Office of Inspector General
Audit Report

REDUCTIONS IN COMPETITION INCREASE AIRLINE FLIGHT DELAYS AND CANCELLATIONS

Federal Aviation Administration

Report Number: CR-2014-040
April 23, 2014

Memorandum

U.S. Department of Transportation
Office of the Secretary of Transportation
Office of Inspector General

Subject: ACTION: Reductions in Competition Increase Airline Flight Delays and Cancellations
Federal Aviation Administration
Report No. CR-2014-040

Date: April 23, 2014

From: Mitchell Behm
Assistant Inspector General for Surface Transportation Audits[1]

Reply to Attn. of: JA-30

To: Federal Aviation Administrator

Since 2005, the U.S. airline industry's service quality—airlines' on-time performance and cancellation rates—has varied greatly. The percentage of late domestic flights has fluctuated between 11 and 33 percent per month, while the rate of cancellations has varied from under 1 percent to over 5 percent per month. Understanding the sources of these variations is important because airline delays and cancellations have affected a large number of flights. For example, 1 percent of domestic flights equaled 60,968 flights in 2012.[2]

There has also been considerable industry consolidation since 2005 with mergers between Delta and Northwest in 2008, United and Continental in 2010, and American and US Airways in late 2013. Public concerns over a possible relationship between the quality of airline service and industry consolidation led to congressional hearings and requests to the accountability community to review these issues.[3] Section 406 of the FAA Modernization and Reform Act of 2012 required our office to assess the effects of limited airline service options on the frequency of delays and cancellations.[4] This report presents the results of our

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[1] The Economics Group, which conducts analyses across all modes and produced this audit, is situated in the Surface Transportation Group as of April 1, 2014.
[2] The figures in this paragraph are derived using the Bureau of Transportation Statistics On-time Performance database. Coverage limitations of the available data on airline delays and cancellations are discussed in *More Comprehensive Data Are Needed to Better Understand the Nation's Flight Delays and Their Causes* (OIG Report No. AV-2014-016), December 18, 2013. OIG reports are available on our Web site: http://www.oig.dot.gov.
[3] The Subcommittee on Antitrust, Competition Policy, and Consumer Rights, Senate Committee on the Judiciary, and the Ranking Member of Subcommittee on Aviation, House Committee on Transportation and Infrastructure requested that the General Accountability Office investigate airline competition issues.
[4] Pub. L. No. 112-95 §406 (2012).

analyses of the relationship between competition, measured at the individual route level, and airline service quality, also measured at the individual route level.

Our objective was to determine whether limited competition affects flight delays and cancellations. Specifically, we determined whether (1) reductions in competition affected the percentage of late flights and the length of flight delays, (2) reductions in competition affected flight cancellation rates, and (3) the effects of reduced competition on airline service quality depended upon the initial level of competition.

We conducted our audit work from October 2012 through March 2014, in accordance with generally accepted Government auditing standards. To conduct our work, we collected data on 2,530 domestic routes[5] flown by 20 airlines[6] from the fourth quarter of calendar year 2005 through the fourth quarter of calendar year 2012. We then constructed econometric models to estimate the effect of competition on the length of arrival delay, the percentage of total flights that were late, and the percentage of total flights that were cancelled. For additional information on our scope and methodology, see exhibit A.

RESULTS IN BRIEF

Our study found that variation in airline service quality related substantially to changes in the level of competition within airline markets. Specifically, when airline markets became less competitive both the average length of flight delays and percentage of late flights increased. The effects of reduced competition on the average length of flight delay were statistically significant and sizeable. We estimated that when a market's service options shrank from three airlines to two,[7] the length of delays in the market increased by 25.3 percent. However, the impact of reduced competition on the percentage of late flights was only minimally statistically significant and small in size.

We also found that when competition declined, cancellation rates increased to an extent that was both highly statistically significant and substantial in size. We estimated that a market that went from being served by three airlines to two experienced nearly a 7 percent increase in the flight cancellation rate due to the loss of competition.

[5] This excludes Alaska, Hawaii and U.S. Territories.
[6] This includes 15 major carriers and 5 national carriers. Major carriers have annual revenues over $1 billion. National carriers have annual revenues between $100 million to $1 billion.
[7] When referenced in this manner, airlines are assumed to be of equal size.

Finally, we found that the degree to which competition affected delay lengths and cancellations depended on initial levels of market competition.[8] We estimated that when a market started out fairly competitive, reduced competition significantly increased the lengths of delays but did not substantially affect delay lengths in a market that started out with little initial competition. Conversely, following a similar reduction in competition, we estimated that passengers in markets initially served by few airlines experienced a greater increase in the cancellation rate than passengers in markets initially served by many airlines.

BACKGROUND

We performed both descriptive and statistical modeling analyses to examine the relationship between service quality and market competition. These two types of analyses differed as follows.

- **Descriptive analyses** – These analyses took into account the level of competition but could not separate its effects from those of other factors, such as weather and labor disputes, which could also affect service quality.

- **Statistical analyses** – These analyses isolated the effects of competition on delays and cancellation rates from the effects of other factors affecting airline service quality—such as weather and congestion—and tested them for statistical significance.[9]

We constructed a sample of over 32.2 million flights with flight performance information from 70 U.S. airports.[10] We used this sample to construct econometric models of airline performance. Our modeling served as the basis for our statistical analyses, allowing us to control for factors other than the level of competition that likely affect airline service quality.[11] We constructed separate models for three service quality measures: average minutes of arrival delay;[12] percentage of total flights that were late;[13] and percentage of total flights that were cancelled.

[8] The effects of reduced competition on the frequency of late flights were the same at all levels of competition and only minimally statistically significant overall.
[9] A relationship or effect is statistically significant if it is unlikely to have occurred through random chance. The less likely it is that the relationship or effect occurred though random chance, the more statistically significant is the relationship or effect. For further detail on our testing for statistical significance, see exhibit B.
[10] Exhibit B details our sample construction process. It was primarily determined by the availability of data on the factors to be included in our analysis, in particular airport congestion and weather.
[11] Our control variables included measures of weather conditions, profitability, labor actions, congestion, and runway expansions (see exhibits A and B).
[12] We measured the length of delay considering both positive minutes of delay as well as negative minutes of delay to incorporate all information on timeliness of all flights in our estimation.
[13] We considered a flight late if it arrived 15 minutes or more after the scheduled arrival time.

We measured competition by constructing a Hirschman-Herfindahl index (HHI), a commonly used measure of market competition based on the distribution of market revenue shares. An HHI ranges from 0 to 1. The index approaches zero when a market is served by a large number of airlines of relatively equal size and reaches one when a market is controlled by a single airline. The index increases both as the number of airlines in a market decreases and as disparity in the size of those airlines increases.

We defined an airline market as a pair of origin and destination airports. The definition includes direct flights[14] and flights requiring one connection, since flights with one connection are often considered reasonable substitutes for direct flights. The definition covers more than 95 percent of the passengers[15] during the sample period. We generated an alternative measure of market competition based only on direct flights for use in checking the robustness of our results.

Based on our measure of the level of competitiveness, we characterize the U.S. domestic airline industry as concentrated, with most markets dominated by two carriers. Thirteen percent of the routes in our sample were monopoly routes dominated by one carrier (HHI of 0.9 to 1.0). Forty-two percent were concentrated routes dominated by two carriers (HHI of 0.5 to 0.9). We categorized the rest of the markets (44 percent) as competitive routes (HHI of 0.0 to 0.5).[16] Even though we considered these routes competitive, the competitiveness was relative because, even though there were more than two carriers, many of these routes were dominated by only three airlines.

DELAYS INCREASED WHEN COMPETITION DECREASED

When competition decreased, both the average length of flight delays and percentage of total flights that were late increased. The relationship of reduced competition to increases in the average length of flight delays was substantial and statistically significant. There is less statistical support to infer that reduced competition increased the percentage of late flights.

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[14] Direct flight refers to non-stop flights and flights with one stop but no change of aircraft. We use this definition because the data in Bureau of Transportation Statistics' Data and Airline Origin and Destination survey (DB1B) does not support distinguishing between non-stop flights and flights with one stop but no change of plane. Most passengers in DB1B are on direct flights.

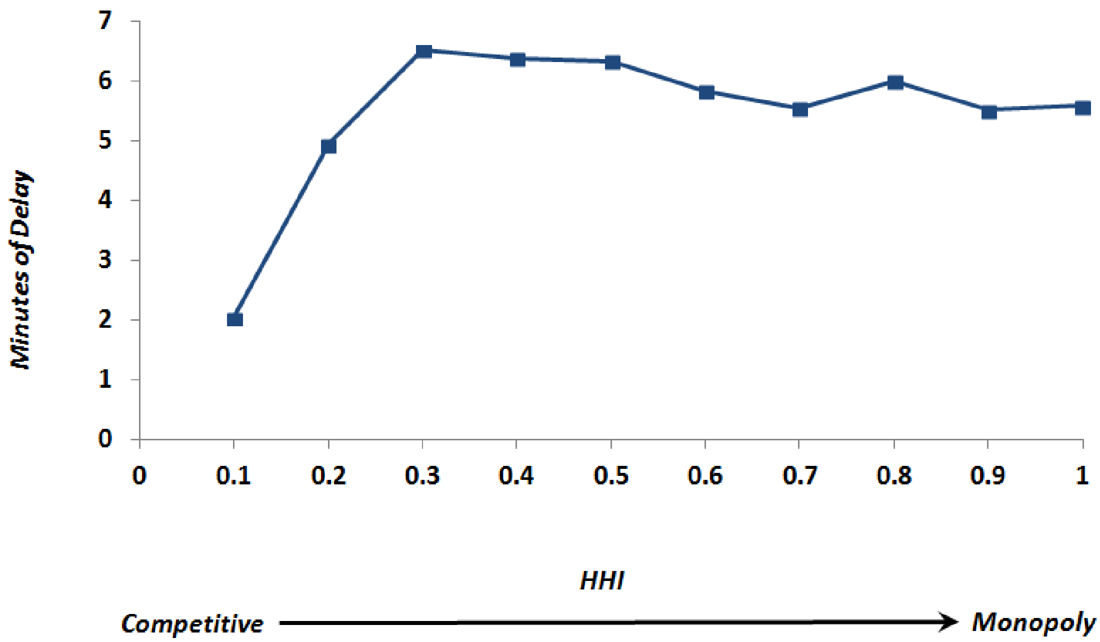
[15] Less than 5 percent of the passengers in our sample had trips with two or more stops.

[16] Rounding error prevents these percentages from adding up to 100.

The Average Length of Flight Delays Increased With Reduced Competition

The average length of flight delays on a route increased as the amount of competition decreased. In our descriptive analyses, we plotted the average length of delay in our sample at each level of our measure of competition. The relationship was most apparent where competition was highest (HHI of 0.1 to 0.3). Across lower levels of competition (HHI of 0.3 to 1.0), there was no apparent relationship between competition and the delay length. See figure 1 for details.

Figure 1. Competition and Average Minutes of Delay

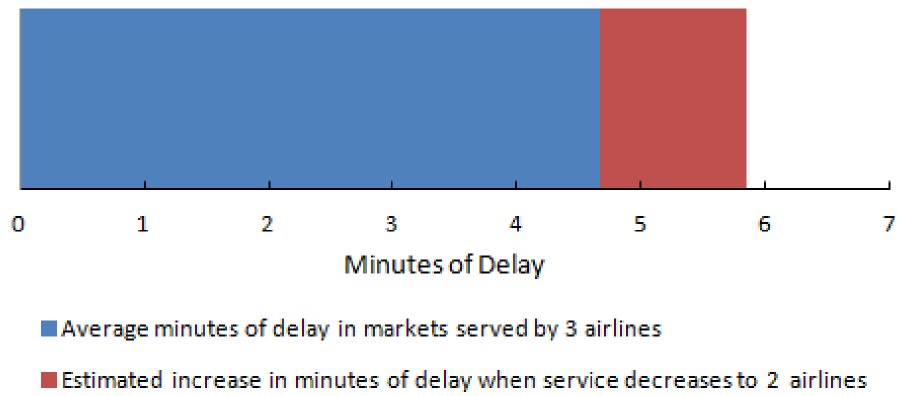


Source: OIG descriptive analysis

Our statistical analyses revealed that the relationship between competition and average minutes of delay was highly statistically significant,[17] and the impact of competition on delay length was sizeable. For example, in our sample, a passenger in a market served by three airlines experienced, on average, a delay of 4 minutes and 40 seconds. However, we estimated that when the number of airlines serving a market decreased from three airlines to two, the reduction in competition increased that average delay by 1 minute and 11 seconds, or 25.3 percent (see figure 2).

[17] It was significant at the 1 percent level.

Figure 2. The Impact of Reduced Competition on Delay Length [18]



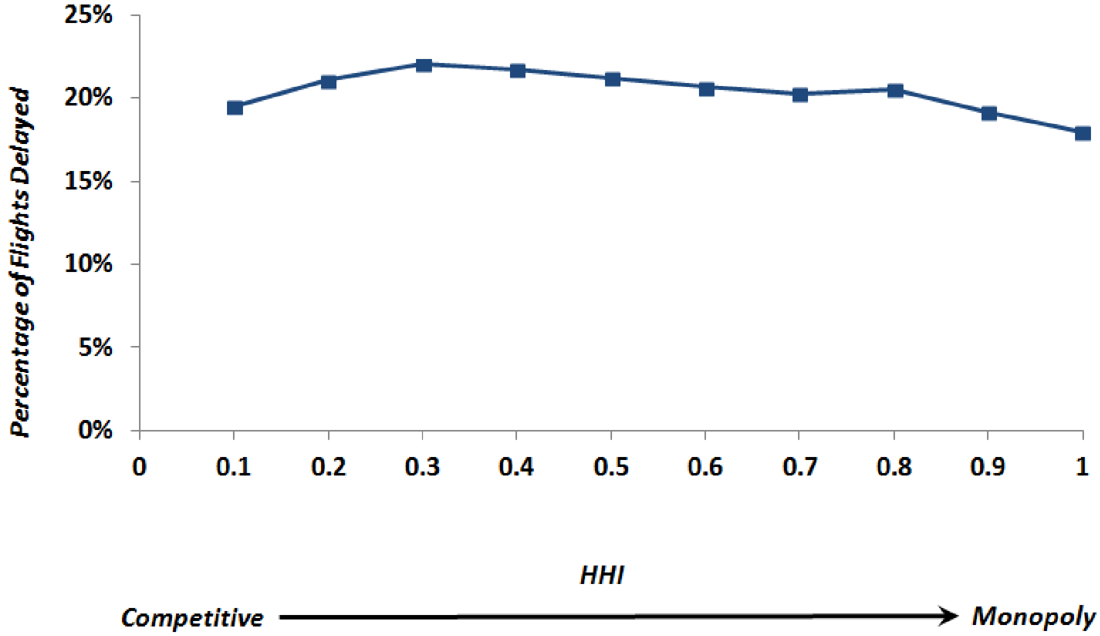
Source: OIG statistical analysis

There Was Little Evidence of a Link Between Competition and the Frequency of Late Flights

There was little evidence of a link between competition and the frequency of late flights. In our descriptive analysis, we plotted airline competition against the percentage of total flights, and found that the results did not show a strong relationship (see figure 3). The percentage of total flights that were late increased slightly when the competition index was low (HHI from 0.1 to 0.3), only to decrease later (HHI from 0.3 to 1.0).

[18] Figures 2, 4, 6, 7 and 8 depict impacts estimated using our econometric models.

Figure 3. Competition and the Percentage of Late Flights

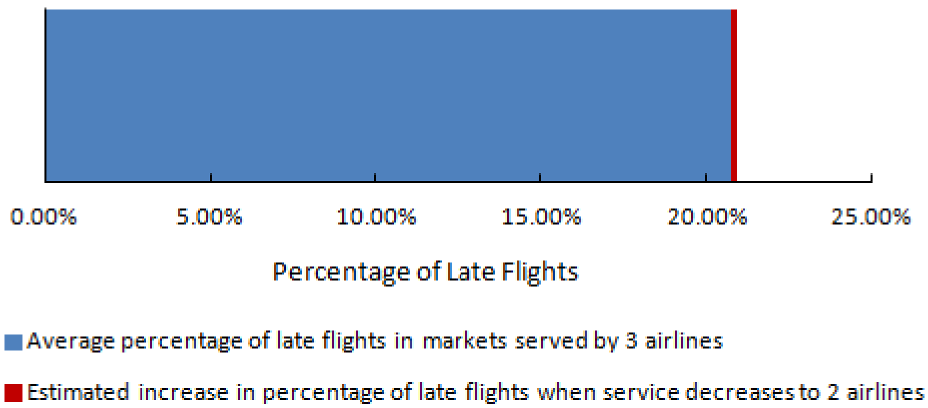


Source: OIG descriptive analysis

According to our statistical analysis, the percentage of late flights increased when competition decreased. However, this relationship was only minimally statistically significant.[19] Furthermore, the effect of a reduction in competition was minor. For example, the average percentage of flights that were late in markets served by 3 airlines was 20.78 percent. When service was reduced to two airlines, we estimated that the average frequency of late flights increased to 20.91 percent—less than 1 percent (see figure 4).

[19] It was only significant at the 10 percent level.

Figure 4. The Impact of Reduced Competition on Percentage of Late Flights

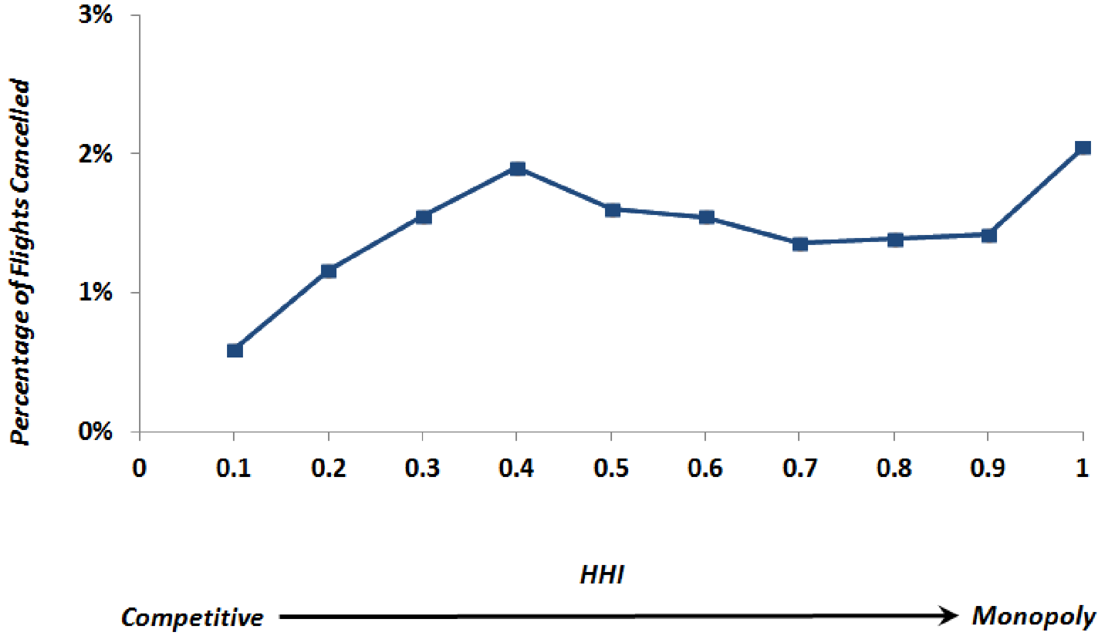


Source: OIG statistical analysis

THE PERCENTAGE OF CANCELLED FLIGHTS INCREASED AS COMPETITION DECREASED

When route competition fell, cancellation rates increased. The descriptive analysis graph (see figure 5) indicated that the overall cancellation rate increased as competition decreased, even though for part of the graph—from an HHI of 0.4 to 0.9—airline competition and cancellations appeared to have no relationship.

Figure 5. Competition and the Cancellation Rate



Source: OIG descriptive analysis

According to our statistical analysis, the impact of competition on cancellation rates was large and highly statistically significant.[20] For example, markets served by three airlines experienced average cancellation rates of 1.46 percent. We estimated the cancellation rates in markets with reductions in service from three airlines to two reached 1.56 percent—close to a 7 percent increase—due to the loss of competition (see figure 6).[21]

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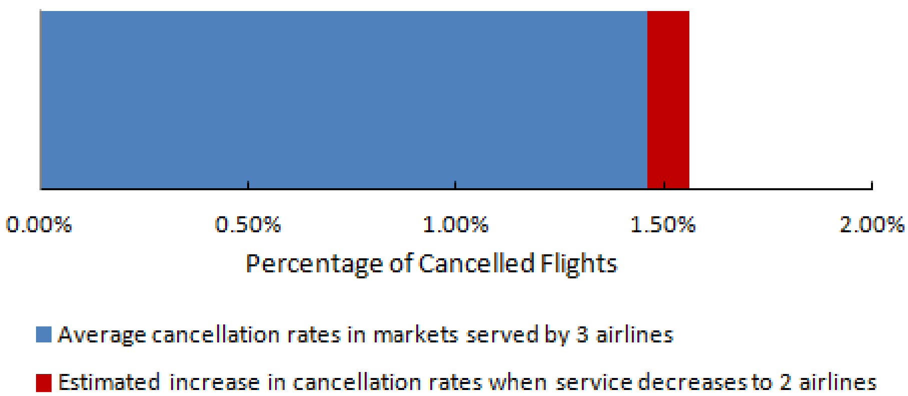
[20] It was significant at the 1 percent level.

[21] These small percentages translate into large numbers of flights. In our sample, roughly 1.6 percent of flights were cancelled, which translated into more than 70,000 cancelled flights annually on average.

Figure 6. The Impact of Reduced Competition on Cancellation Rates



Source: OIG statistical analysis

EFFECTS OF REDUCED COMPETITION ON AIRLINE SERVICE QUALITY DEPENDED ON INITIAL COMPETITION LEVELS[22]

The degree to which reduced competition affected delay lengths and cancellation rates depended on initial competition levels. We estimated that reduced competition had a marked increase on lengths of delays in a market initially served by many airlines but did not substantially affect delays in markets that started out with a low level of competition. Conversely, we estimated that when a market started with a high level of competition, a reduction in competition did not substantially increase the rate of flight cancellations but did increase them in markets with initially limited service options.

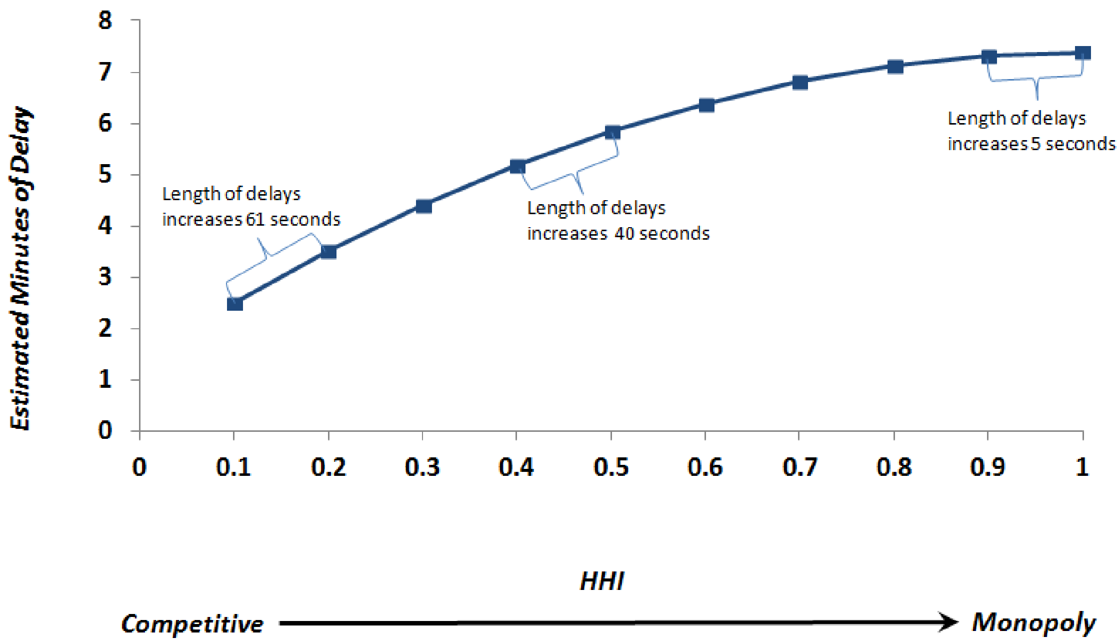
The Largest Increases in Average Delay Lengths Occurred in Markets with Reductions in Initially High Levels of Competition

When a market was initially served by several carriers, we estimated that lengths of delays increased substantially with reduced competition. However, we also estimated that subsequent reductions in competition had less impact. For example, we estimated that when the number of airlines serving a market went from three to two, the market experienced a 25.3 percent increase in average minutes of delay. The increase experienced in a market that went from two airlines to one was not much larger, 26.5 percent, even though the latter change represents a substantially larger competition reduction as measured by the HHI–0.500 versus 0.167.[23] As illustrated in figure 7, when the HHI increased by 0.1, the estimated effect on a

[22] All the results reported in this section derive from our statistical analysis.
[23] These HHI change estimates assume all airlines split the market equally.

market's average minutes of delay varies from approximately 61 seconds to as little as 5 seconds, with the smaller impacts associated with the less competitive markets.

Figure 7. Estimated Relationship Between Competition and Minutes of Delay

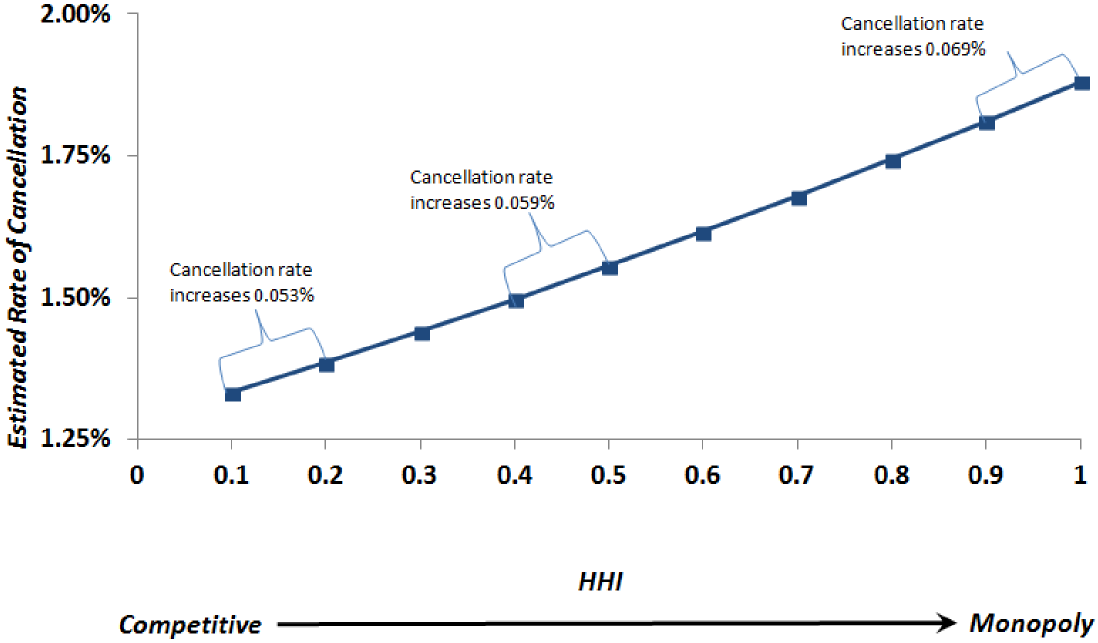


Source: OIG statistical analysis

The Largest Increases in Flight Cancellation Rates Occurred In Markets with Little Initial Competition

In a market with many airlines, we estimated that reduced competition had less impact on the percentage of total cancelled flights than a similar reduction in a market with little initial competition. For example, as seen in figure 8, we estimated that a 0.1 increase in the HHI was associated with increments to the cancellation rate from .053 to .069 percent, with the larger increases associated with the less competitive markets. Consequently, we estimated that the largest increase in cancellation rates occurred in markets that became monopolies.

Figure 8. Estimated Relationship Between Competition and Cancellation Rates



Source: OIG statistical analysis

CONCLUDING OBSERVATIONS

Through our statistical analysis, we determined that variation in airline service quality related substantially to changes in the level of competition within airline markets. Specifically, reduced airline competition increased both the length of delays in some markets and the number of flight cancellations in others. Further, passengers in historically competitive markets experienced a substantial increase in the length of flight delays as competition declined. On the other hand, passengers in historically less competitive markets experienced a larger increase in cancellation rates following a reduction in competition. This type of economic analysis serves to inform FAA and the Department of Transportation about the impacts of reduced competition on airline service quality, and can be used as information in future planning to advance an efficient air traffic system for the traveling public.

AGENCY COMMENTS AND OFFICE OF INSPECTOR GENERAL RESPONSE

On March 20, 2014, we provided copies of this draft report to FAA and the Office of the Secretary. Both informed us that they had no comments on this independent analysis. No actions are required.

We appreciate the courtesies and cooperation of Department of Transportation representatives during this audit. If you have any questions concerning this report, please call me at (202) 366-9970, or Betty Krier, Program Director, at (202) 366-1422.

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cc: Assistant Secretary for Aviation and International Affairs
FAA Deputy Administrator
DOT Audit Liaison, M1
FAA Audit Liaison, AAE-100

EXHIBIT A. SCOPE AND METHODOLOGY

We conducted our work from October 2012 through March 2014, in accordance with generally accepted Government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings based on our audit objectives.

The FAA Modernization and Reform Act of 2012 directed our office to assess the effect that limited air carrier service options have on the frequency of delays and cancellations. Our audit objective was to determine whether limited competition has substantially affected flight delays and cancellations. We defined competition using a standard index based on airlines' market shares. We defined substantially affect as having a statistically and economically significant impact.

To conduct our work, we performed an econometric analysis using airline data on 2,530 domestic directional airport-pairs from the fourth quarter of 2005 through the fourth quarter of 2012. Our sample contained 20 airlines, 15 of which were major carriers.[24] The Bureau of Transportation Statistics (BTS) defines a major carrier as one with annual revenues in excess of $1 billion. The remaining airlines were national carriers,[25] which BTS defines as having annual revenues between $100 million and $1 billion.

We began construction of our sample by combining the on-time performance data from the Airline Service Quality Performance (ASQP) database and the Data and Airline Origin and Destination survey (DB1B) information, both of which BTS maintains. DB1B is a quarterly 10 percent sample of all airline tickets issued by reporting carriers.[26] We measured competition by constructing HHIs based on data from DB1B. We defined an airline market as a directional origin and destination airport-pair. We used BTS's Air Carrier Statistics Database (T-100) to identify service type. The T-100 data also included data on aircraft characteristics and load factors, defined as the monthly average ratio of total passengers and seats. We used weather data from the National Climatic Data Center. We obtained airport capacity utilization data from the FAA's Aviation Performance Metrics (APM) Airport Efficiency System.[27]

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[24] These were: ATA, AirTran, Alaska, American, American Eagle, Comair, Continental, Delta, Frontier, JetBlue, Northwest, SkyWest, Southwest, US Airways, and United.
[25] These were: Atlantic Southeast, ExpressJet, Mesa, Pinnacle, and Virgin America.
[26] All airlines operating any aircraft having over 60 seats are required to report.
[27] The capacity utilization data was based on FAA's "called rates," which are the maximum hourly number of arriving and departing flights an airport can safely handle as determined by air traffic control given existing operational conditions, such as wind direction and weather. See Exhibit B for further information.

To ensure sufficient time series variation for statistical estimation, we omitted route-carrier groups with data spanning less than one year. We also excluded observations with either an origin or destination outside the continental U.S. and flights that arrived more than one hour early or six hours late. We excluded any route that reported less than eight flights per month. The sample was substantially reduced after merging with airport capacity utilization data, because that data is only available for 77 large airports, and only 73 of these are within the continental U.S. With 2,530 directional airport-pairs, 5,481 route-carrier combinations, and 298,389 monthly observations (298,523 for our cancellation analyses), our final sample encompassed approximately 71 percent of the total number of flights during the sample period in the ASQP database.[28]

We built three econometric models to investigate the effect of airline competition on flight delays and cancellations. The dependent variables, or measures whose variation we were seeking to explain, were minutes of arrival delays, percentage of late flights, and percentage of cancelled flights. We also developed a list of factors, or control variables, to account or control for variation in the airline service measures that was not associated with the degree of competition. We developed the list of control variables in part from interviews with the vice president/chief economist at Airlines for America and an independent airline expert. We also drew from economics literature on factors significantly affecting airline service quality. The list of control variables was the same for all three models.

We categorized our control variables into weather factors (heavy rain and freezing rain), profitability measure (load factor), and route-carrier specific covariates. Examples of route-carrier controls included monthly departures in various time windows, congestion measures, and aircraft types. Our congestion measures were unique because they were route-carrier specific based on our construction and accessibility to FAA airport capacity utilization data. The variable of focus was the competition measure, which was an HHI generated with airlines' shares of market revenues. To check the robustness of our findings, we also measured competition using shares of market passengers. The results changed very little with this alternative definition. Sensitivity analyses are detailed in Exhibit B.

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[28] *More Comprehensive Data Are Needed To Better Understand the Nation's Flight Delays and Their Causes,* OIG Report Number AV-2014-016,,December 18, 2013, discusses the coverage limitations of this data.

EXHIBIT B. DETAILED SCOPE AND METHODOLOGY

This exhibit describes our scope and methodology in technical detail. It is organized as follows. First, we describe the sources, construction, and characteristics of our estimation sample. Second, we detail our model specifications and estimation approaches. The last section discusses our results and sensitivity analyses.

Data Sources and the Estimation Sample

We constructed our sample using various data sources. All data was converted into monthly averages and covered the period of 2005:4Q-2012:4Q. Flight delay, measured by minutes of arrival delay, and cancellation data came from BTS's ASQP database, which contains flight-level performance data for non-stop domestic flights by the larger air carriers. Our sample contains 20 airlines. Fifteen of these are major carriers, defined by BTS as having annual revenues in excess of $1 billion.[29] The remaining airlines are national carriers, defined as having annual revenues between $100 million and $1 billion.[30]

To ensure sufficient time series variation for estimating each panel, we omitted route-carrier groups with data spanning less than one year. Furthermore, we excluded observations with either an origin or destination outside the continental U.S. and for flights that arrived more than one hour early or six hours late. We also ignored any route that reported less than eight flights per month. To ensure our sample captured scheduled passenger service exclusively, we used performance data in combination with BTS's T-100 database to identify service type. The T-100 data also included data on aircraft characteristics and load factors, defined as the monthly average ratio of total passengers and seats.

We constructed HHIs, which we used to gauge market competition, based on data from BTS's DB1B database.[31] Our analyses focused on an HHI based on airlines' shares of market revenues.[32] We defined an airline "market" as a directional origin and destination airport-pair. Since less than 5 percent of the passengers in our sample used flights with two or more stops, we only included direct flights and

[29] They are: ATA, AirTran, Alaska, America West, American, American Eagle, Comair, Continental, Delta, Frontier, JetBlue, Northwest, SkyWest, Southwest, US Airways, and United.
[30] They are: Atlantic Southeast, ExpressJet, Mesa, Pinnacle, and Virgin America.
[31] Data Base Products was the provider of our DB1B data. They identify and eliminate a number of data errors, and consolidate the data into a more manageable format.
[32] We also constructed HHIs based on shares of market passengers, shares of non-stop service revenues, and shares of market revenues from all flights connecting metropolitan statistical areas rather than airport-pairs. We used these additional HHIs to conduct sensitivity analyses.

flights requiring one connection as competitors.[33] The market definition is directional so that Washington Dulles (IAD) to Raleigh–Durham International (RDU) is considered to be a different route or airport-pair than RDU to IAD. We chose the directional definition because our measures of service quality often differ for opposite directions on the same route.

We formed our baseline sample by combining the on-time performance data and DB1B-based information.[34] This produced 5,351 directional airport-pairs. The sample size was somewhat reduced after merging with weather data from the National Climatic Data Center because weather information was unavailable for routes where either endpoint airport does not belong to a Metropolitan Statistical Area. The sample was substantially reduced after merging with airport capacity utilization data from the FAA's APM Airport Efficiency System, as that data is only available for 73 of the larger airports.[35] The hourly airport capacity utilization data represents the number of arriving and departing flights an airport completes divided by the maximum number it can safely complete based on the configuration and weather conditions. The merger with this data reduced the final number of directional airport-pairs to 2,530, with 5,481 route-carrier combinations, and 298,389 monthly observations (298,523 for our cancellation model). Even though the number of directional airport-pairs covered in our final sample only accounted for about 50 percent of what we had before the merger with the capacity utilization data, these routes encompassed approximately 71 percent of the total number of flights in the ASQP database.

Model Specification

The basic structure of our model is

$$Y_{ijt} = \alpha X_{jt} + \beta Z_{ijt} + \varepsilon_t + c_{ij} + \mu_{ijt} \quad (1)$$

where *i* indexes airline, j indexes route, and *t* indexes time. The dependent variable Y_{ijt} is a service quality variable measuring flight delays or cancellations for airline

[33] A direct flight means a non-stop flight, although technically, it also includes a flight with one stop but no change of aircraft. This definition arises because the data in DB1B does not support distinguishing between a non-stop flight versus a flight with one stop but no change of plane. Most passengers in DB1B are on direct flights.

[34] The merging process presented a challenge as the Aviation On-Time Performance Data is associated with the operating carrier, while each observation in the DB1B data is tied to a combination of an operating carrier and a marketing carrier. Further, we base the HHI calculation on the marketing carriers. Since about 50 percent of the observations have an operating carrier that is different from the marketing carrier, we merged these two data sets by operating carrier using the following rules: (1) for records that link multiple operating carriers to the same marketing carrier, we simply merged by operating carrier. (2) For records that link multiple marketing carriers to the same operating carrier, we identified the dominant marketing carrier, which for 99.5 percent of these observations was the one with equal to or greater than 50 percent O&D passenger share and performed the merger by eliminating duplicate records with the same operating carrier.

[35] FAA collects data on a total of 77 airports, but only 73 airports are within the lower 48 states. Merging with the data on cancellations and on delays further reduced our coverage to 70 airports. The airport capacity data is not publicly available. We gained access through FAA.

i on route *j* at month *t*. We used two alternative delay definitions. $Delay_{ijt}$ is airline *i*'s monthly average minutes of arrival delays for all flights on route *j* in month *t*. $Late\ Flight_{ijt}$ is the monthly percent of airline *i*'s flights on route *j* that are at least 15 minutes late.[36] $Cancel_{ijt}$ is the monthly percent of airline *i*'s flights on route *j* that are cancelled. We ran three separate estimations for each definition of service quality.

The vector X_{jt} measures airline route or market competition. The vector Z_{ijt} contains other explanatory variables varying by route-carrier and time. ε_t is a vector of yearly and quarterly time effects. In part, ε_t serves to absorb shifts in macroeconomic variables, such as the unemployment rate, as they generally exhibit time series variation but change little across panels. c_{ij} represents the route-carrier heterogeneity. It captures the time invariant factors for each route-carrier combination, such as distance and demographic elements.

In most of our estimations, X_{jt} is comprised of HHI_{jt}, the revenue-based Hirschman-Herfindahl index on route *j* for month *t*, so equation (1) becomes

$$Y_{ijt} = \alpha HHI_{jt} + \beta Z_{ijt} + \varepsilon_t + c_{ij} + \mu_{ijt} \ (2)$$

The endogeneity of HHI in empirical models of airline ticket prices is well documented. We used lagged HHI to instrument for HHI in the current period.

We pursued different approaches to allow for nonlinearities in modeling the length of flight delays versus the percent of late flights and percent of flights cancelled. In the model of delay length, we added a quadratic term, HHI_{jt}^2. In the models of the percent of late and cancelled flights, the dependent variables are bounded by zero and one, so those models are appropriately estimated using a fractional response method.[37] Because this estimation method allows for variable marginal effects, it also readily accommodates any nonlinearities.

The model of delay length was estimated using two-stage least-squares (2SLS).[38] As an alternative means of carrying out the instrumentation, we also used the control function (CF) approach. We used correlated random effects (CRE) to estimate the models of the percent of late and cancelled flights. We followed the implementation in Papke and Wooldridge (2008). We applied the CRE approach to the estimation of the models of the percent of late and cancelled flights in a fractional probit framework. For those models, we corrected for the endogeneity

[36] BTS designates a flight late if it arrives at least 15 minutes past schedule.
[37] The application of panel data methods to fractional response models is explained in detail by Papke and Wooldridge (2008).
[38] We predicted the values of the linear and quadratic forms of HHI separately in the first stage.

of HHI in the estimation by using the CF approach, as opposed to 2SLS, due to the distinct advantages of applying CF over 2SLS in nonlinear models.[39] In all estimations, we weighted each monthly observation for each route-carrier by the number of flights captured by that monthly average.

Control variables

We categorized our control variables into weather factors, profitability measures, and route-carrier specific covariates. We used heavy rain and freezing rain to capture the weather events that would be most likely to cause airline delays and cancellations. $Heavy\ Rain\ Origin_{jt}$ is the percent of days in month *t* at the origin airport of route *j* with precipitation in excess of the 95th percentile for that airport over the entire sample period. $Freezing\ Rain\ Origin_{jt}$ captures the percent of days in month *t* with greater than 95th percentile precipitation and a temperature below 32 degrees at the origin airport of route *j*. $Heavy\ Rain\ Dest_{jt}$ and $Freezing\ Rain\ Dest_{jt}$ similarly capture extreme weather at the destination airport of route j.

We used airline load factors to measure profitability. $Load\ Factor_{ijt}$ is airline *i*'s load factor on route j in month *t*. Load factor is the total number of passengers divided by the total number of seats. $Depart\ Early_{ijt}$, $Depart\ 6\ am\ to\ 12\ noon_{ijt}$, $Depart\ 12\ noon\ to\ 6\ pm_{ijt}$, *and* $Depart\ 6\ pm\ to\ 12\ midnight_{ijt}$ represent the monthly percent of route-carrier specific total departures from midnight to 6 am, 6 am to 12 noon, 12 noon to 6 pm, and 6 pm to midnight, respectively. $Depart\ Early_{ijt}$ was our reference group. We introduced these coefficients to capture the effect of cumulative delays, which cause flights scheduled later in a day to be more likely to experience delays and cancellations.

We adapted the congestion measure to the route-carrier level. The airport capacity utilization data reports on the average level of congestion for the airport on an hourly basis. We multiplied this information by the monthly average number of flights for each route-carrier in each hourly interval. This produced a measure allowing two airlines serving the same route to experience different congestion levels at the same airport if one schedules more flights during the morning rush while the other predominantly schedules flights in the afternoon. Accordingly $Congestion\ Origin_{ijt}$ is the sum of the total number of actual flights divided by the maximum allowable number of flights at the origination airport interacted with airline *i*'s hourly departures on route *j*. Similarly $Congestion\ Dest_{ijt}$ captures the route-carrier specific capacity utilization level at the destination airport.

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[39] These advantages are discussed in Wooldridge (2010a), pp. 126-128 and 589.

We controlled for the effects of airline hubbing with variables constructed using DB1B data. $Connections\ Origin_{jt}$ tracks the total number of locations to which there are direct flights from the origin airport of route j in the quarter containing month t. $Connections\ Dest_{jt}$ measures the total number of locations from which there are direct flights to the destination airport of route j in the quarter containing month t.

We also included aircraft characteristics. We assembled information on aircraft model for each route-carrier combination from T100 data. The seating capacity for each model was identified using data from various aircraft manufacturer Web sites. All aircraft types in our sample were grouped into five categories based on the number of seats. We calculated the monthly average percent of aircraft within each group for each route-carrier combination. $Aircraft\ Group\ 1_{ijt}$ is the monthly percent of all aircraft used by carrier *i* on route *j* comprised of turbo-prop aircraft having up to 70 seats. $Aircraft\ Group\ 2_{ijt}$ to $Aircraft\ Group\ 5_{ijt}$ were generated in similar fashion with higher group numbers representing greater seating capacity.[40]

Other controls included dummy variables for airport expansion and labor actions. Specifically, one set of dummies indicates the completion of airport runway projects in November 2008 at three major airports: Seattle-Tacoma (SEA), Chicago O'Hare (ORD), and Washington Dulles (IAD). For example, $SEA\ Runway\ Origin_{jt}$ is set to one starting November 2008 if the origination airport on route j is the Seattle-Tacoma International Airport, and is zero otherwise. $SEA\ Runway\ Dest_{jt}$ similarly indexes the destination airport. The other set of dummies, $Labor\ Strikes_{it}$, indicate periods of labor strikes and slowdowns occurring at different airlines during our sample.[41]

Results

Table B1 displays our regression results, with the standard errors shown in parentheses. The results for the model of arrival delays incorporating the quadratic term clearly indicate that the relationship between the level of competition and minutes of delay is nonlinear. In the FE CF estimation, *v2hat_lag1*, the CF indicator of the need to correct for the endogeneity of the competition measures, is significant. It makes little difference whether we make the correction using 2SLS or the CF.

[40] Group 2 includes regional jets with up to 70 seats. Group 3 contains regional jets with 70 to 100 seats. Group 4 is made up of narrow body planes having more than 100 seats. Group 5 represents all wide body aircraft.

[41] We collected information on airline labor actions from sources such as the Wall Street Journal, the Chicago Tribune, the Bureau of Labor Statistics, CNN, USA Today, NBC news, TribLive, and Highbeam. Four events were identified during our sample, affecting: (1) Northwest Airlines from October to November 2005; (2) Northwest Airlines in November 2006; (3) US Airways in April 2006; and (4) American Airlines from September to October 2012.

To further examine the diminishing effects of marginal changes in competition on average delay length, we generated estimates of the marginal effects at different HHI levels. Specifically, we calculated the marginal effects at HHI levels from 0.1 through 0.9, in increments of 0.1, based on the FE CF estimation. Table B2 displays the results. The reported marginal effects of a .1 increase in HHI peak at over 1 minute at HHI=0.1 and decline, as the level of HHI increases, to less than 16 seconds at HHI=.8. They are insignificant at HHI=0.9.

We also found the relationship between competition and airline service quality to be nonlinear when using the flight cancellation rate as the measure of service quality. Table B1 shows the results of estimating the cancellations model using fractional probit with CRE and CF. The fractional probit approach allows us to identify how the average partial effect (APE) changes with the level of HHI. Table B2 presents the APEs evaluated from HHI=0.1 to HHI=0.9 at increments of 0.1. The size of the impact of an increase in competition on the cancellation rate grows at an increasing rate with the level of HHI. Specifically, the APE grows from .055 percent at HHI=0.1 to .073 percent at HHI=0.9. Further, the APE is statistically significant at every HHI level.

The relationship between competition and the percent of late flights is only significant at the 10 percent level in the fractional probit estimation, as Table B1 shows. Table B2 presents the APEs evaluated at different levels of HHI. They do not change much with the level of HHI, but some are significant at the 5 percent level.

Sensitivity Analyses

We tested the sensitivity of our results to the use of different lags of HHI in the instrumentation process and to the use of alternative HHI measures. The other HHI measures included indices of competition: (1) restricted to direct flights connecting airport-pairs; and (2) between all direct and one-stop flights connecting pairs of metropolitan statistical areas (MSA).[42] Lastly, since our panels were unbalanced, we investigated the extent to which attrition and addition in our panel were correlated with idiosyncratic shocks.

Table B3 displays the sensitivity test results derived using the different HHI measures. We found that the relationship between delay length and competition in a linear specification was robust to the instrument being lagged as much as 6 quarters. The relationship between the cancellation rate and competition, is also robust to use of longer lags of the instrumental variable, except in the case of the

[42] Another set of specifications we tried used HHIs based on the number of passengers in each market. The results differed little from those produced using revenue--based indices, so we only report on the revenue-based HHI estimations.

MSA-pair HHI. In the model of the percent of late flights, the competition measures remain relatively insignificant at all lags of the instrumental variable. Use of the HHI based only on direct flights does not change the qualitative results in any model. However, use of the HHI calculated for MSA-pairs does produce different results: the HHI coefficient is insignificant in the cancellation rate model, and is significant and negative in the model of the percent of late flights.

Wooldridge (2010b) suggests several alternative estimation strategies to address selection bias in the nonlinear CRE framework, including using only those observations for which a balanced panel is available, and performing a separate estimation for each time period. The relationship between competition and cancellation rates was the same or even stronger using these alternative estimation strategies than in our other estimations.

References

Papke, L. E. and J. M. Wooldridge (2008) Panel Data Methods for Fractional Response Variables with an Application to Test Pass Rates, *Journal of Econometrics*, 145, 121-33.

Wooldridge, J.M. (2010a) Econometric Analysis of Cross Section and Panel Data, Second Edition.

Wooldridge, J. M. (2010b) Correlated Random Effects Models with Unbalanced Panels, working paper.

Table B1: Models of Minutes of Arrival Delays, Percent of Cancelled Flights, and Percent of Late Flights

Dependent Variable	**Average Length of Arrival Delays**	**Average Length of Arrival Delays**	**Average Percent of Cancelled Flights**	**Average Percent of Late Flights**
	FE 2SLS (IV: 1 Q lagged HHI)	FE CF (IV: 1 Q lagged HHI)	Fprobit CRE CF (IV: 1 Q lagged HHI)	Fprobit CRE CF (IV: 1 Q lagged HHI)
			APE	APE
Revenue Based HHI	11.89***	10.17***	0.00656***	0.00863*
	(3.395)	(2.403)	(0.00113)	(0.00440)
Revenue Based HHI^2	-5.809**	-4.430**		
	(2.554)	(1.751)		
Heavy Rain Origin	20.32***	20.32***	0.0235***	0.213***
	(0.458)	(0.462)	(0.00134)	(0.00491)
Heavy Rain Dest	18.67***	18.67***	0.0226***	0.218***
	(0.449)	(0.453)	(0.00134)	(0.00470)
Freezing Rain Origin	31.68***	31.68***	0.0523***	0.366***
	(0.588)	(0.594)	(0.00131)	(0.00613)
Freezing Rain Dest	18.66***	18.66***	0.0500***	0.197***
	(0.592)	(0.597)	(0.00131)	(0.00603)
Load Factor	19.70***	19.70***	-0.0196***	0.193***
	(0.372)	(0.375)	(0.000937)	(0.00408)
Labor Strikes	7.970***	7.964***	0.00923***	0.107***
	(0.359)	(0.362)	(0.000916)	(0.00443)
Departure 6 am to 12 noon	-3.071***	-3.067***	0.00143	-0.0347***
	(0.511)	(0.516)	(0.00102)	(0.00616)
Departure 12 noon to 6 pm	1.816***	1.823***	0.00503***	0.0269***
	(0.530)	(0.536)	(0.00107)	(0.00637)
Departure 6 pm to 12 midnight	7.032***	7.036***	0.00510***	0.0914***
	(0.558)	(0.564)	(0.00113)	(0.00662)
Connections Origin	0.0454***	0.0449***	-3.61e-05***	0.000429***
	(0.00586)	(0.00591)	(1.26e-05)	(6.31e-05)
Connections Dest	0.00626	0.00586	2.33e-05**	0.000107*
	(0.00548)	(0.00553)	(1.17e-05)	(6.03e-05)
Congestion Origin	10.14***	10.14***	-0.00318***	0.124***
	(0.517)	(0.523)	(0.00116)	(0.00621)
Congestion Dest	12.69***	12.69***	0.00116	0.149***
	(0.588)	(0.593)	(0.00113)	(0.00668)

SEA Runway Origin	-2.479***	-2.479***	-0.00384**	-0.0545***
	(0.519)	(0.520)	(0.00161)	(0.00796)
ORD Runway Origin	-5.153***	-5.158***	-0.00720***	-0.0335***
	(0.428)	(0.433)	(0.000504)	(0.00368)
IAD Runway Origin	-2.603***	-2.597***	-0.00246***	-0.0234***
	(0.595)	(0.607)	(0.000870)	(0.00612)
SEA Runway Dest	-4.415***	-4.414***	-0.00673***	-0.0596***
	(0.744)	(0.746)	(0.00160)	(0.00928)
ORD Runway Dest	-6.840***	-6.845***	-0.00686***	-0.0440***
	(0.403)	(0.408)	(0.000445)	(0.00344)
IAD Runway Dest	-0.316	-0.311	-0.00343***	-0.00114
	(0.572)	(0.579)	(0.000873)	(0.00600)
Aircraft Type Group 3	0.0126	0.0143	-0.00410***	-0.00652
	(0.388)	(0.391)	(0.000504)	(0.00415)
Aircraft Type Group 4	0.176	0.177	-0.00579***	-0.00432
	(0.426)	(0.429)	(0.000605)	(0.00461)
Aircraft Type Group 5	0.672	0.666	-0.00786***	-0.00113
	(0.862)	(0.870)	(0.00102)	(0.00841)
Year 2007	0.0978	0.0976	0.00156***	0.00196*
	(0.0922)	(0.0929)	(0.000199)	(0.00111)
Year 2008	-2.478***	-2.481***	-0.00274***	-0.0286***
	(0.0974)	(0.0977)	(0.000230)	(0.00112)
Year 2009	-5.087***	-5.091***	-0.00700***	-0.0515***
	(0.109)	(0.110)	(0.000261)	(0.00121)
Year 2010	-6.088***	-6.092***	-0.00250***	-0.0591***
	(0.142)	(0.144)	(0.000261)	(0.00148)
Year 2011	-5.373***	-5.378***	-0.00104***	-0.0588***
	(0.128)	(0.129)	(0.000263)	(0.00141)
Year 2012	-6.732***	-6.737***	-0.00493***	-0.0757***
	(0.151)	(0.152)	(0.000301)	(0.00171)
Quarter 2	1.170***	1.171***	-0.00297***	0.00120**
	(0.0536)	(0.0542)	(0.000153)	(0.000595)
Quarter 3	0.715***	0.714***	-0.00272***	-0.00776***
	(0.0603)	(0.0607)	(0.000164)	(0.000729)
Quarter 4	-1.018***	-1.019***	-0.00507***	-0.0145***
	(0.0408)	(0.0412)	(0.000150)	(0.000484)
v2hat_lag1		-4.058***	-0.0128***	-0.0194***
		(0.632)	(0.00105)	(0.00489)
Observations	289,248	289,248	288,954	288,810
R-squared	0.216	0.419		

Exhibit B. Detailed Scope and Methodology

Route Carrier Combinations	5,485			

Notes: *Significant at the 10 percent level. **Significant at the 5 percent level. ***Significant at the 1 percent level.

Table B2: Estimated HHI Marginal and Average Partial Effects (APE)

	Length of Delay (Marginal Effects)	**Percent of Cancelled Flights (APEs)**	**Percent of Late Flights (APEs)**
	Revenue Based HHI (Direct and One-Stop Flights)	**Revenue Based HHI (Direct and One-Stop Flights)**	**Revenue Based HHI (Direct and One-Stop Flights)**
HHI=0.1	10.73***	0.00553***	0.00852**
	(2.906)	(0.000792)	(0.0043)
HHI=0.2	9.569***	0.00573***	0.00855**
	(2.409)	(0.000857)	(0.00432)
HHI=0.3	8.407***	0.00595***	0.00857**
	(1.920)	(0.000926)	(0.00434)
HHI=0.4	7.245***	0.00616***	0.00859**
	(1.450)	(0.000997)	(0.00436)
HHI=0.5	6.083***	0.00639***	0.00861**
	(1.023)	(0.00107)	(0.00439)
HHI=0.6	4.921***	0.00661***	0.00863*
	(0.719)	(0.00115)	(0.00441)
HHI=0.7	3.759***	0.00685***	0.00865*
	(0.719)	(0.00123)	(0.00443)
HHI=0.8	2.597**	0.00709***	0.00867*
	(1.022)	(0.00131)	(0.00445)
HHI=0.9	1.436	0.00734***	0.00869*
	(1.449)	(0.00140)	(0.00447)

Notes: *Significant at the 10 percent level. **Significant at the 5 percent level. ***Significant at the 1 percent level.

Table B3: Sensitivity Test HHI Estimates

	Airport-Pair: Revenue Based HHI (Direct and One-Stop Flights)	**Airport-Pair: Revenue Based HHI (Direct Flight Only)**	**MSA-Pair: Revenue Based HHI (Direct and One-Stop Flights)**
	Minutes of Delay Model		
IV: 1 Quarter Lag	4.648***	3.693***	4.457***
	(0.661)	(0.517)	(0.850)
IV: 2 Quarter Lag	5.767***	5.142***	5.590***
	(0.931)	(0.741)	(1.165)
IV: 3 Quarter Lag	4.206***	3.966***	3.006**
	(1.264)	(1.011)	(1.453)
IV: 4 Quarter Lag	4.881***	5.362***	2.040
	(1.611)	(1.307)	(1.656)
IV: 5 Quarter Lag	5.901**	6.992***	2.357
	(2.617)	(2.137)	(2.481)
IV: 6 Quarter Lag	13.89***	14.70***	6.842*
	(4.815)	(4.153)	(3.742)
	Percent of Cancelled Flight Model		
IV: 1 Quarter Lag	0.00656***	0.00272***	0.000876
	(0.00113)	(0.000932)	(0.00108)
IV: 2 Quarter Lag	0.00661***	0.00282***	0.000812
	(0.00117)	(0.000964)	(0.00110)
IV: 3 Quarter Lag	0.00650***	0.00281***	0.000593
	(0.00119)	(0.000992)	(0.00112)
IV: 4 Quarter Lag	0.00639***	0.00275***	0.000656
	(0.00121)	(0.00101)	(0.00114)
IV: 5 Quarter Lag	0.00662***	0.00333***	0.00113
	(0.00122)	(0.00102)	(0.00118)
IV: 6 Quarter Lag	0.00646***	0.00341***	0.00128
	(0.00121)	(0.00101)	(0.00118)
	Percent of Late Flight Model		
IV: 1 Quarter Lag	0.00863*	0.00256	-0.0198***
	(0.00440)	(0.00384)	(0.00494)
IV: 2 Quarter Lag	0.00788*	0.00223	-0.0204***
	(0.00455)	(0.00399)	(0.00509)
IV: 3 Quarter Lag	0.00474	-0.000623	-0.0223***
	(0.00466)	(0.00408)	(0.00519)
IV: 4 Quarter Lag	0.00396	-0.000498	-0.0236***
	(0.00472)	(0.00415)	(0.00526)

IV: 5 Quarter Lag	0.00392	-0.000435	-0.0244***
	(0.00481)	(0.00424)	(0.00540)
IV: 6 Quarter Lag	0.00667	0.00207	-0.0228***
	(0.00492)	(0.00435)	(0.00559

Notes: *Significant at the 10 percent level. **Significant at the 5 percent level. ***Significant at the 1 percent level.

Exhibit B. Detailed Scope and Methodology

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