCC competition thus maintaining harm to consumer welfare through high airline ticket prices.

The aforementioned problem about slots was at the forefront of the divestiture. By the time of the merger approval the DOJ mandated the transfer of 104 slots at DCA and 34 slots at LGA. Recall that a slot is only a take-off or a landing, thus 104 slots and 34 slots correspond respectively to 52 and 17 landing & take-off slot pairs each accommodating a single flight. At both of these airports the slot divestitures accompany divestiture of gates, air bridges, ticket counters and other airport facilities. Furthermore, the recipients of these divestitures – after much opposition from Delta Airlines – can only be airlines designated LCC. In the cases of DCA and LGA each slot has gone to one of the following airlines: Southwest, JetBlue, and Virgin America.

The remaining elements to this divestiture involve five additional airports: Chicago O’Hare (ORD), Logan Airport in Boston (BOS), Miami International Airport (MIA), Dallas Love Field (DAL), and Los Angeles International Airport (LAX). At each of these airports the divestiture involved the merging airlines forfeiture of two gates as well as ticket counter space and other miscellaneous airport facilities. Like the agreements at DCA and LGA, these additional divestitures were restricted to LCC recipients. These forfeitures and the reallocation of slots at DCA and LGA completed the DOJ’s final judgement in the merger, and it was approved in March, 2014. The final US Airways flight took place a little over a year later on October 17, 2015.[[18]](#footnote-18)

One final note, two other firms Alaska Airlines and Southwest Airlines have each been involved in much smaller mergers with Virgin America and AirTran Airways respectively. In both of these cases the final judgements were much smaller than that described above; although, the Alaska Airlines – Virgin America merger did prohibit direct competition with several routes currently served by American Airlines. In total this mass consolidation in the airline industry has made considerable changes to the concentration of flights and competition within city-pairs throughout the nation a matter to which I will return in more detail in later sections.[[19]](#footnote-19)

The research which has given rise to this project argues that flight delays are more likely to occur with less competition because there is no incentive for airlines to maintain their schedules in markets where consumers have no substitute.[[20]](#footnote-20) The research proceeds with an econometric analysis of over 800,000 flights covering 2,450 origins & destinations (city-pairs) all from January, April, and July of 2000. At that time the U.S. airline industry consisted of ten major airlines operating nationwide, and the author collected individual flight level data from each of them. He then estimates a model in which a delay is a function of city-pair concentration indexes, airlines, weather, day of week, etc. In addition to basic OLS regressions, the author used probits to determine the probability of flight delay using flight delay as a binary variable.

This approach has yielded several significant results supporting the central hypothesis. As the author states,

*“…this paper examines the hypothesis that the market power which dominant carriers* [airlines] *enjoy allows them to provide a lower quality of service through increasing flight delays – to their customers on less competitive routes. Margins may be higher on monopoly routes because airlines that do not face competitive pressures can save the costs that would be needed to provide higher quality on-time service. The results of this paper indicate that, in fact, flights are less frequently on time on routes that are served by only one airline in the cases where the carriers market shares at the airports served are higher…”[[21]](#footnote-21)*

As mentioned previously, my report also investigates the effects of competition on service quality – albeit limited to flight delay – in a manner similar to the aforementioned research. I do however make several changes.

My research uses a sample covering two years 2015 and 2017. In 2015 only four of the ten airlines mentioned in the previous research were still in operation – the 10th, TWA, exited the market in 2001 via a merger with American Airlines. By 2017 the remaining nine airlines had been reduced to five through the series of four mergers mentioned previously. This research focuses the most recent and also the most controversial of the mergers – the US Airways & American Airlines merger. Specifically, I compare delay patterns from 2015 to those of 2017.

I have sampled data from March, 2015 and August, 2017. March 2015 was the last month in which US Airways operated independently, thus the last data sample in which one can collect data on US Airways flights. In order to more accurately capture the post-merger effects, I am using the most recent data available with the post-merger American Airlines. In both samples – as well as the research mentioned above – are collections of individual flight data. My sample has a total of 29,032 observations each of which are individual flights.

Analyzing data pre-merger and post-merger extends the previous research by measuring delayed flights of specific airlines over a span of time in which the marketplace has changed significantly.

Airport category is a DOT designation of each airport in the nation. These designations fall into categories that compose the National Plan of Integrated Airport Systems (NPIAS).[[22]](#footnote-22) All commercial service airports are either primary or non-primary. All primary airports are listed as one of the following based on passenger boarding (enplanements): large hub, medium hub, & small hub primary commercial service airports and non-hub primary commercial service. In order to be qualified as one of the three hubs, and airport must have at least 0.5% of enplanements nationwide from the calendar year preceding the current fiscal year. Airports are reassigned based on changes in enplanements from year to year.

My research uses flight data from a total of 7 airports which account for a total of 42 city-pairs. The seven airports are those involved in the US Airways & American Airlines divestiture. With one exception, each airport is a large-hub primary airport. The exception is Dallas Love Field DAL which is a medium-hub primary airport.

Now I will turn to a more detailed description of my dataset, the variables in it, and some other summary statistics and graphics.

**Data**

The data used in the estimated model that follows is cross-sectional; however, the data does not come from a survey of airlines, passengers, or any other demographic. The data are measurements of industrial performance, and their assembly is mandated and completed by the federal government. The only exception is the variable, *hhi*. The *hhi* data is calculated from a quarterly survey of airlines called the *Origin and Destination Survey* or *DB1B.* The *DB1B* surveys 10% of the tickets sold by each reporting airline.

The complete dataset includes two samples. One each from March, 2015 and August, 2017.

The U.S. Bureau of Transportation Statistics’ Office of Airline Information, a bureau of the DOT, maintains a data library from which I have assembled all of the data for this research. The data library maintains 18 databases with a large variety of aviation related information and surveys. The bureau also maintains other similar databases on other modes of transportation, safety & accident reporting, firm’s financial information, and many other things. I have gathered data from the *Airline On-Time Performance Data* database. This database records data from those airlines which account for at least 1% of all domestic scheduled passenger revenues.[[23]](#footnote-23) This database contains records at the individual flight level including all arrival times: early, on-time, delayed, cancelled, or diverted.

 To begin, my dependent variable, *groups*, is constructed from an original variable *arrivalgroup.* The latter is a discrete variable which groups the minutes of a flight’s arrival into numerical categories ranging from -2 to 12. Each of the numbers, with the exception of -2 and 15 indicate a period of 15 minutes. The first and last numbers, -2 & 15 fit all observations for flights that arrive > 15 minutes early and > 210 minutes late respectively. I have rearranged this information to construct *groups* in which the -2 to 12 are placed into three groups 1, 2, & 3 meaning on time, delayed, & severely delayed respectively.

Now I will describe the regressors. My first two regressors are *flighttime* which is the time in flight and *distance* which is the distance, in nautical miles, of the flight*.* Next, I computed three Herfindahl-Hirschman indexes (HHIs) *hhi, originhhi, desthhi* which are HHIs for the city-pair, origin airport, and destination airport respectively. Also, there is the variable *arrivaltime* which indicates the arrival time of the flight in a 24-hour span. These six are the continuous regressors used in the estimation.

Next, through several steps of maneuvering within the dataset I divided the variable *arrivaltime -* into four groups each corresponding to a 6-hour period of the day. Night indicates flights that arrived between midnight and 5:59 AM. Morning indicates arrivals from 6:00 to 11:59, and afternoon indicates the arrivals from 12:00 to 5:59 PM. Finally, the evening variable indicates the arrivals between 6:00 and 11:59 PM. Each of these variables is divided into two groups the flights in 2015 and those in 2017 for a total of eight variables named *night15, morning15…evening17*. Each of these eight variables is a ratio of all flights that have arrived in the time period indicated to all flights that have arrived the entire day. The purpose of these eight variables is to have a measure of airport congestion at the time of each arrival. Ratio variables like these will be used as parameters the empirical analysis to measure the effect of varying levels of airport congestion on the pattern of delay.

My next set of variables are *airline, weather, nas, security,* and *late* which indicate the reason for a flight’s delay measured in minutes. Each of these variables contain an abundance of zeros, but they contain valuable information about the specific causes of a delay. When these variables are summed they form another summary variable that I chose to eliminate from the dataset for collinearity reasons. Although none of these five are perfectly collinear with the summary variable, they do equal it in total. Keeping the summary variable seemed redundant, so I removed it.

In addition to these variables I have constructed a day-of-the-week variable. There are also dummy variables to indicate a flight originating or departing from the operating airline’s hub. Another dummy variable indicates a late departure. Also, there are string variables – with corresponding numerical labels to indicate origin and destination airports and airlines. Although these do not play a central role in the analysis, there inclusion is essential for regressions and inquiries in which I want to limit the observations for more specific results. Last, I constructed two dummy variables, one each for 2015 and 2017.

Note, many of the flights in the dataset are operated by airlines other than US Airways, American, and the other legacy and LCC carriers. For simplicity I have done some combining with the legacy and the regional airlines. In most cases regional airlines operate as a subsidiary or a contractor to a legacy airline; however, they sell tickets under the name of the legacy airline. For these reasons I have combined each regional airline with the legacy airline with which it operates in this dataset. For example, American Airlines and Envoy Air will both appear in the dataset as American Airlines

 Table 2 shows the summary statistics of these variables. To conserve space, I have not included all of the dummy variables.

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| --- | --- | --- | --- | --- | --- | --- |
| Table 2 |   |   |   |   |   |   |
|   |   |   |   |   |   |   |
| **Variable** | **Obs** | **Mean** | **Std.Dev** | **Min** | **Max** |
| *groups* |   | 29032 | 1.3091 | 0.60437 | 1 | 3 |
| *arrivalgroup* | 29032 | -0.046 | 2.4661 | -2 | 12 |
| *desthhi* |   | 29032 | 2787.8 | 1560.72 | 1807.5 | 8689.3 |
| *hhi* |   | 29032 | 4865.6 | 1890 | 2084 | 10000 |
| *distance* |   | 29032 | 1058.4 | 663.566 | 184 | 2611 |
| *flighttime* | 29032 | 143.73 | 77.3196 | 30 | 432 |
| *arrivetime* | 29032 | 1487.7 | 540.584 | 1 | 2400 |
| *carrier* |   | 29032 | 3.5304 | 21.3265 | 0 | 1167 |
| *weather* | 29032 | 0.7753 | 11.0099 | 0 | 955 |
| *nas* |   | 29032 | 4.8369 | 19.1769 | 0 | 435 |
| *security* |   | 29032 | 0.008 | 0.61418 | 0 | 94 |
| *late* |   | 29032 | 4.995 | 23.1172 | 0 | 844 |

**Empirical Analysis & Results**

 At first glance some immediate problems arise that preclude the use of certain regression models. As I have mentioned the dependent variable *groups* has characteristics that do not make it suitable for OLS regression. As I have mentioned, *groups,* the dependent variable,is formed from the original variable *arrivalgroup* whichis a discrete variable that ranges from -2 to 12. Each integer represents a 15-minute period a flight is delayed. For example, a flight that is on time – i.e. lands within 15 minutes after its scheduled arrival – is listed zero while another flight that is 15 minutes early is listed as -1. On the other hand, a 15 minutes late arrival is listed as 1. This process proceeds for all 29032 flights in the dataset. Each integer from -1 to 11 represents a single 15-minute period, and, in total, -1 – 11 capture the majority of flights. At the far ends of the distribution there is a change. All flights that arrive at least 16 minutes early are listed as -2. A total of 22,260 flights are all represented by the same number.

On the other end of the distribution the range is even larger. All flights delayed at least 3 hours are listed as 12, yet the time range of delays listed as 12 increases to 20 hours 50 minutes. There are 2,202 flights in the dataset with these severe delays. The reminder, 4,570 flights, fall in the middle with shorter delays anywhere between 16 minutes and 60 minutes. Below are histograms of *arrivalgroup* and *group*s.

 

G*roups* is an ordinal dependent variable. As a result, OLS regression will not be suitable for model estimation. A standard OLS regression model would result in meaningless inconsistent coefficients. As we can see from the histograms above most flights are either on-time or early. Although the data sample is not truncated, the large imbalance in the data did not seem well suited for OLS. On the other hand, it seems well suited for estimation with a Tobit model.

However, there are problems with using a Tobit mode as well. Aside from the problems with the dependent variable there are several distributional assumptions about the regressors as well as a difficulty in hypothesis testing and interpretation.[[24]](#footnote-24) Ultimately, I decided not to use the Tobit model. Not in the case of the Tobit nor regular OLS would I be able to analyze my question properly. For proper model estimation with ordinal variables, like that of other categorical variables, maximum likelihood estimation is much more suitable.

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 An important question to pose before conducting maximum likelihood estimation is that of the nature of the dependent variable. Unlike categorical dependent variables which are used in conditional and multinomial logit models, the dependent variable in this study, *groups,* represents an ordered outcome. Each flight is either on-time, delayed, or severely delayed. By contrast, categorical dependent variable models group data based on the results of a survey or some other type of unordered categorization.

For example, in a typical categorical dependent variable model numbers 1-5 can be assigned to responses from a question about social-class. Respondents could answer lower class, lower middle class, middle class, upper middle class, or upper class. Here categories are pre-determined by the survey designer. In another context respondent answers can be grouped together after a survey is conducted. In an open-ended survey of patients who have undergone surgery a question such as “How do you feel?” could be answered in many ways. Answers have to be categorized. They could be binary “well” or “not well”; alternatively, they could be categorical “strong, ok, weak, or depressed.” Regardless the numbers used in a regression model that analyzes these types of data represent non-numerical information.

In this study *groups* represents a category of flight arrival status. The value is not the amount of time delayed, nor is it a binary variable indicating delay or no delay. The observations of this variable are categorized as 1 (on-time), 2(delayed), or 3 (severely delayed). Noticing the skewed distribution of *groups* as well as its antecedent *arrivalgroup* raises questions about the distances between the categories in each variable and the ways in which consumers respond to them.

Analyzing trends in flight delays before and after a merger can be done by using a binary dependent variable, but the results would be unrevealing. Given certain parameter values a probability can be made about a flight being delayed, and these probabilities can be compared over time. The information gain from this exercise tells us little about how changes in levels of competition are affecting delays. Yes, a flight may be more prone to delay in one period versus the other, but richer information is gained by examining the degree of delay. With a more nuanced approach that groups delay into categories based on length we can determine if the US Airways / American Airlines merger has led to enhancements in consumer welfare. In other words, has the emergent American Airlines improved on-time performance? If not is a reduction in on-time performance trivial or substantial? [[25]](#footnote-25)

For these reasons I chose to create the *groups* variable with three categories. Assuming that all consumers prefer arrivals on-time or early, and assuming they do not prefer delays is my first step in forming groups. I also assume that as the time of delay increases, consumers become increasingly concerned about the opportunity costs of their delays. For example, travelers who are officially delayed meaning they have arrived 16 minutes past their scheduled arrival will be less concerned about their opportunity costs than another group of travelers who are delayed 75 minutes.

I have chosen 1 hour past each flight’s scheduled arrival time as the threshold between flights I consider delayed versus those that are severely delayed. Without a survey designed to collect traveler’s tolerances for flight delays, I have to make a rough categorization of the variable. There are of course other ways to divide the groups, but these three categories are the most parsimonious above a purely binary variable.

Now for the first step in the model estimation. I use the Stata command Ologit for two regressions. The first uses some of the dummy variables to capture the effects of the two 2015 pre-merger airlines. The second regression uses the dummy variables pertinent to 2017 post-merger. Note, dummy variables for US Airways and American Airlines were not in the original data explanation. I created them in the midst of performing these regressions due to some unforeseen problems with the *airline* variable. The results are given below.[[26]](#footnote-26)

|  |  |
| --- | --- |
| Stata Command:  | *ologit groups distance flighttime hhi desthhi i.y15 i.usair i.aa* |
| Iteration 0: log likelihood = -20041 |   |   |   |   |
| Iteration 1: log likelihood = -19722 |   |   |   |   |
| Iteration 2: log likelihood = -19717 |   |   |   |   |
| Iteration 3: log likelihood = -19717 |   |   |   |   |
|   |   |   |   |   |   |  n = 29032 |
| Ordered Logistic Regression |   |   |   |   | LR chi2(7) = 648.65 |
| Log likelihood -19716.531 |   |   |   |   | Prob > chi2 = 0 |
|   |   |   |   |   |   | Pseudo R2 = 0.0162 |
| *Groups* | Coefficient | Std.Error | z | P>|z| |   | 95% Confidence Interval |
| *Distance* | -0.0024431 | 0.000107 | -22.88 | 0 | -0.0026523 | -0.0022338 |
| *Flighttime* | 0.0205426 | 0.000891 | 23.06 | 0 | 0.0187964 | 0.0222888 |
| *Hhi* | 0.0000141 | 8.05E-06 | 1.75 | 0.08 | -1.69E-06 | 0.0000299 |
| *Desthhi* | -0.0000429 | 9.45E-06 | -4.54 | 0 | -0.0000614 | -0.0000244 |
| *1.y15* | 0.2014098 | 0.029322 | 6.87 | 0 | 0.1439389 | 0.2588806 |
| *1.usair* | -0.153258 | 0.058453 | -2.62 | 0.009 | -0.2678235 | -0.0386924 |
| *1.aa* | -0.158485 | 0.03045 | -5.2 | 0 | -0.218166 | -0.098804 |
| /cut1 | 1.558654 | 0.05403 | 1.4528 | 1.665 |   |   |
| /cut2 | 2.892196 | 0.057084 | 2.7803 | 3.004 |   |   |

|  |  |  |
| --- | --- | --- |
|  Stata Command: | *ologit groups flighttime distance hhi desthhi i.y17 i.aa* |   |
| Iteration 0:  | log likelihood = -20040.855 |   |   |   |   |
| Iteration 1:  | log likelihood = -19725.068 |   |   |   |   |
| Iteration 2:  | log likelihood = -19720.006 |   |   |   |   |
| Iteration 3:  | log likelihood = -19720.005 |   |   |   |   |
|   |   |   |   |   |   | n = 29032 |   |
|   |   |   |   |   |   | LR chi2(6) =641.7 |
| Ordered logistic regression  |   |   |   | Prob > chi2 = 0 |
| Log likelihood = -19720.005 |   |   |   |   |   | Pseudo R2 = 0.016 |
|   | *groups* | Coefficient  | Std. Err. | Z | P > |z|  | 95% Confidence Interval |
|   | *distance* | -0.00243 | 0.00011 | -22.77 | 0 | -0.002634 | -0.0022 |
|   | *flighttime* | 0.02055 | 0.00089 | 23.06 | 0 | 0.018803 | 0.0223 |
|   | *Hhi* | 9.53E-06 | 7.88E-06 | 1.21 | 0.226 | -5.90E-06 | 2.5E-05 |
|   | *desthhi* | -3.9E-05 | 9.35E-06 | -4.2 | 0 | -5.76E-05 | -2E-05 |
|   | *1.y17* | -0.18087 | 0.02832 | -6.39 | 0 | -0.236378 | -0.1254 |
|   | *1.aa* | -0.13754 | 0.02943 | -4.67 | 0 | -0.19523 | -0.0799 |
|   | /cut1 | 1.39597 | 0.05362 | 1.2909 | 1.5011 |   |   |
|   | /cut2 | 2.72929 | 0.05661 | 2.6183 | 2.8402 |   |   |

 The common question about regression output is how reliable are the results? Before discussing coefficients, it is important to note the “cut1” & “cut2” in both of the tables. These figures indicate the boundaries in the dependent variable *groups* between on-time, delayed, and severely delayed flights.

In the two models above all coefficients are statistically significant except that of *hhi.* For example, in the top table testing 2015 flights, a change in *y15* – in other words moving from 0 to 1 meaning a flight that took place in 2015 – is associated with a 0.204 increase in the log of the odds ratio of being in a higher level of *groups* ceteris paribus. Similarly, changes in *i.usair* and *i.aa* are associated with decreases of 0.153 and 0.159 respectively in the log of odds ratios. In the bottom table testing 2017 flights there is a reverse. The year dummy variable *y17* is associated with a 0.180 decrease in the log odds of an increase in *groups.* As in the 2015 table, the *i.aa* variable is again associated with a decrease in the log odds. These results suggest that there are differences in the patterns of flight delays depending on the year of the flight – pre-merger or post-merger – and the airline. Additionally, the likelihood ratio chi-squares of both models suggest the significance of the entire model; however, more tests need to be completed on both of these models.

Several tests can be performed on the z-values to better assess the reliability of these results. Furthermore, with an ordinal logit regression model like this one Wald tests and Likelihood Ratio tests can both be performed on variables. Both tests usually give similar results.[[27]](#footnote-27)

Tests of individual variables as well as their interactions with other variables give some insight into validity of the model, but more information is needed prior to making any conclusions about a model. Before proceeding with any further analysis some general tests of the entire models are needed. Model estimation with ordinal logit models assumes that the coefficients would be the same for any category of the dependent variable. For example, in this model the dependent variable *groups* is divided into 3 categories representing on-time, delayed, and severely delayed flights. Under the proportional odds assumption, the estimated coefficients for each of the three categories – estimated individually – will be the same. The proportional odds assumption can be tested in several ways. Here, I use Stata’s omodel command to obtain a likelihood ratio test of the proportional odds assumption. Additionally, I obtain additional information by using the brant command which performs a Wald test of proportional odds. The results of each are given on the next page.

The top table shows the likelihood ratio test for both 2015 and 2017. When conducting this test, the omodel command does not accept dummy variables, so this first test holds for both 2015 and 2017. The bottom table shows the results the Brandt test which again is a variation of the Wald test. Here dummy variables are recognized, so separate results are given for 2015 and 2017. For both of these tests, H0: β­1 = β2 = …βn-1 for each of the three response categories – on-time, delayed, severely delayed – in the dependent variable *groups.[[28]](#footnote-28)*

|  |  |
| --- | --- |
| Stata Command: |  *omodel logit groups distance flighttime hhi desthhi* |
| Iteration 0: log likelihood = -20040.855 |   |   |   |
| Iteration 1: log likelihood = -19760.254 |   |   |   |
| Iteration 2: log likelihood = -19756.06 |   |   |   |
| Iteration 3: log likelihood = -19756.058 |   |   |   |
|   |   |   |   |   | n = 29032 |
| Ordered logit estimates |   |   |   | LR chi2(4) = 569.59 |
| Log likelihood = -19756.058 |   |   |   | Prob > chi2 = 0.0000 |
|   |   |   |   |   | Pseudo R2 = 0.0142 |
| *Groups* | Coefficient | Std. Error | x | P>|x| | 95% Confident Interval |
| *Distance* | -0.0024957 0.0001065 -23.44 0.000 -0.0027044 -.002287 |
| *Flighttime* |  0.0209347 0.0008903 23.51 0.000 0.0191897 .0226797 |
| *Hhi* |  6.24e-07 7.64e-06 0.08 0.935 -0.0000143 .0000156 |
| *Desthhi* | -0.0000329 9.33e-06 -3.52 0.000 -0.0000512 -.0000146 |
| \_cut1 | 1.49891 0.0515208 |   |   |   |
| \_cut2 | 2.830115 0.054696 |   |   |   |
| Approximate likelihood-ratio test of proportionality of odds across response categories: |
| chi2(4) = **87.33** |   |   |   |   |   |
| Prob > chi2 = 0.0000 |   |   |   |   |

|  |  |
| --- | --- |
| Brant tests of parallel regression assumption for both 2015 & 2017 models |   |
|   |   |   |   |   |   |   |   |   |
|   | chi2 | p>chi2 | df |   |   | chi2 | p>chi2 | df |
| 2015 | **112.6** | 0 | 7 |   | 2017 | **102.1** | 0 | 6 |
| *Distance* | 5.65 | 0.018 | 1 |   | *distance* | 6.49 | 0.011 | 1 |
| *Flighttime* | 13.92 | 0 | 1 |   | *flighttime* | 13.8 | 0 | 1 |
| *Hhi* | 2.94 | 0.086 | 1 |   | *hhi* | 5.71 | 0.017 | 1 |
| *Desthhi* | 9.17 | 0.002 | 1 |   | *desthhi* | 7.32 | 1 | 1 |
| *1.y15* | 15.88 | 0 | 1 |   | *1.y17* | 25.25 | 0 | 1 |
| *1.usair* | 8.21 | 0.004 | 1 |   | *1.aa* | 8.04 | 1 | 1 |
| *1.aa* | 11.9 | 0.001 | 1 |   |   |   |   |   |
|   |   |   |   |   |   |   |   |   |
| A significant test statistic provides evidence that the proportional odds assumption has been violated. |

In all three test results H­0 is rejected indicating that the proportional odds assumption fails in this model. In other words, this evidence suggests that the βs are not the same for each of the three categories of *groups.*

In order to proceed the estimation has to be made with a generalized ordinal logit model. For the remainder of this study I have used Stata’s gologit2 command to estimate a generalized ordinal logit model. I now perform some regressions using the same variables as in the original two. The results are in the tables on the following page.

As we see the coefficient estimates in the generalized ordered logit are similar to those of the ordered logit regressions. The key difference in these outputs is the presence of two model estimations. This occurs because the generalized ordered logit model is accounting for the violation of the proportional odds assumptions which we discussed earlier. Since the dependent variable *groups* has three outcomes, there are two estimations. The first shows the coefficients for the model for the on-time outcome and the second shows coefficients for the delayed outcome. The coefficients in each are interpreted – as in the original regression - as increases or decreases in the log odds. For example, in the first table the negative and statistically significant coefficients on *usair* and *aa* suggest a 0.129 & 0.146 decrease in the log odds of a US Airways or American Airlines flight becoming delayed. The same pattern repeats in the “delayed” estimation. Here, the coefficients suggest 0.353 & 0.289 decreases in the log odd of the associated airline’s flight becoming severely delayed.[[29]](#footnote-29)

In both the 2015 and 2017 regressions the coefficients on the airline variables are negative and statistically significant. The coefficient on *y15* in the “on-time” estimation is positive and statistically significant while the analogous *y17* is negative and statistically significant. These results suggest that on-time performance may be increasing in the period after the merger. These same coefficients in the “delayed” estimations are not statistically significant, nor are any of the coefficients on *hhi.*

Another way to interpret these results is by making probability predictions. Making probability predictions can help ease interpretation of the estimation results. In this case, my primary interest is to determine how changes over time and between the airlines before and after the merger have affected flight delays in the sample airports. Here I will use the *groups* variable as the outcome of choice and determine the probabilities of the three outcomes given changes in some of the regressors.

|  |  |
| --- | --- |
| Stata Command: gologit2 groups flighttime distance hhi desthhi usair aa y15 |   |
|   |   |   |   |   |   |   |   |   |
| Generalized Ordered Logit Estimates |   |   |   | n = 29032 |   |
|   |   |   |   |   |   |   | LR chi2(14) = 775.22 |
|   |   |   |   |   |   |   | Prob > chi2 = 0  |
| Log likelihood = -19653.25 |   |   |   | Pseudo R2 = 0.0193 |
|   |   |   |   |   |   |   |   |   |
|   | *groups* |   | Coefficient | Std. Error | z | P > |z| | 95% Confidence Interval |
| ontime |  |   |   |   |   |   |   |   |
|   | *flighttime* | 0.0216601 | 0.0009222 | 23.49 | 0 | 0.01985 | 0.0234677 |
|   | *distance* | -0.002552 | 0.0001101 | -23.19 | 0 | -0.0028 | -0.002337 |
|   | *Hhi* |   | 0.0000156 | 8.14E-06 | 1.91 | 0.056 | -3.89E-07 | 0.0000315 |
|   | *desthhi* |   | -4.02E-05 | 9.55E-06 | -4.2 | 0 | -6E-05 | -2.14E-05 |
|   | *Usair* |   | -0.129218 | 0.0591083 | -2.19 | 0.029 | -0.2451 | -0.013368 |
|   | *Aa* |   | -0.145573 | 0.0307368 | -4.74 | 0 | -0.2058 | -0.08533 |
|   | *y15* |   | 0.2172717 | 0.0296007 | 7.34 | 0 | 0.15926 | 0.2752881 |
|   | \_cons |   | -1.633532 | 0.0546945 | -29.87 | 0 | -1.7407 | -1.526332 |
| delayed |  |   |   |   |   |   |   |   |
|   | *flighttime* | 0.0159447 | 0.0013215 | 12.07 | 0 | 0.01335 | 0.0185348 |
|   | *distance* | -0.002081 | 0.0001587 | -13.11 | 0 | -0.0024 | -0.00177 |
|   | *Hhi* |   | -3.74E-06 | 0.0000137 | -0.27 | 0.786 | -3E-05 | 0.0000232 |
|   | *desthhi* |   | -8.43E-05 | 0.000017 | -4.96 | 0 | -0.0001 | -0.000051 |
|   | Usair |   | -0.352784 | 0.0942092 | -3.74 | 0 | -0.5374 | -0.168138 |
|   | *Aa* |   | -0.288727 | 0.0488862 | -5.91 | 0 | -0.3845 | -0.192912 |
|   | *y15* |   | 0.0215338 | 0.0466095 | 0.46 | 0.644 | -0.0698 | 0.1128868 |
|   | \_cons |   | -2.241749 | 0.0880826 | -25.45 | 0 | -2.4144 | -2.06911 |

|  |  |  |
| --- | --- | --- |
| Stata Command: gologit2 groups flighttime distance hhi desthhi aa y17 |   |   |
|   |   |   |   |   |   |   |   |   |
| Generalized Ordered Logit Estimates |   |   |   | n = 29032 |   |
|   |   |   |   |   |   |   | LR chi2(12) = 760.51 |
|  |   |   |   |   |   |   | Prob > chi2 = 0  |
| Log likelihood = -19660.6 |   |   |   |   | Pseudo R2 = 0.0190 |
|   | *Groups* |   | Coefficient | Std. Error | z | P > |z| | 95% Confidence Interval |
| ontime |  |   |   |   |   |   |   |   |
|   | *flighttime* | 0.0216751 | 0.0009224 | 23.5 | 0 | 0.019867 | 0.0234829 |
|   | *distance* | -0.002538 | 0.0001099 | -23.1 | 0 | -0.00275 | -0.002323 |
|   | *Hhi* |   | 0.0000117 | 7.96E-06 | 1.47 | 0.141 | -3.89E-06 | 0.0000273 |
|   | *Desthhi* |   | -3.71E-05 | 9.45E-06 | -3.92 | 0 | -5.6E-05 | -1.85E-05 |
|   | *Aa* |   | -0.127853 | 0.0297148 | -4.3 | 0 | -0.18609 | -0.069613 |
|   | *y17* |   | -0.19998 | 0.0285792 | -7 | 0 | -0.25599 | -0.143965 |
|   | \_cons |   | -1.449297 | 0.0543083 | -26.69 | 0 | -1.55574 | -1.342854 |
| delayed |  |   |   |   |   |   |   |   |
|   | *flighttime* | 0.0158754 | 0.0013231 | 12 | 0 | 0.013282 | 0.0184686 |
|   | *distance* | -0.002033 | 0.0001584 | -12.84 | 0 | -0.00234 | -0.001723 |
|   | *Hhi* |   | -1.49E-05 | 0.0000135 | -1.11 | 0.269 | -4.1E-05 | 0.0000115 |
|   | *Desthhi* |   | -7.71E-05 | 0.0000169 | -4.57 | 0 | -0.00011 | -4.41E-05 |
|   | *Aa* |   | -0.243524 | 0.047629 | -5.11 | 0 | -0.33687 | -0.150173 |
|   | *y17* |   | 0.0251221 | 0.0453596 | 0.55 | 0.58 | -0.06378 | 0.1140253 |
|   | \_cons |   | -2.294041 | 0.0869961 | -26.37 | 0 | -2.46455 | -2.123531 |

Below are some predicted probabilities. To conserve space, I have limited the following to results for *y17* & *aa*.

|  |
| --- |
| Stata Command: forevalues i=1/3 { margins, at(y17=1 aa=1) predict(outcome(`i))} |
| Warning: cannot perform check for estimable functions |   |   |   |
|   |   |   |   |   |   |   |   |   |
| Predictive margins |   |   |   | n = 29032 |   |
| Model VCE: OIM |   | Delta - Method |   |   |   |
|   |   |   |   |   |   |   |   |   |
| at *y17*=1, *aa=1* |   | Margin | Std. Error | z | P> |z| | 95% Conf. Interval |
|   |   |   |   |   |   |   |   |   |
| Expression: | Pr(groups==1), predict outcome(1)) |   |   |   |
|   | \_cons |   | 0.796 | 0.00407 | 195.5 | 0 | 0.788 | 0.80418 |
|   |   |   |   |   |   |   |   |   |
| Expression: | Pr(group==2), predict(outcome(2)) |   |   |   |
|   | \_cons |   | 0.137 | 0.0035 | 39.07 | 0 | 0.13 | 0.1435 |
|   |   |   |   |   |   |   |   |   |
| Expression: | Pr(groups==3), predict(outcome(3)) |   |   |   |
|   | \_cons |   | 0.067 | 0.00256 | 26.23 | 0 | 0.062 | 0.07218 |

The results in the table above show that an American Airlines flight in 2017 has a predicted probability of 0.80 of being either on-time or early. The predicted probability of it being delayed is 0.14, the severely delayed probability is 0.07. These results make sense based on the distribution of delays throughout the dataset. Making predictions like these relative to other the other airlines in both time periods as well as comparing these predictions to the 2015 US Airways and American Airlines flights will give more useful insights into the pattern of delays.

More conclusive interpretations are needed in this research. It remains unclear how a recent airline merger like that of US Airways and American Airlines has affected consumer welfare. I believe my design using an ordinal variable can yield useful results, but the sample size has to increase dramatically. Perhaps limiting the sample to those flights between seven major airports does not allow for enough variation that could yield more insights into the delay patterns. A larger sample with all US Airways and American Airlines city-pairs for a multi-year period with all the data to date for the new American Airlines city-pairs may have an adequate amount of variation.

Furthermore, I am surprised to see the consistent lack of statistical significance in the *hhi* variable throughout the estimations. The *hhi* measures the concentration of competition on the city-pairs – i.e. the air routes. I expected to find a significance in some direction. For the flights in which the merger causes a higher hhi – meaning less competition – delays would increase if Mazzeo’s hypothesis is correct.

On the other hand, the divestiture mandated an increase in LCC competition on many of these routes. The new competition would result in a decrease in the hhi for each route, thus, according to the hypothesis, those city-pairs would experience better on-time performance. The hhi proved to be rather meaningless in the analysis, and I expected it to be a more significant variable.

Altogether, I cannot determine the effects the US Airways and American Airlines merger have had on delay patterns at these airports. Although I do believe the ordinal logit model is appropriate for the analysis, more data are needed before any meaningful results can be determined. Additionally, if I attempt to expand this research at another time, I will design a survey for air travelers to better determine their preferences of prices and their tolerances for delays. Perhaps this approach would yield insight into a more suitable way to form an ordinal variable similar my *groups* variable.

**Policy Options**

 Although the findings in this study are not conclusive, the research question is quite relevant to public policy. There are a couple of public policy solutions to flight delays all of which focus on the proper allocation of airport resources to alleviate current delays and the potential for more delays in the future. There are a small range of solutions being discussed in academia and industry groups, and here I will outline each.

 To begin, the first question of policymakers and business leaders is who is responsible for preventing delays? Is it solely the airlines, the airport authorities, the FAA, the National Weather Service? Each of these organizations has some role in providing the data used to analyze flight delays, but it is difficult to place full responsibility onto any one organization. The first obvious solution is to do nothing. Maybe delays will grow, or maybe they will decrease through some unregulated airline practices or effective relationship building between airlines and airport authorities. Whatever the mechanism, leaving things alone, letting markets work and relationships grow could always, in theory, create a solution in the long run.

 Economists at the DOJs Antitrust division have proposed enhancement of the slot program. A team of government economists argue that the slots at DCA, ORD, LGA, & JFK which were discussed in previous sections can be augmented to enhance consumer welfare by lowering the amount of delays. While they admit that the slot program is not perfect, its imperfections are due to too much government regulation. For instance, when the program began the FAA awarded slots to airlines based on service levels in the late 1960s. There were no provisions in the original plan for succession of the slots. Over time the FAA has added slots and given them to startup airlines, but, for the most part, slots are property of the airlines. The airlines can keep them in perpetuity and use them to prevent competition.

 The DOJ economists argue that the basic plan of slots can work quite well at airports throughout the country if the airlines are not able to keep them in perpetuity. They argue that the FAA should hold auctions for the slots at regular intervals. With slot auctions, there would likely be a changing of airline schedules and services based on the regular switching ownership of the slots. In addition to the auctions, the economists believe that bids won for slots should have expiration dates at which the slots will re-enter the market.[[30]](#footnote-30)

 If a process such as this one described above were to take place all over the country at each of the highest traffic airports basic supply and demand without perverse incentives will create a slot market that will allocate LCCs and legacy airlines to the markets where they can achieve optimal operation.

 On the other end of the spectrum are economists that believe the slot program should be eliminated entirely. Some researchers look to the examples of each of the slot controlled airports the harm to consumers that comes when airlines have perpetual control of slots. The secondary markets that are created by these practices let airlines exercise economic power enabling them to stifle competition. This consumer harming practice alongside an FAA that does little to regulate the primary or secondary markets for the slots result in inefficiencies that can be fixed by total elimination of the slot program.[[31]](#footnote-31)

 Another option discussed in the academic literature is that of airport taxes. There is a thriving debate about the efficacy of airport taxes, and the central question is, do the airlines internalize their externalities? Ample empirical research supports both alternatives.

 Regardless of the debate about externality internalization economists agree that some form of taxation will likely lead to better efficiency at our airports, thus a reduction in delays. The question of taxation then becomes, should it be uniform or selective? In other words, should an airport landing tax be set like toll rates on a turnpike or bridge? Or, on the other hand, should they be set based on the externality created by the airline?[[32]](#footnote-32)

 In conclusion, the competitive effects of the last merger of two legacy airlines has yet to be fully understood. Evidence suggests that less competition on some routes will result in more delays because there is little incentive for airlines to maintain schedules when there is a low amount of competition. However, this idea is offset – in this merger at least – by the DOJ’s divestiture mandate that restricted the sale of slots, gates, ticket counters, air bridges, and other airport assets to LCCs. With the introduction of LCC competition there is an obvious and longstanding benefit to consumers because ticket prices almost always decrease in many city-pairs.

 An analysis larger in scope than what has been completed in this study is necessary to properly assess the impacts of the US Airways & American Airlines merger on flight delays. Whether or not the merger has had a substantial impact, flight delays are still an all to common phenomenon that are likely to increase in the years to come without the attention of policy makers.

 Despite much optimism about the feasibility of Pigouvian-style taxes on airlines and subsequent investments in airport infrastructure, taxes will likely be passed on to consumers, and infrastructure expansion is finite. I am convinced that the best solution is the argument for an overhaul and expansion of the slot control program. If it can be implemented as the DOJ economists recommend, competition will be maintained without accrual of market power at our major airports. Additionally, any expenditures on the part of the airlines to gain slots may temporarily be passed on to consumers, but excessive taxation of the airlines – thus consumers – for long-term infrastructure projects could potentially be avoided.

 One parting thought, I have found nothing in the academic literature that explores the cost and benefits of developing the existing, underutilized aviation facilities in many regions of the country. For example, airports in Gary, IN; Wooster, MA; Wilmington, DE, and many other places have the capability to support scheduled air service, yet there is little effort being made to optimize these resources. Perhaps their development is another possible solution to the flight delay problem.

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5. I have calculated the gross wages using the federal minimum wage rate for each year in the sample. If per-capita income for the metropolitan statistical area (MSA) of each airport is used, the gross wages are even larger. Measured in hours the collective time equals 105,108 days. [↑](#footnote-ref-5)
6. Gandt, Robert., (1995) *Sky Gods: The Fall of Pan Am*. William Morrow & Company. [↑](#footnote-ref-6)
7. The average load factor for 2005 was 77.16%. Load factors have been mostly increasing annually, and they are 84.67% as of August, 2017. Data can be easily retrieved at <https://www.transtats.bts.gov/data_elements.aspx?data=5> I do not mean to intend that load factors less than 77% operate at a loss. Break even points vary considerably by aircraft type and aircraft configuration. By 2017 averages, any flight with a load factor below 77% will likely be considered low; even though, low load factors do not indicate that a flight will automatically be cancelled. A trend of load factors around 75%-80% or lower can be incentives for airlines to discontinue a route or an individual flight. [↑](#footnote-ref-7)
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