Further Investigations into the Causes of Flight Delays

Nicholas G. Rupp*

Department of Economics

East Carolina University

Greenville, NC 27858-4353

May 20, 2007

Abstract

A recent empirical study by Mayer and Sinai (2003a) finds that air traffic congestion due to airline hubbing and over-scheduling of flights at airport facilities are the primary causes of flight delays. Mayer and Sinai's (2003a) analysis, however, relies on a non-traditional flight delay measure: travel time in excess of the route's monthly minimum. While carriers may make such delay calculations, we argue that passengers do not. Hence this paper further investigates flight delays from both the airline and passenger perspectives. Moreover this paper provides a robustness check and critique of Mayer and Sinai's (2003a) flight delay findings when more traditional measures of flight delays are employed.

JEL Classifications: L13, L93

Keywords: Airport Congestion, Airline Hubbing, Flight Delays

*Contact at ruppn@ecu.edu or (252) 328-6821. I thank Junhua Yu for her valuable research assistanc. Marc Fusaro, Stuart Gurrea, and participants at the Southern Economic Assocation Meeting and International Industrial Organization Conference for their helpful comments.

1 Introduction

One of the critical questions confronting the airline industry in the 21st century is how to handle a growing problem of airport and air traffic congestion. Between 2000 and 2007 twenty percent of all U.S. commercial flights were delayed (arriving 15+ minutes late). The Federal Aviation Administration (FAA) estimates that commercial aviation delays cost airlines in excess of $3 billion dollars per year (www.faa.gov), an amount that exceeds the $2.4 billion of direct financial assistance to the airline industry provided by the federal government under the 2003 Emergency Wartime Supplemental Appropriations Act (GAO, 2004). Airport congestion in the future is likely to get worse due to an increase in demand due to the expansion of low-cost carriers, growth of regional jets,[1] and more business aviation flights, while the supply of airport runway capacity will likely remain constant. Given that air traffic delays are likely to persist in the future, we seek to learn more about the causes of flight delays.

A recent empirical study by Mayer and Sinai (2003a) finds that air traffic congestion due to airline hubbing and over-scheduling of flights at airport facilities are the primary causes of flight delays. Mayer and Sinai's (2003a) analysis, however, relies on a non-traditional flight delay measure: travel time in excess of the route's monthly minimum (hereafter excess travel time). While excess travel time provides an accurate depiction of travel time sans congestion, one problem with using the monthly minimum to calculate flight delays is this variable relies on outliers which can be influenced by both weather (strong tail winds) and aircraft model used (faster cruising speeds). More importantly, excess travel time does not reflect the perceived length of delay by passengers since they do not make such delay calculations. Passengers are more likely to be concerned with how the actual arrival and departure times differ from flight schedules.

[1] For a detailed examination of the impact of regional jets on the airline industry see Brueckner and Pai (2007).

In addition to delays being costly, poor on-time performance has increased the number of disgruntled passengers. The University of Michigan's American Customer Satisfaction Index score for U.S. airlines in 2007 registered 63 out of 100 points, which is the lowest airline score in the past seven years and down two points from the previous year. Of the sixteen industries rated by the ACSI, only one other industry (cable and satellite TV) fared worse than airlines in the 2007 customer satisfaction ratings.[2] The purpose of this paper is to further investigate flight delays from both the airlines (excess travel time) and passenger (departure and arrival delays) perspective. Moreover the paper will provide a robustness check and critique of Mayer and Sinai's (2003a) flight delay findings when more traditional measures of flight delays are employed.

We argue that excess travel time does not reflect passenger perceptions of flight delays. A simple example illustrates the shortcoming of using excess travel time to measure flight delays. For example, if dinner is served at 6 pm, then how do you know if you are late? The excess travel time variable employed by Mayer and Sinai (2003a) compares the actual commuting time with the monthly minimum to determine tardiness. Suppose that the typical evening weekday commute (in heavy traffic) takes 45 minutes, while on weekends (in light traffic) this same drive takes just 15 minutes. Even if you arrive promptly at 6 pm, after a 45 minute weekday commute, the excess travel time variable indicates that you are 30 minutes late (since this is a 15 minute trip on the weekend). Whereas, we argue that 6 pm serves as the on-time benchmark/measuring stick which determines whether an individual is late/early. If the individual arrives at 6 pm, after a 45 minute weekday commute, then the individual is on-time rather than 30 minutes late. Similarly, for air travel, we believe that flight arrival and departure schedules serve as benchmarks used by passengers to determine the tardiness (or promptness) of a flight. Given the above mentioned caveats with excess travel time as a delay measure, we think it is prudent to consider a broader set

[2] For more details see http://www.theacsi.org/images/stories/images/news/0507q1.pdf accessed 17 May 2007.

of delay measures which reflect the length of delay experienced by passengers when investigating the causes of flight delays.

The differences between these flight delay measures can also be seen graphically. Figure 1 plots the scheduled block times, minimal feasible time, and actual travel time for a popular shuttle route from Boston (BOS) to New York LaGuardia (LGA), which is served by carriers (American, Delta, and US Airways) in July 2003. The minimum travel time recorded during the month was 40 minutes. In comparison, the scheduled block time varies between 63 and 74 minutes, while actual travel time (hourly average) had an even larger variation from 61 minutes (for 12 p.m. departures) to 81 minutes (for 6 p.m. departures). Figure 1 indicates that movements in scheduled and actual travel times during the day are highly correlated, rising and falling together. This suggests that carriers anticipate the peak congestion periods (8 a.m., 12 p.m., and 6 p.m.) by adding time to the scheduled flight. Finally, this figure also reveals notable differences between the flight delay measures. For example, 8 a.m. departures from BOS to LGA had the longest schedule block time (74 minutes). In July 2003, the actual and scheduled block times differed by only 1 minute for 8 a.m. departures which suggests that passengers experienced only minimal air traffic delays; whereas, excess travel time (the difference between actual and minimum travel time) indicates that 8 a.m. departures had 34 minutes of air traffic delay. Hence one can arrive at very different conclusions based on which flight delay measure is used.

Using three different measures of flight delays, this paper investigates the causes of flight delays from both the carrier and passenger perspectives by examining individual flight data over a ten year period (1995-2004). A key distinction that appears when flight delays are considered from the passenger's viewpoint occurs at highly concentrated airports. We document higher departure and arrival delays at highly concentrated airports. Whereas recent theoretical (Brueckner, 2002) and empirical (Mayer and Sinai, 2003a) studies indicate that dominant airport carriers do not overschedule flights because the dominant carrier would bear the cost of overscheduling (since its own flights are delayed). Our findings indicate that congestion pricing may have a larger impact on flight scheduling than previously suggested in the literature. This paper is organized as follows. The next section discusses the causes of flight delays, followed by the data and econometric model. We then propose some hypotheses and present the estimation results. The conclusion offers some comments on the potential effectiveness of congestion-based pricing.

2 The Causes of Flight Delays

Between 1995 and 2004 an average of one in five flights were delayed. The annual delay rates ranged from 16.5% (2003) to 25.5% (1996). Beginning in June 2003, domestic carriers are required to report the causes of flight delays (by selecting one of five broad delay categories) to the Bureau of Transportation Statistics (BTS). For example, in 2004 when 20% of all flights were delayed, these BTS data provide the following flight delay reasons (the proportion of all flights delayed is in parentheses): weather (6.4%), late arriving aircraft (5.9%), air carrier delay due to maintenance, equipment, or crew problems (5.2%), heavy traffic volume (1.6%), closed runways (0.4%), security delays (0.1%), and other (0.5%). The primary drivers of delays: weather and late arriving aircraft are subject to seasonal fluctuations with poor weather typically occurring in the winter while late arrivals are more common during the busy summer travel season.

This seasonality is apparent when flight delay rates are ranked by month between 1995 and 2007 (through March). We find that the top decile (fewest delays) is dominated by September and October while six months never appeared (January, March, May, June, July, August, and December). The most frequent months in the bottom decile (most delays) are December, January, and June while five months never appeared (March, April, September, October, and November).

Before we can understand the causes of flight delays, we need to define the difference between carrier's and passenger's perspectives on flight delays. Carriers are keenly interested in the overall flight time (T) of a route since this determines the availability of an aircraft for the next flight. Flight time is comprised of three components: minimum (M) travel time for the route, scheduled (S) excess travel time, and delay (D). Scheduled excess travel time S(C) depends on average airport and air traffic congestion (C) at both origination and destination. Delay D(C, X, ϵ) depends on congestion (C) since more congested airports are subject to greater disruption from random events, economic and competitive factors (X) that represent an airline's willingness to accept delay (for example, seating capacity, yield, monopoly route, etc.), and random influences ϵ (for example, weather, maintenance issue, equipment failure, etc.). Hence flight time is represented as:

$$T = M + S(C) + D(C, X, \epsilon) \tag{1}$$

Airport congestion (C) depends on whether the airport is a *hub*, the airport concentration rate also known as Hirschman-Herfindahl Index (*hhi*), and the volume of airport operations. Thus equation (1) can be re-written as:

$$T = M + S(hub, hhi) + D(hub, hhi, X, \epsilon) \tag{2}$$

Hence the definition of delays from an airline's perspective is the difference between actual and minimum travel time, where M serves as a benchmark of flight time without congestion:

$$Excess = T - M = S(hub, hhi) + D(hub, hhi, X, \epsilon) \tag{3}$$

The key point here is that the effects of *hub* and *hhi* on excess travel time appear in both scheduled excess travel time and delay. In comparison, flight delays from the passenger's perspective are simply the difference between actual and scheduled travel time:

$$Delay = D(C, X, \epsilon) \tag{4}$$

For consumers the flight schedule, rather than the minimum travel time, serves as the benchmark to measure the length of flight delay.

Regardless of the flight delay metric used, there remains a clear link between air travel delays and airport congestion. Economists have proposed a variety of solutions to reduce airport and air traffic congestion. Morrison and Winston (2006a) suggest that an increase in spending by the FAA on air traffic control facilities would reduce air travel delays. Even before airline deregulation, economists suggested using congestion-based pricing to allocate landings and take-offs at the nation's busiest airports (for example, Levine 1969; Carlin and Park 1970; Borins 1978). More recently, due to increased airport congestion, economists have revisited the issue of charging congestion-based airport tolls (Daniel 2001; Daniel and Pahwa 2000; Morrison and Winston 2006b; Pels and Verhoef 2004). Morrison and Winston (1989) estimate that implementing optimal congestion pricing would increase total welfare by approximately \$4 billion (1988) dollars annually due to a reduction in carrier operating costs and lower passenger delay costs. Daniel (1995) reports that the Minneapolis-St. Paul airport could accommodate 30% more traffic by using congestion pricing due to the de-peaking of departures and arrivals.

The FAA is currently considering whether to implement congestion-based-pricing for landing and take-off rights in lieu of the existing weight-based landing fee structure at New York LaGuardia Airport (LGA). The current weight-based landing (and take-off) fees does not reflect the market value assigned to using this scarce resource. Airport runways suffer from "the tragedy of the commons" since there is an incentive to over-use a resource when its benefit clearly exceeds the cost. Congestion costs rise, however, as more of a carrier's flights are delayed due to the over-scheduling of its own flights at the airport. (Or, carriers are more cognizant of congestion costs when its own aircraft are the source of the airport congestion). Congestion-based pricing can efficiently reduce airport congestion if it causes carriers to internalize the delay externality. Before implementing such a fundamental policy shift, it behooves us to gather more about the causes of flight delays from both the airline and passenger perspectives.

3 Data

All U.S. carriers with revenues from domestic passenger flights of at least one percent of total industry revenues are required to report flight ontime performance data. We use Bureau of Transportation Statistics (BTS) data for every domestic flight between January 1995 and December 2004 by mainline carriers.[3] All variables are constructed from the original data set of 50 million flights during this sample period. Due to the computational constraints presented by such a large data set, we randomly select a 1 percent sample from this ten year period. Incomplete data reporting (most notably weather-related) in addition to missing/incorrect aircraft tail numbers slightly reduces the sample to 505,127. We have also omitted a handful of on-time performance observations that may have been coded incorrectly (such as, flights that arrive more than an hour early or 17+ hours late).

This paper compares three different measures of flight delays (measures in minutes): excess travel time, arrival delays, and departure delays. Mayer and Sinai (2003a) construct this measure

[3] Regional and commuter flights (i.e., American Eagle or Comair) are excluded.

of airport congestion by subtracting actual travel time between two airport pairs from the monthly minimum, which we term "excess travel time". This delay definition has theoretical appeal since it is not subject to manipulation or schedule padding[4] by carriers. In addition, this variable provides an accurate measure of how quickly carriers could transport passengers between airports absent of any air traffic congestion. One caveat, however, of this delay definition is that it is sensitive to outliers.

For example, in our sample for both medium (600 to 1000 miles) and long-haul (1000+ miles) flights, the minimum travel time on a route lies more than one-standard deviation away from the mean.[5] Minimum travel time is also sensitive to aircraft type. With the exception of Southwest (which only operates Boeing 737s), carriers use a variety of aircraft on the same route. Since the typical cruising speed differs for each aircraft, this causes modest fluctuations in travel times along the same route.[6] These travel time differences are most apparent on routes served by both turboprop and regional jets.[7] Hence excess travel time is capturing both speed differences between aircraft models *and* airport congestion effects. One final disadvantage of excess travel time variable is that it may not reflect passenger's flight delay experience.

Consumers are more likely to use flight schedules as benchmarks to determine whether their flight arrive (or depart) "ontime" rather than a route's minimum travel time. Flight performance that significantly differs from these benchmarks are likely to be deemed "late" by consumers. Passenger perceptions of delays may also be important for another reason, passengers who experience

[4]When carriers schedule more time then needed for a flight segment this phenomena is known as "schedule padding." Carriers pad schedules in an effort to improve on-time performance rates.

[5]The mean and standard deviation (in parentheses) for minutes of excess travel time for medium-haul and long-haul flights is 32.4 (32.0) and 39.2 (36.8), respectively.

[6]For example, US Airways uses six different aircraft (Boeing 737-300 & 737-400; Canadair Regional Jet & Regional Jet 900; Airbus A319 & A321) for its nine daily flights between Charlotte and La Guardia on December 23, 2006. The minimum travel time on this route was 1:45 (Airbus A321) and the maximum time was 1:53 (Candian Regional Jet).

[7]For example, between Greenville, NC and Charlotte, NC US Airways uses both the Dehavilland Dash 8 (turbo prop) and the Canadair Regional Jet. The minimum travel time on December 23, 2006 for these aircraft types was 1:16 and 59 minutes, respectively.

repeated delays may be more inclined to switch carriers when making future travel plans (for example, Suzuki 2000). Moreover, Januszewski (2004) finds lower ticket prices on routes that are more often delayed. Hence in an effort to gauge passenger perceptions of flight delays, this paper also uses two additional measures of flight delays: minutes of arrival delay (the difference between scheduled and actual arrival time at the gate) and minutes of departure delay[8] (the difference between scheduled and actual time leaving the gate)[9]. These two delay measures are based on the U.S. Department of Transportation definition of flight delay and are widely reported by the media. Finally, we note that minutes of

Figure 2 plots the three flight delay measures during the ten-year sample period. The average excess travel time (31 minutes) is considerably larger than the average departure (eight minutes) and arrival delays (seven minutes). While there is a large gap between these delay measures, their movements, however, appear correlated. The excess travel time variable indicates that if there were no airport congestion, then flight travel times would be reduced by an average of 31 minutes. Figure 2 also illustrates that for every year in the sample, the average departure delay exceeds the arrival delay. This suggests that flight schedules are being padded since flights are consistently leaving the gate an average of eight minutes late, yet arriving an average of just seven minutes late.[10]

Finally, summary statistics from Table 1 show a noticeable improvement in airline on-time performance immediately following the September 11th terrorist attacks as the average minutes of departure delay drops by three minutes (from nine to less than six minutes) and minutes of arrival delay is cut in half (from eight to just four minutes). These on-time performance improvements

[8]Departure delay is subject to less schedule padding than arrival delay since carriers pad flight schedules by adding time to their scheduled arrival time, rather than manipulating their departure time.

[9]The U.S. Department of Transportation defines a flight as an "ontime" arrival (departure) if it arrives (departs) at the gate within 15 minutes of its scheduled arrival (departure) time.

[10]For an indepth look at schedule padding, see Mayer and Sinai (2003b).

are attributed to a reduction in the demand for air travel since September 11th (Ito and Lee, 2005) and a reduction in air traffic congestion due to 700,000 fewer domestic scheduled flights in 2002 compared to 2001. Scheduled flights, however, rebounded in 2003 and 2004 and now exceed the flight operations totals from 2001. The return of travellers has caused airport congestion to resurface in 2004 as the proportion of late arrivals (20 percent) has returned to its historical average.[11]

A majority of our variables are constructed from BTS flight data. We match the aircraft tail numbers provided by the BTS to the FAA Aircraft Registry database to determine aircraft *seating capacity*.[12] We also match individual flights to quarterly passenger fare data from the U.S. Office of Airline Information's *Airline Origin and Destination (O&D) Survey*. This survey is a 10% sample of domestic airline tickets from reporting carriers. These fare data enable us to estimate flight yield since actual yield for individual flights is unavailable. *Yield* is the average nonstop one-way air fare (adjusted for inflation using the CPI) for carrier j on route r divided by the flight distance for the route.[13] The average yield is \$0.36 per mile (in 2004 dollars). Another economic measure is *load factor* which is the proportion of total seats that are occupied by passengers. This variable is obtained from the T-100 domestic market data. In our sample the national U.S. average load factor is 67 percent (or approximately two-thirds of airline seats were occupied between 1995 and 2004).

To measure the effect of airline hubbing on schedule reliability we include indicator variables for both airline hub origination and destination flights. Performance of hub carriers is critical to maintaining flight networks and may also have revenue implications since consumer demand

[11] More recently, in 2005 and 2006 flight delays average 20% and 22%, respectively.

[12] In situations where the tail number is unknown, *seating capacity* is found by substituting the median value of seats on comparable flights (i.e., same carrier, route, flight number, and month).

[13] We divide round-trip itineraries by two to obtain one-way air fare. Average air fare is the "local fare" (i.e., passengers flying nonstop).

is higher for airlines with large operations from an origin city (Morrison and Winston, 1989). Moreover given the large number of passengers who make domestic and international connections at hub airports, carriers are very interested in having on-time arrivals at their hub airports. A flight delay (or cancellation) for a *hub destination* flight can cause considerable passenger inconvenience, especially for those making connections.[14]

We also examine the effect of route competition on schedule reliability.[15] Monopoly routes comprise slightly more than half (53.6 percent) of the sample. Following Ito and Lee (2007) we use airport pairs (instead of city pairs) as our unit of observation since airport congestion varies substantially between airports in the same city (for example, Chicago O'Hare and Chicago Midway).

Since most U.S. airports are active weather reporting stations, we collect daily weather data at both origination and destination airports[16] from the U.S. National Oceanic & Atmospheric Administration (NOAA).[17] Given that the BTS finds that weather is the leading cause of flight delay, it is important to control for daily weather events at both origination and destination airports.

3.1 Estimation

This paper uses individual flight data for U.S. domestic flights between 1995 and 2004. These data enable us to control for flight-specific characteristics. For example, since airport congestion tends to build throughout the day, we can control for the scheduled departure time of each flight. We normalize the scheduled departure time to a continuous variable ranging from 0 (midnight)

[14] For an examination of flight cancellations see Rupp and Holmes (2006).

[15] We explored other measures of route competition, including indicator variables for routes served by small and large duopoly carriers. In comparison to the monopoly results, the findings were similar, however, the magnitude of the duopoly effects were smaller. These results are available upon request.

[16] In cases of missing airport weather data, we use the nearest weather reporting station within twenty-five miles.

[17] We would prefer to include both wind and snow, however, many weather stations fail to report these data.

to 1 (11:59 p.m.). In addition, we also control for the *seating capacity* of the aircraft since flight delays of larger aircraft typically affect more travelers than flight delays of smaller aircraft.

Airlines are profit maximizers. Since profitability figures are not available at the route level, we use route *yield* as a profit proxy. Carriers can increase revenues by offering more flights at attractive travel times at desirable airports. The cost, however, of overscheduling flights at peak travel times is increased airport congestion and hence more air travel delays. Flight delays impose costs on both the airline (aircraft operating costs, paying pilots and flight attendants) and passengers (value of passengers time). In fact, Morrison and Winston (2006a) estimate that the median cost of a flight delay is $99 per minute when both airline and passenger costs are considered. Hence a carrier faces a complicated scheduling task of offering desirable travel times on popular routes while not over-burdening airport facilities.

Based on previous findings in the literature, we expect to find more flight delays at hub airports, especially for a hub airline, since these airports are typically more congested due to the clustering or "peaking" of flights by the hub airline. Congestion problems are also likely to be more acute at larger hub airports.

The dominant carrier has a greater incentive to internalize the delay externality at more concentrated airports. Therefore, all else equal, fewer delays are expected at more concentrated airports. Finally, we expect carriers to provide better service (fewer delays) on their more profitable (higher yield) routes. We suspect that carriers may be more inclined to "opportunistically" delay flights on routes served by a single carrier (monopoly route) since air travellers who experience delays are unable to switch to alternative carriers. Borenstein and Netz (1999), however, show that monopolists have greater scheduled dispersion thereby avoiding the peak travel times, which should reduce the occurrence of flight delays. Therefore the expected sign of the monopoly variable is ambiguous due to these countervailing effects on flight delays.

We examine the above hypotheses by estimating the following baseline delay model for flight i on carrier j at day t:

$$\begin{aligned} Delay_{ijt} &= f(hub\ airport_{orig}, hub\ airport_{dest}, airport\ concent_{orig}, airport\ concent_{dest} \\ &\quad demand_{orig}, demand_{dest}, carrier_j, month_t, year_t, airport_{orig}, airport_{dest}) \end{aligned} \quad (5)$$

In the above estimation the subscripts *orig* and *dest* represent origination and destination airports, respectively. We follow the Mayer and Sinai (2003a) convention and define *hub airport* (and *hub airline*) on the basis of the connectivity of the airport. For example, airports (airlines) provide service to between 26-45 destinations are considered a *small hub airport* (*hub airline*); 46-70 destinations is a *medium hub airport* (*hub airline*); and, 71+ destinations is a *large hub airport* (*hub airline*). The $airport\ conc_{orig}$ (destination) (also known as the Hirschman-Herfindahl Index) is the sum of the squared carrier shares as a percentage of all daily flights at the origination (destination) airport. Because we suspect that delays for a particular carrier likely occur in bunches due to unobserved events such as a weather event that we cannot control for (such as high winds at hub airport) or unobserved labor unrest, we cluster standard errors into the following groups: carrier × month × year (for example, Delta August 2002).

Following Mayer and Sinai (2003a) in order to control for the variation in local demand that could contribute to flight delays, the variable *demand* represents Metropolitan Statistical Area (MSA) annual population, per capita income, and employment at both origination and destination.[18] In addition, since some MSAs include multiple airports, we interact their MSA demand values with an indicator variable that equals 1 if the airport is the largest in the MSA.

[18] An overwhelming proportion of our sample (98.7%) involves flights that both originate and are destined for MSA airports.

For non-MSA airports, we interact a non-MSA dummy variable with national demand averages. To address the seasonal demand fluctuations all estimations include indicator variables for each *month*. We also include *carrier* and *year* indicators.

Finally, $airport_{orig}$ and $airport_{dest}$ represent indicator variables for each origination and destination airport to control for unobserved airport specific effects that may affect delays, such as equipment, maintenance facilities, and airport capacity. This eliminates any time invariant airport specific effect (like airport capacity); hence, identification of these coefficients relies on changes over time during the 1995-2004 sample period. For example, in January 1995, there were 18 small hub airports. Nine years later (January 2004), there are 20 small hub airports. The composition of the small airport hubs changed as 7 of the 20 airports in January 2004 were not considered small hub airports in January 1995. Table 2 provides a summary of the changes in airport concentration, number of connections, and hub airport status at the 35 busiest airports in the U.S. at two points in the sample: January 15, 1995 and January 15, 2004. Over this nine year period, we find that 10 of the 35 airports experience a hub size change and 3 of the 35 airports have airport concentration changes of one-standard deviation (0.22 points) or more.

After the baseline model estimations, we present our preferred specification which includes economic and competitive factors along with logistical and weather variables. In addition to *seating capacity*, we also include other economic factors that may influence flight delays including average monthly $load\ factor$ (proportion of occupied seats on the route), *yield* per flight, and a *monopoly route* indicator variable that takes the value of 1 if the carrier is the only provider of non-stop air service on the route. We also control for logistical factors that may contribute to flight delays such as *normalized departure time* and flight *distance* since longer flights give carriers more opportunities to make-up time while airborne. Our preferred specification for flight delays is:

$$
\begin{aligned}
Delay_{ijt} \quad = \quad & f(hub\ airport_{orig}, hub\ airport_{dest}, airport\ concent_{orig}, airport\ concent_{dest} \\
& hub\ airline_{orig}, hub\ airline_{dest}, demand_{orig}, demand_{dest}, economic_{i}, \\
& logistical_{i}, weather_{orig}, weather_{dest}, carrier_{j}, month_{t}, year_{t}, \\
& airport_{orig}, airport_{dest}) \qquad (6)
\end{aligned}
$$

We control for daily weather conditions at both origination and destination airports by including measures of precipitation, minimum temperature, and frozen precipitation (this interaction term is found by multiplying the precipitation by one if daily minimum temperature is below 33 degrees, and zero otherwise).

In addition to estimating flight delays from both the airline and consumer perspectives using the baseline and preferred specifications, we also conduct three robustness checks of our results. First, given the considerable impact on the air travel market from the terrorist attacks of September 11, 2001, we estimate flight delays for both the pre- and post-September 2001 periods.[19] Second, we estimate flight delays for the subset of non-slot constrained airports. Carriers at these facilities are free to set any operating schedule that they desire.[20] The four airports during the sample period that operated under the FAA's High Density Traffic Airports Rule (HDR) established in 1969 are ORD (Chicago O'Hare), LGA (LaGuardia New York), JFK (New York), and DCA (Washington Reagan). This rule limited the number of flight operations at these airports by requiring that each carrier obtain a "slot" permit[21] for each takeoff or landing during a specified 60 minute period.

[19] All flights for the month of September 2001 are excluded from the sample.

[20] Of course, some airports have restrictions on operating hours (i.e., no flights before 6 a.m. or after 10 p.m.). This is not a slot constraint.

[21] A slot is a landing or a take-off.

The FAA has tried lifting slot restrictions at both ORD (in 2002) and LGA (in 2000). In both cases the result was a dramatic increase in flight delays due to carriers overscheduling airport operations at these facilities. Shortly after the slot restrictions were lifted at LGA, the FAA imposed an operational cap (a maximum of 81 total scheduled operations per hour) at LGA. A similar agreement was reached at ORD after the FAA met with the two hub airlines (American and United) and these carriers agreed voluntarily agreed to reduce the number of scheduled flight offerings.

Since airport congestion occurs at different times during the day, the third and final robustness check controls for within-day fluctuations of airport congestion. At peak-travel times (especially at hub airports) scheduled operations can exceed the maximum airport capacity. We calculate the hourly airport capacity utilization by dividing the number of scheduled operations (takeoffs and landings) by the airport's hourly capacity (during optimum operating conditions) using the FAA's Airport Capacity Benchmark Report (2001 and 2004). We include both origination and destination airport capacity utilization rates in our preferred specification estimates (equation 6).

4 Results

4.1 Baseline Model

Table 3 presents results from our baseline specification (equation 5) for three delay measures: excess travel time, departure delay, and arrival delay. This baseline specification replicates Mayer and Sinai (2003a) who estimate the identical model for an earlier time period (1988-2000). Each delay measure is estimated both including and excluding airport fixed effects. First, we examine flight delays from the airline perspective by looking at excess travel times. The results from models 1 and 2 are quite comparable to Mayer and Sinai (2003a) as both papers report significant hub airport and airport concentration effects. Both papers find longer excess travel times at larger hub airports (both origination and destination) while airport concentration is negatively correlated with excess travel time. The magnitude of the airport hubbing effect, however, is considerably larger than the airport concentration effect as flights originating at small, medium, and large hubs experience about four, eight, and eight minutes longer excess travel time, respectively, compared to non-hub originating flights. In comparison, a one standard deviation (0.22) increase in airport concentration at the origination airport reduces excess travel time by about one minute.

Consistent with Mayer and Sinai (2003a), we also find that including airport fixed effects (model 2) considerably reduces the magnitude of coefficient estimates. This finding suggests that the bulk of the air traffic delays are due to time invariant airport effects such as airport capacity. Nonetheless the implications remain the same: airport hubbing has a larger effect on minutes of excess travel time than airport concentration. The only notable difference in results for our baseline excess travel time estimation compared to Mayer and Sinai (2003a) is that we find one variable (*airport concentration at destination* in model 2) loses its explanatory power with the inclusion of airport fixed effects. Next, we turn to other measures of flight delay.

Baseline estimations for flight delays from the passenger perspective also appear on Table 3 as results for departure delays (models 3 and 4) and arrival delays (models 5 and 6) are reported. Due to the large time invariant airport effects and for the sake of brevity, we limit our discussion of results to models that control for airport fixed effects. Just like the excess travel time estimations, models 4 and 6 show that both departure and arrival delays, respectively, monotonically increase with the size of the hub airport operations. The magnitude of these hub airport effects on departure and arrival delays range from about one minute (small hub airports) to two minutes (large hub airports). The hub origination airport typically has a larger effect (about one-half a minute) on departure and arrival delays than a similar sized hub destination airport.

The most noticeable difference when comparing flight delays from the airline versus consumer perspective occurs for airport concentration. We find more concentrated airports (for both origination and destination) are correlated with significantly longer departure and arrival delays, yet airport concentration has the opposite effect on excess travel time (significantly shorter excess travel times at more concentrated origination airports). These airport concentration effects on arrival and departure delays are non-trivial. For example, model 4 indicates that a one-standard deviation increase in airport concentration at destination has approximately the same effect on departure delays (about one minute) as a flight originating from a small hub airport. For arrival delays, model 6 shows that a one-standard deviation increase in airport concentration at destination has a comparable effect on arrival delays as flights originating from medium-sized hub airports.

Brueckner's (2002) theoretical flight delay model and corresponding empirical evidence show that more concentrated airports experience fewer flight delays due to the dominant carrier adjusting its schedule to avoid self-inflicted airport congestion. Mayer and Sinai (2003a) and this paper both find shorter excess travel times at more concentrated airports, consistent with Brueckner's theory. When we expand the definition of flight delays, however, to include arrival and departure delays, we find the opposite result. Perhaps this result can be attributed to the more recent flight data, hence we now examine flight delays before and after September 11, 2001.

4.2 Flight Delays Before and After September 2001

Figure 2 reveals a reduction in the minutes of flight delay for each of the three delay measures in the two years immediately following the terrorist attacks in 2001. Airport congestion returned in 2004 since each of the three delay measures has risen. Table 4 presents estimates of three flight delay measures both pre- and post-September 11, 2001. Since the pre- and post-periods are relatively short, there is not enough variation over time to identify airport hub size effects if we include controls for airport specific effects. Hence all estimations in these comparison periods exclude airport fixed effects. We estimate the baseline model (equation 5) for both the pre- and post-periods.

For each delay estimation we test whether the eight coefficients (three hub airport originations, three hub airport destinations, and two airport concentration estimates) are equivalent across the sample periods. An F-test of their joint equivalence is clearly rejected for each delay estimation, suggesting that the coefficients are not equivalent in the two sample periods. While quantitatively, the estimates may not be equivalent, qualitatively most estimated coefficients have the same sign and statistical significance between the sample periods.

Two trends are apparent from Table 4. First, most delay estimations reveal a reduction in the magnitude of the airport hub size effects since September 2001. This diminished hub effect persists across each of the three delay measures. For example, flights originating from small hub airports have shorter excess travel times (2.5 minutes) and shorter departure and arrival delays (about one minute) in the post-September 2001 period. This result is likely due to a reduction in airport congestion immediately after September 2001. In the post-period, the one exception to the trend of shorter hub airport delays occurs for flights destined for large hub airports which experienced longer delays for each of our three delay measures.

The second trend apparent on Table 4 is that the inverse relationship between airport concentration and flight delays has weakened (become less negative) after September 2001 and in some cases (airport concentration at origination for departure/arrival delays) there is a positive and significant relationship between airport concentration and flight delays. For the entire sample we previously documented longer departure and arrival delays at more concentrated airports, the results from Table 4 suggest that this result is being driven by the post-September 2001 flights. Nonetheless, for the remainder of the paper we pool the sample periods when analyzing flight delays for two reasons. First, the longer sample period enables us to control for important airport specific effects that influence delays. And second, qualitatively there is little change since most coefficient estimates from Table 4 retain the same sign and statistical significance across the two sample periods. Next we examine the effect of hub airline operations on flight delays.

4.3 Hub Airline Effects

We now add hub airline effects to the baseline model (equation 5). Table 5 presents separate estimation results based on the inclusion (or exclusion) of airport fixed effects for our three delay measures. Once again we will focus on flight delay estimations that include airport fixed effects for excess travel time (model 14), departure delay (model 16), and arrival delay (model 18). Three stylized facts appear from Table 5. First, all three delay measures show a consistent result: hub airline effects have a larger impact on flight delays than hub airport effects. This finding reveals that hub airlines are their own worst enemies when it comes to flight delays since hub airlines are creating self-inflicted congestion from the peaking of flight arrivals and departures in order to minimize connection times. While there are modest delays for flights destined for an airline's hub, we find that the longest delays occur for flights originating from hub airlines. Moreover, the length of the flight delay monotonically increases with the size of the hub airline operations. For example, departure delays for flights originating from a hub airline increase from two minutes (small hub airlines), to almost three minutes (medium hub airlines), to four minutes (large hub airlines).

The second stylized fact from Table 5 is that airport hub effects have a significant impact on all three flight delay measures, even after controlling for hub airline effects. Once again, larger hub airports have longer delays. These findings indicate that non-hub airlines that operate at hub airports (for example, United Airlines at Atlanta Hartsfield) also experience delays, however, the length of delay is longer for the hub airline. For example, flights originating from medium hub airports are delayed between 1 and 1.6 minutes (depending on the delay measure used). In comparison, a hub airline operating at a medium hub airport experiences the previously mentioned hub airport delay plus an additional 2.2 to 3.6 minutes of delay (based on the delay measure used) due to the hub airline effect.

The third stylized fact is the link between airport concentration and flight delay depends on which delay measure is used. From the airline's viewpoint, highly concentrated origination airports have significantly shorter excess travel times (consistent with Mayer and Sinai 2003a), while from the passenger's vantage point there is no link between the origination airport concentration and flight delays (either departure or arrival delays). Whereas at more concentrated destination airports the converse occurs: significantly longer departure and arrival delays while excess travel time is now insignificant. A one-standard deviation increase in airport concentration at destination has a similar order of magnitude effect on departure and arrival delays as flights destined for a small and medium airport hub, respectively. These arrival and departure delay findings contradict our expectation that carriers internalize the delay externality. What might explain this scheduling snafu?

Carriers have multiple operations objectives. They aim to get all planes, passengers, and baggage to their destinations safely and on-time while making a profit. There are instances, however, when these objectives cannot all be simultaneously satisfied. For example, conducting a more thorough safety inspection takes time and may prevent an on-time flight. Likewise, the demand for airline tickets is higher for 8 a.m. departures (compared to 5 a.m. departures). A carrier may schedule flights that exceed an airport's capacity at peak times if doing so is profitable. While flight delays are costly, the higher ticket sales may more than offset the additional delay costs at peak travel times. In sum, a carrier must strike a balance between the revenue from scheduling flights at peak travel times given existing airport capacity and maintaining an ontime flight schedule. Therefore our preferred specification, to which we now turn, includes controls for potentially important economic and competitive factors such as route yield, aircraft size, average number of passengers, and monopoly routes. In addition, this specification also controls for important logistical factors (such as scheduled departure time) and daily weather conditions.

4.4 Preferred Specification

Estimations from our preferred specification for all three delay measures using both the entire sample and the subset of non-slot controlled airports appear on Table 6. There are two noteworthy findings from Table 6. First, economic, logistical, and weather factors[22] all have large impacts on flight delays. For the entire sample (models 19, 21, and 23) we find longer delays are more prevalent for large aircraft, high load factors, and low yields (departure delays only). Depending upon one's perspective on flight delays, you can arrive at different conclusions about how monopoly routes effect flight delays. From the airline's viewpoint, monopoly routes have significantly shorter delays (excess travel time); however, passengers' delay experience would suggest the opposite occurs as longer departure and arrival delays occur on monopoly routes. How can both of these

[22] We do not report estimates for the weather variables: rain, temperature, and freezing rain; however, the results are as expected: longer delays occur during poor weather conditions.

seemly contrary delay findings both be true? Monopoly routes typically involve at least one small (uncongested) airport, hence there is a reduction in excess travel times. On the other hand, should an issue arise (for example, mechanical failure or unavailable flight crew) at a small airport, it may take longer for the problem to be resolved which can lengthen the average minutes of departure and arrival delays.

Regardless of the delay measure used, we find that both airlines and passengers can agree that scheduled departures later in the day are subject to significantly longer flight delays. This suggests that delays propagate[23] during the day, a problem initially termed "cascading delays" by Mazzeo (2003). This result underscores the need to control for a flight's schedule departure time when examining air travel delays. Long-haul flights are subject to longer excess travel times, however, we find shorter departure and arrival delays for longer flights. This result is not surprising given that longer flights provide the pilots with a greater opportunity to shorten delays by making-up time while airborne.

Second, after controlling for economic, logistical, and weather factors, the airline hub size effects on delays are still significant, yet they are noticeably diminished. Airport hub size effects, on the other hand, are little changed in the preferred specification. Finally, we note that airport concentration at both origination and destination has no effect on excess travel time. On the other hand, more concentrated airports are correlated with longer departure and arrival delays. This suggests that dominant airport carriers are not internalizing the delay externality

Table 6 present estimates for the subset of non-slot restricted airports for excess travel time (model 20), departure delays (model 22), and arrival delays (model 24). These results are informative because they reflect carrier flight schedules which are not subject to airport-mandated scheduling constraints. Excluding slot restricted airports, we find very similar results compared

[23] For an indepth look at delay propagation see Ahmadbeygi et al. (2007).

to the entire sample with a few exceptions. The foremost exception is that airport concentration at destination is now positively and significantly correlated with excess travel time (a result that previously only occurred for departure and arrival delays). This suggests that at airports where carriers are free to set their own schedule, more concentrated airports have increased congestion which results in longer travel times regardless of the delay measure. Hence we find little evidence to support the claim that carriers internalize the delay externality when making flight schedules.

Finally, we explored the link between flight delays and hourly fluctuations in airport congestion. It is not surprising to learn that higher airport utilization rates at both origination and destination are associated with significantly longer excess travel times, departure delays, and arrival delays (see Table A1). These airport utilization estimates reveal that airport congestion at the origination has a much larger effect on delays (four times as large for excess travel time and twice as large for departure and arrival delays) compared to congestion at the destination airport. These results appear in the appendix for two reasons. First, the FAA only estimates airport capacity benchmarks at the busiest 31 U.S. airports, hence limiting our sample to just 31 airports. Second, all estimations exclude important airport fixed effects due to a lack of variation in airport capacity utilization because we only observe airport capacity at two points in time (2001 and 2004).

5 Conclusion

In sum, this paper investigates the causes of flight delays from both the airline and passenger perspectives. There are three main findings of this paper. First, after replicating the Mayer and Sinai (2003a) results for excess travel time (which we term the "airline perspective" for flight delays), we document some considerable differences when using alternative measures of flight delays (minutes of arrival/departure delay which we label the “passenger perspective”). For example, in our baseline specification, there is a positive correlation between departure/arrival delays and airport concentration; while the opposite occurs for excess travel time. Second, the paper shows that economic factors (seating capacity and load factor) and logistical factors (departure time and distance) have significant effects on flight delays. Third, at airports which are free of slot controls, we find longer excess travel time, departure, and arrival delays at more concentrated airport destinations. We also find that after controlling for airport-specific effects, most estimations indicate that airport concentration at origination has both longer departure and arrival delays. While theoretical (Brueckner, 2002) and empirical work (Mayer and Sinai, 2003a) suggests that carriers with a dominant airport market share internalize the delay externality, we present evidence that suggests otherwise. What can account for these differences?

First, the sample periods are different as Mayer and Sinai (2003a) examine (1988-2000) flight data while we use more recent flight operations (1995-2004). The difference in the sample period matters since we find that airport concentration is linked to more delays for both departures and arrivals post-September 2001. Second, in addition to the sample periods, other data differences exist between this paper and Mayer and Sinai (2003a) since the later includes only Friday flights in their data, whereas this paper includes a random sample of flights from each day of the week. Finally, and perhaps more importantly, Mayer and Sinai aggregate their data to monthly averages by airline for each route, whereas this paper uses individual flight data.

Do our findings suggest that carriers ignore the delay externality and, hence, schedule flights without concern for the existing airport capacity at peak periods? We think not. Our findings are more in line with a recent paper by Zhang and Yuen (2004), who modify the Brueckner (2002) model by using variable passenger time costs and find an increase in airport congestion across every market structure in comparison to Brueckner. Moreover, profit maximizing carriers have competing objectives when developing and implementing flight schedules. A flight schedule that minimizes flight delays may not be maximizing profits, and vice versa. Moreover, carriers with a dominant airport market position which cannot satisfy consumer demand for air travel by offering enough peak period flights on a route leave the door open for entry by competitors.

One public policy implication from this research is that congestion pricing may play a larger role than previously indicated in the literature, especially at airports that are not subject to slot restrictions. Given that more delays occur at highly concentrated airports, these results suggest that longer delays are likely if further consolidation occurs in the airline industry.

A significant source of flight delays in the U.S. is due to airline hub size effects. Larger hub airlines have longer flight delays. Flights originating from an airline's hub experience longer flight delays due to the peaking of hub airline flights. The effects of flight peaking occur primarily at the origination, rather than at the destination airport. This result is attributed to two factors. First, hub carriers typically have a more even distribution of flight arrivals compared to the spiking of flight departures at peak travel times. Second, a hub carrier needs on-time arrivals at the hub in order to maintain their hub-spoke network.

The peaking of flight schedules may also explain why hub carriers schedule longer periods at the gate or "turnaround" between the aircraft arrival and next scheduled departure compared to non-hub airlines. For example, for every U.S. domestic flight in April 2003, the average turnaround time for non-hub carriers is 53 minutes (excluding aircraft parked overnight). In comparison hub carriers averaged 77 minutes of turnaround time, with larger hubs scheduling longer buffers.[24] Even with these longer aircraft lay-over periods, the hub airlines still have difficulty in pushing

[24] Average scheduled buffers for small, medium, and large hub airlines were 63, 80, and 85 minutes, respectively in April 2003.

back from the gate ontime as we document significantly longer hub departure delays.

We find that hub airlines, not hub airports, are the primary source of flight delays between 1995 and 2004. These findings may explain why several carriers have recently begun to reschedule their hub airport traffic in order to avoid peak congestion periods since this posses the greatest opportunity to reduce air travel delays. For example, Continental credits its improved flight operations to de-peaking its Newark hub in the summer of 2000, while American began experimenting with evening out flights at Chicago O'Hare in October, 2000 (McCartney, 2000). Due to its successful experiment in Chicago, American decided to reschedule operations at its largest hub, Dallas-Fort Worth, starting in November, 2002 (McCartney, 2002). US Airways made smoothing the flow of flights to avoid peak congestion periods at both Philadelphia and Charlotte beginning in February 2005 part of its bankruptcy turnaround plan (Carey, 2004). Finally, Delta Airlines announced a "revolutionary schedule change" effective January 31, 2005 to mark the beginning of its efforts to de-peak Atlanta in order to improve on-time performance (news.delta.com).

This paper examines the causes of flight delays. Left unanswered are the effects of flight delays. Specifically, how is service affected? Are carriers not providing service at airports or reducing their flight offerings due to airport congestion concerns? Likewise, do flight delays cause passengers to choose alternative carriers or other means of transportation? These unanswered questions are topics for future research.

References

Ahmadbeygi, Shervin A., Amy Cohn, Yihan Guan, and Peter Belobaba. 2007. 'Analysis of the Potential for Delay Propagation in Passenger Aviation Flight Networks', working paper University of Michigan, Industrial and Operations Engineering.

Borenstein, Severin and Janet Netz. 1999. 'Why Do All Flights Leave at 8 AM?: Competition and Departure-Time Differentiation in Airline Markets', *International Journal of Industrial Organization*, 17:5, p. 611-40.

Borins, Sandford F. 1978. 'Pricing and Investment in a Transportation Network: The Case of Toronto Airport', *Canadian Journal of Economics*, 11:4, p. 680-700.

Brueckner, Jan K. 2002. 'Airport Congestion when Carriers have Market Power', *American Economic Review*, 92:5, p. 1357-75.

Brueckner, Jan K and Vivek Pai. 2007. 'Technological Innovation in the Airline Industry: The Impact of Regional Jets', working paper University of California Irvine, Economics Department.

Carey, Susan. 2004. 'US Air Presents Turnaround Plans', *Wall Street Journal*, 19 October 2004, p. D8.

Carlin, A. and R. Park. 1970. 'Marginal Cost Pricing of Airport Runway Capacity', *American Economic Review,* 60:3, p. 310-19.

Daniel, Joseph I. 1995. 'Congestion Pricing and Capacity of Large Hub Airports: A Bottleneck Model with Stochastic Queues', *Econometrica*, 63:2, p. 327-70.

_____. 2001. 'Distributional Consequences of Airport Congestion Pricing', *Journal of Urban Economics*, 50, p. 230-58.

Daniel, Joseph I. and Munish Pahwa. 2000. 'Comparison of Three Empirical Models of Airport Congestion Pricing,' *Journal of Urban Economics*, 47, p. 1-38.

Ito, Harumi and Darin Lee. 2005. 'Assessing the Impact of the September 11th Terrorist Attacks on U.S. Airline Demand', *Journal of Economics and Business*, 57:1, p. 75-95.

_____. 2007. 'Domestic Codesharing, Alliances and Airfares in the U.S. Airline Industry', forthcoming *Journal of Law and Economics.*

Januszewski, Silke I. 2004. 'The Effect of Airline Traffic Delays on Airline Prices', working paper, UC San Diego Department of Economics.

Levine, Michael E. 1969. 'Landing Fees and the Airport Congestion Problem', *Journal of Law and Economics,* 12:1 p. 79-108.

Mayer, Christopher and Todd Sinai. 2003a. 'Network Effects, Congestion Externalities, and Air Traffic Delays: or Why All Delays Are Not Evil', *American Economic Review*, 93:4, p. 1194-1215.

Mayer, Christopher and Todd Sinai. 2003b. 'Why Do Airline Schedules Systematically Underestimate Travel Time?', working paper, Wharton School of Business.

Mazzeo, Michael J. 2003. 'Competition and Service Quality in the U.S. Airline Industry', *Review of Industrial Organization*, 22:4, p. 275-96.

McCartney, Scott. 2000. 'American Airlines Will Reschedule Traffic at Its Hubs', *Wall Street Journal*, 13 September 2000, p. A4.

McCartney, Scott. 2002. 'American Airlines to Retrench in Bid to Beat Discount Carriers: Carrier Plans Overhaul of 'Hub' System', *Wall Street Journal*, 13 August 2002, p. A1.

Morrison, Steven and Clifford Winston. 1989. 'Enhancing the Performance of the Deregulated Air Transportation System', *Brookings Papers on Economic Activity: Microeconomics,* 1, p. 61-112.

_____. 2006a. 'The Effect of FAA Expenditures on Air Travel Delays', working paper, Brookings Institute.

_____. 2006b. 'Another Look at Airport Congestion Pricing', forthcoming *American Economic Review.*

Pels, Eric and Erik T. Verhoef. 2004. 'The Economics of Airport Congestion Pricing', *Journal of Urban Economics*, 55, p. 257-77.

Rupp, Nicholas G. and George M. Holmes. 2006. 'An Investigation Into the Determinants of Flight Cancellations', *Economica,* 73:292, p. 749-84.

Suzuki, Yoshinori. 2000. 'The Relationship between On-time Performance and Airline Market Share', *Transportation Research: Part E: Logistics and Transportation Review,* 36:2, p. 139-54.

US Department of Transportation. 2001 (and 2004). Federal Aviation Administration, *Airport Capacity Benchmark Report 2001*, Washington, D.C.: US Government Printing Office.

Zhang, Anming and Andrew Yuen. 2004. 'Airport Congestion and Market Structure: The Case of Variable Passenger Time Costs', working paper, University of British Columbia, Sauder School of Business.

Table A1: The Effect of Airline Hubbing, Airport Concentration, and Airport Utilization on Flight Delays for the 31 Busiest U.S. Airports (1% sample from Domestic Flights, 1995-2004).

Dependent Variable: Minutes of…	Excess Travel Time (A1)			Departure Delay (A2)			Arrival Delay (A3)		
	Coeff		Std Error	Coeff		Std Error	Coeff		Std Error
Economic/Competitive Factors									
Seating Capacity (100s of seats)	1.16	**	0.22	1.05	**	0.17	1.16	**	0.19
Load Factor	3.76	**	0.92	10.04	**	0.68	11.38	**	0.83
Yield	0.12		0.48	-1.45	**	0.37	-0.32		0.43
Monopoly Route	-2.89	**	0.23	-0.12		0.17	-0.08		0.19
Logistical Factors									
Normalized Departure Time	21.15	**	0.62	19.99	**	0.44	20.89	**	0.54
Distance (100s of miles)	0.62	**	0.02	-0.06	**	0.01	-0.19	**	0.02
Airport Congestion									
Airport Utilization at origination	24.15	**	0.80	7.29	**	0.55	12.07	**	0.62
Airport Utilization at destination	6.18	**	1.67	3.07	**	0.61	6.03	**	0.95
Airline Hub Size									
Small hub airline at origination	1.57	**	0.36	1.77	**	0.25	1.03	**	0.28
Medium hub airline at origination	3.20	**	0.41	1.67	**	0.27	1.16	**	0.33
Large hub airline at origination	3.28	**	0.44	2.73	**	0.34	2.39	**	0.40
Small hub airline at destination	0.10		0.34	0.53	*	0.24	-0.19		0.29
Medium hub airline at destination	2.25	**	0.40	0.47		0.29	0.43		0.36
Large hub airline at destination	1.19	**	0.46	0.32		0.34	-0.79		0.42
Airport Hub Size									
Small hub airport at origination	-1.81		0.95	0.49		0.52	0.11		0.62
Medium hub airport at origination	-1.39		0.99	0.11		0.54	-0.26		0.64
Large hub airport at origination	-3.19	**	1.05	-0.68		0.59	-1.67	*	0.70
Small hub airport at destination	1.17		0.63	0.09		0.45	0.48		0.56
Medium hub airport at destination	2.32	**	0.68	0.48		0.46	0.91		0.58
Large hub airport at destination	5.26	**	0.81	0.57		0.51	1.11		0.65
Airport concentration at origination	-5.66	**	0.80	0.75		0.55	1.74	**	0.66
Airport concentration at destination	-4.91	**	0.72	-1.20	*	0.49	-0.82		0.61
Airport fixed effects?	No			No			No		
R^2	0.09			0.06			0.07		
Observations	213,267			213,814			213,267		

Note: Standard errors (in parentheses) are clustered by carrier, month, and year (i.e., Delta August 2002). Regressions include indicator variables for carrier, month, and year in addition to economic demand variables (income, population, and employment) mentioned in the paper. Small, medium, and large hubs are defined as airports that serve 26-45, 46-70, and 71+ markets. The slightly larger number of observations for Departure Delays reflects the inclusion of diverted flights (when the flight lands at an unscheduled destination). The month of September 2001 is excluded. ^, *, and ** indicate 10%, 5%, and 1% significance levels, respectively. Airport utilization is the number of scheduled hourly operations divided by hourly capacity benchmark under good weather conditions (U.S. DOT *Airport Capacity Benchmark Reports 2001 & 2004*).

Table 1: Summary statistics from 1% sample U.S. domestic flights, 1995-2004

Sample	Whole		Before Sep. 2001		After Sep. 2001	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Flight Departures						
Excess Travel Time	31.12	32.18	31.12	32.30	31.12	31.90
Departure Delay[1]	8.18	26.74	9.16	27.26	5.85	25.31
Arrival Delay[2]	6.93	30.14	8.17	30.57	3.96	28.87
Proportion departure delay (≥15 min late	0.18	0.39	0.20	0.40	0.15	0.36
Proportion arrival delay (≥15 min late)	0.22	0.42	0.24	0.43	0.18	0.39
Proportion canceled	0.02	0.14	0.02	0.15	0.01	0.11
Proportion diverted	0.002	0.05	0.002	0.05	0.002	0.04
Origination Airport Hub Size						
Small hub airport	0.24	0.43	0.24	0.43	0.25	0.43
Medium hub airport	0.27	0.44	0.26	0.44	0.31	0.46
Large hub airport	0.24	0.43	0.26	0.44	0.20	0.40
Origination Airline Hub Size						
Small airline hub	0.10	0.30	0.09	0.29	0.12	0.32
Medium airline hub	0.15	0.36	0.14	0.35	0.17	0.38
Large airline hub	0.16	0.36	0.17	0.38	0.12	0.33
Origination airport concentration	0.43	0.22	0.43	0.22	0.45	0.22
Origination airport utilization[3]	0.35	0.14	0.37	0.14	0.32	0.13
Logistical Variables						
Distance (in 100's miles)	7.61	5.68	7.37	5.55	8.18	5.95
Normalized Departure Time	0.57	0.20	0.57	0.20	0.57	0.19
Economic Variables						
Yield (in 2004 dollars)	0.36	0.32	0.38	0.33	0.30	0.27
Route load factor (monthly average)	0.67	0.13	0.66	0.13	0.69	0.13
Seating capacity of aircraft (in 100's)	1.58	0.42	1.56	0.42	1.63	0.43
Monopoly route	0.54	0.50	0.52	0.50	0.58	0.49
Observations		505,127		356,018		149,107

Note: Variables are constructed from the original data set of every domestic flight for mainline carriers.

[1]Departure delay is the difference between scheduled departure and actual pushback time from gate.

[2]Arrival delay is the difference between scheduled arrival and actual time arriving at gate.

[3]Utilitization is hourly scheduled airport operations divided by hourly airportly capacity benchmark in optimal weather conditions for the 31 busiest U.S. airports (DOT *Airport Capacity Benchmark*).

Table 2: Airport Concentration, Number of Connections and Hub Status at the 35 Busiest Airports in the U.S.							
	January 15, 1995				January 15, 2004		
	Airport Concentration	Connections	Hub Size		Airport Concentration	Connections	Hub Size
Atlanta	0.69	99	Large		0.77	94	Large
Baltimore	0.31	48	Medium		0.44	50	Medium
Boston	0.20	46	Medium		0.19	35	Small
Charlotte	0.90	82	Large		0.80	54	Medium
Chicago Midway	0.43	17	No hub		**0.70**	34	Small
Chicago O'Hare	0.38	99	Large		0.39	77	Large
Cincinnati	0.78	61	Medium		0.94	54	Medium
Cleveland	0.32	39	Small		0.28	27	Small
Dallas/Fort Worth	0.48	90	Large		0.64	77	Large
Denver	0.59	70	Medium		0.53	57	Medium
Detroit	0.58	71	Large		0.67	72	Large
Fort Lauderdale	0.23	28	Small		0.19	31	Small
Honolulu	0.23	11	No hub		**0.47**	24	Small
Houston Bush	0.63	53	Medium		0.62	67	Medium
Las Vegas	0.23	47	Medium		0.27	67	Medium
Los Angeles	0.17	48	Medium		0.18	51	Medium
Memphis	0.57	45	Small		**0.79**	40	Small
Miami	0.31	38	Small		0.50	36	Small
Minneapolis	0.64	77	Large		0.67	87	Large
New York JFK	0.23	32	Small		0.30	24	Small
New York LaGuardia	0.22	44	Small		0.22	28	Small
Newark	0.35	48	Medium		0.39	49	Medium
Orlando	0.20	46	Medium		0.18	54	Medium
Philadelphia	0.45	50	Medium		0.47	40	Small
Phoenix	0.27	50	Medium		0.33	64	Medium
Pittsburgh	0.82	87	Large		0.65	39	Small
Portland, OR	0.23	27	Small		0.22	29	Small
Salt Lake City	0.49	48	Medium		0.42	39	Small
San Diego	0.23	30	Small		0.25	34	Small
San Francisco	0.36	44	Small		0.32	37	Small
Seattle	0.22	38	Small		0.26	49	Medium
St. Louis	0.48	71	Large		0.31	39	Small
Tampa	0.21	38	Small		0.20	47	Medium
Washington Dulles	0.37	27	Small		0.37	27	Small
Washington Reagan	0.22	42	Small		0.23	31	Small

*These are the 35 busiest airports as of 2004 according to the U.S. Department of Transportation's *Airport Capacity Benchmark Report 2004.* Connections is the total number of destinations served by all carriers at the airport. Hub size is based on number of connections with small hubs (24-45 connections), medium hubs (46-70 connections), and large hubs (71+ connections). The bolded airport concentration indicates an approx. one-standard deviation (or more) change in airport concentration between 1995 and 2004.

Table 3: The Effect of Airline Hubbing and Airport Concentration on Flight Delays, 1% sample of U.S. domestic flights, 1995-2004.

Dependent Variable: Minutes of…	Excess Travel Time				Departure Delay				Arrival Delay			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Airport Hub Size												
Small hub airport at origination	3.40 **	0.18	1.04 **	0.38	1.25 **	0.14	1.07 **	0.31	0.70 **	0.15	0.56	0.36
Medium hub airport at origination	7.75 **	0.23	2.11 **	0.60	2.45 **	0.13	1.82 **	0.43	1.98 **	0.15	1.28 **	0.48
Large hub airport at origination	7.85 **	0.25	2.91 **	0.69	3.83 **	0.18	2.16 **	0.52	3.55 **	0.21	1.63 **	0.60
Small hub airport at destination	3.56 **	0.15	0.89 **	0.33	0.36 **	0.12	0.88 **	0.27	0.15	0.13	1.03 **	0.32
Medium hub airport at destination	5.84 **	0.17	1.64 **	0.48	0.49 **	0.12	1.17 **	0.39	0.32 *	0.15	1.08 *	0.47
Large hub airport at destination	8.24 **	0.22	1.65 **	0.59	0.66 **	0.16	1.74 **	0.49	0.87 **	0.19	1.21 *	0.57
Airport concentration at origination	-5.52 **	0.35	-2.68 ^	1.40	0.39	0.25	2.21 *	1.10	0.87 **	0.28	2.32 ^	1.30
Airport concentration at destination	-4.90 **	0.35	1.25	1.14	-1.82 **	0.24	4.32 **	0.99	-1.25 **	0.27	5.32 **	1.13
Airport fixed effects?	No		Yes		No		Yes		No		Yes	
R^2	0.04		0.06		0.01		0.02		0.01		0.02	
Observations	503,998		503,998		505,127		505,127		503,998		503,998	

Note: Standard errors (in parentheses) are clustered by carrier, month, and year (i.e., Delta August 2002). Regressions include indicator variables for carrier, month, and year in addition to economic demand variables (income, population, and employment) mentioned in the paper. Small, medium, and large hubs are defined as airports that serve 26-45, 46-70, and 71+ markets. The slightly larger number of observations for Departure Delays reflects the inclusion of diverted flights (when the flight lands at an unscheduled destination). The month of September 2001 is excluded. ^, *, and ** indicate 10%, 5%, and 1% significance levels, respectively.

Table 4: Airline Hubbing and Airport Concentration Effects on Flight Delays Pre- and Post-September 2001, 1% sample of U.S. domestic flights

Dependent Variable: Minutes of…	Excess Travel Time				Departure Delay				Arrival Delay			
Sample	Jan 95 - Aug 01		Oct 01 - Dec 04		Jan 95 - Aug 01		Oct 01 - Dec 04		Jan 95 - Aug 01		Oct 01 - Dec 04	
	(7)		(8)		(9)		(10)		(11)		(12)	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Airport Hub Size												
Small hub airport at origination	4.05 **	0.21	1.58 **	0.32	1.44 **	0.17	0.67 **	0.24	0.96 **	0.18	0.11	0.27
Medium hub airport at origination	8.20 **	0.28	5.66 **	0.41	2.44 **	0.17	1.99 **	0.25	2.13 **	0.19	1.42 **	0.28
Large hub airport at origination	8.11 **	0.30	6.16 **	0.51	3.75 **	0.22	3.75 **	0.35	3.43 **	0.25	3.91 **	0.41
Small hub airport at destination	3.93 **	0.18	2.65 **	0.24	0.52 **	0.14	-0.16	0.19	0.46 **	0.16	-0.69 **	0.22
Medium hub airport at destination	5.99 **	0.22	5.60 **	0.28	0.60 **	0.16	0.16	0.20	0.70 **	0.18	-0.43 ^	0.25
Large hub airport at destination	7.45 **	0.25	10.76 **	0.44	0.38 *	0.18	1.61 **	0.30	0.82 **	0.21	1.46 **	0.39
Airport concentration at origination	-5.30 **	0.41	-4.54 **	0.62	-0.02	0.30	1.44 **	0.42	0.39	0.34	1.92 **	0.49
Airport concentration at destination	-5.14 **	0.41	-4.28 **	0.60	-1.99 **	0.29	-1.68 **	0.40	-1.91 **	0.33	-0.06	0.46
Airport fixed effects?	No		No		No		No		No		No	
F test joint equivalence of Pre- and Post-September 2001 periods[1]	49.42 **				13.49 **				19.29 **			
R^2	0.04		0.04		0.01		0.02		0.01		0.01	
Observations	355,145		148,853		356,018		149,109		355,145		148,853	

Note: Standard errors (in parentheses) are clustered by carrier, month, and year (i.e., Delta August 2002). Regressions include indicator variables for carrier, month, and year in addition to economic demand variables (income, population, and employment) mentioned in the paper. Small, medium, and large hubs are defined as airports that serve 26-45, 46-70, and 71+ markets. The slightly larger number of observations for Departure Delays reflects the inclusion of diverted flights (when the flight lands at an unscheduled destination). The month of September 2001 is excluded. ^, *, and ** indicate 10%, 5%, and 1% significance levels, respectively.

[1] Each of these F tests clearly reject the joint hypothesis that the above eight coefficients are equivalent in the Pre- and Post- Sep 2001 sample periods.

Table 5: Airline and Airport Hub Effects on Flight Delays, 1% sample of U.S. domestic flights, 1995-2004.

Dependent Variable: Minutes of…	Excess Travel Time						Departure Delay						Arrival Delay					
	(13)			(14)			(15)			(16)			(17)			(18)		
	Coeff		Std Error	Coeff		Std Error	Coeff		Std Error	Coeff		Std Error	Coeff		Std Error	Coeff		Std Error
Airline Hub Size																		
Small hub airline at origination	1.33	**	0.31	1.86	**	0.34	2.16	**	0.20	2.24	**	0.22	1.68	**	0.22	1.71	**	0.24
Medium hub airline at origination	0.53	^	0.31	3.59	**	0.37	2.04	**	0.22	2.71	**	0.24	1.97	**	0.26	2.21	**	0.30
Large hub airline at origination	0.47		0.37	3.43	**	0.38	3.01	**	0.28	4.02	**	0.30	2.69	**	0.34	3.31	**	0.36
Small hub airline at destination	-1.38	**	0.29	-0.62	*	0.28	0.12		0.20	0.02		0.21	-0.37		0.23	-0.61	*	0.26
Medium hub airline at destination	-1.68	**	0.29	1.40	**	0.32	-0.55	*	0.21	0.36		0.25	-0.08		0.26	0.20		0.31
Large hub airline at destination	-2.40	**	0.37	1.00	**	0.38	-0.26		0.27	0.92	**	0.28	-1.02	**	0.34	-0.09		0.36
Airport Hub Size																		
Small hub airport at origination	3.00	**	0.19	1.01	**	0.38	0.86	**	0.14	0.97	**	0.31	0.37	*	0.16	0.50		0.36
Medium hub airport at origination	7.06	**	0.23	1.64	**	0.60	1.50	**	0.15	1.41	**	0.43	1.09	**	0.17	0.95	*	0.48
Large hub airport at origination	7.09	**	0.29	2.50	**	0.73	1.99	**	0.22	0.87		0.54	1.83	**	0.25	0.57		0.63
Small hub airport at destination	3.88	**	0.15	0.97	**	0.33	0.59	**	0.12	0.87	**	0.27	0.45	**	0.14	1.06	**	0.32
Medium hub airport at destination	6.69	**	0.20	1.55	**	0.48	1.10	**	0.14	1.15	**	0.39	0.80	**	0.17	1.11	*	0.47
Large hub airport at destination	9.86	**	0.29	1.84	**	0.64	1.49	**	0.20	1.39	**	0.51	2.04	**	0.24	1.45	*	0.61
Airport concentration at origination	-6.24	**	0.37	-3.81	**	1.39	-0.84	**	0.26	1.04		1.10	-0.31		0.30	1.40		1.30
Airport concentration at destination	-3.83	**	0.36	1.08		1.15	-1.04	**	0.25	4.25	**	0.99	-0.60	*	0.29	5.44	**	1.14
Airport fixed effects?	No			Yes			No			Yes			No			Yes		
R^2	0.04			0.06			0.02			0.02			0.02			0.02		
Observations	503,998			503,998			505,127			505,127			503,998			503,998		

Note: Standard errors (in parentheses) are clustered by carrier, month, and year (i.e., Delta August 2002). Regressions include indicator variables for carrier, month, and year in addition to economic demand variables (income, population, and employment) mentioned in the paper. Small, medium, and large hubs are defined as airports that serve 26-45, 46-70, and 71+ markets. The slightly larger number of observations for Departure Delays reflects the inclusion of diverted flights (when the flight lands at an unscheduled destination). The month of September 2001 is excluded. ^, *, and ** indicate 10%, 5%, and 1% significance levels, respectively.

Table 6: Economic Factors for Individual Flights and Airline and Airport Hub Effects on Flight Delays, 1% sample of U.S. domestic flights, 1995-2004.

Dependent Variable: Minutes of…	Excess Travel Time				Departure Delay				Arrival Delay			
Sample	Whole		Exclude Slot-restricted airports		Whole		Exclude Slot-restricted airports		Whole		Exclude Slot-restricted airports	
	(19)		(20)		(21)		(22)		(23)		(24)	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
Economic/Competitive Factors												
Seating Capacity (100s of seats)	0.98 **	0.18	1.33 **	0.20	0.79 **	0.14	1.04 **	0.15	1.09 **	0.16	1.41 **	0.17
Load Factor	8.12 **	0.63	7.07 **	0.65	9.16 **	0.49	8.61 **	0.51	10.72 **	0.58	9.98 **	0.59
Yield	-0.33	0.26	-0.13	0.26	-0.60 **	0.22	-0.33	0.23	-0.31	0.24	-0.05	0.25
Monopoly Route	-2.00 **	0.16	-2.44 **	0.18	0.32 **	0.12	0.07	0.13	0.39 **	0.14	0.09	0.15
Logistical Factors												
Normalized Departure Time	18.19 **	0.41	16.61 **	0.42	17.92 **	0.36	17.15 **	0.38	18.02 **	0.41	17.13 **	0.42
Distance (100s of miles)	0.55 **	0.02	0.54 **	0.02	-0.04 **	0.01	-0.05 **	0.01	-0.21 **	0.02	-0.22 **	0.02
Airline Hub Size												
Small hub airline at origination	1.58 **	0.35	2.18 **	0.38	1.49 **	0.22	1.65 **	0.24	0.83 **	0.24	1.07 **	0.26
Medium hub airline at origination	2.49 **	0.41	3.42 **	0.49	1.07 **	0.26	1.47 **	0.29	0.46	0.31	1.02 **	0.35
Large hub airline at origination	2.27 **	0.41	3.38 **	0.46	2.38 **	0.32	2.82 **	0.36	1.63 **	0.38	1.80 **	0.44
Small hub airline at destination	-0.34	0.28	0.13	0.30	-0.14	0.22	0.07	0.23	-0.88 **	0.26	-0.76 **	0.27
Medium hub airline at destination	1.30 **	0.35	1.63 **	0.38	-0.17	0.27	0.31	0.29	-0.49	0.33	-0.15	0.35
Large hub airline at destination	0.60	0.42	2.12 **	0.48	0.22	0.30	0.43	0.35	-0.84 *	0.38	-0.48	0.42
Airport Hub Size												
Small hub airport at origination	1.06 **	0.37	1.10 **	0.39	1.31 **	0.31	1.13 **	0.33	0.96 **	0.35	0.70 ^	0.36
Medium hub airport at origination	1.40 *	0.60	1.71 **	0.60	1.72 **	0.42	1.77 **	0.44	1.53 **	0.46	1.49 **	0.48
Large hub airport at origination	1.77 *	0.72	1.99 **	0.72	0.85	0.53	0.96 ^	0.56	0.94	0.61	1.30 *	0.63
Small hub airport at destination	0.94 **	0.33	0.60 ^	0.35	1.06 **	0.28	0.99 **	0.30	1.37 **	0.32	0.99 **	0.34
Medium hub airport at destination	1.47 **	0.48	1.24 *	0.50	1.33 **	0.39	1.28 **	0.42	1.54 **	0.46	1.26 **	0.49
Large hub airport at destination	1.53 *	0.64	0.25	0.67	1.40 **	0.52	1.29 *	0.56	1.79 **	0.61	1.15 ^	0.64
Airport concentration at origination	-2.01	1.41	-1.30	1.36	1.97 ^	1.12	2.64 *	1.07	2.02	1.30	2.88 *	1.23
Airport concentration at destination	1.62	1.15	3.21 **	1.16	4.12 **	1.02	4.55 **	1.03	4.64 **	1.13	5.58 **	1.13
Airport Fixed Effects?	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.11		0.10		0.05		0.05		0.07		0.06	
Observations	456,031		378,140		457,036		378,910		456,031		378,140	

Note: Robust standard errors are reported. Regressions include indicator variables for carrier, month, and year in addition to economic demand variables (income, population, and employment) and weather variables (rain, frozen precipitation, and temperature) at both origination and destination airports. Small, medium, and large hubs are defined as airports that serve 26-45, 46-70, and 71+ markets. The slightly larger number of Departure Delays reflects the inclusion of diverted flights (when the flight lands at an unscheduled destination). The month of September 2001 is excluded.

* and ** indicate 5% and 1% significance levels.

Figure 1: Actual, Scheduled, & Minimum Travel Times BOS to LGA, July 2003

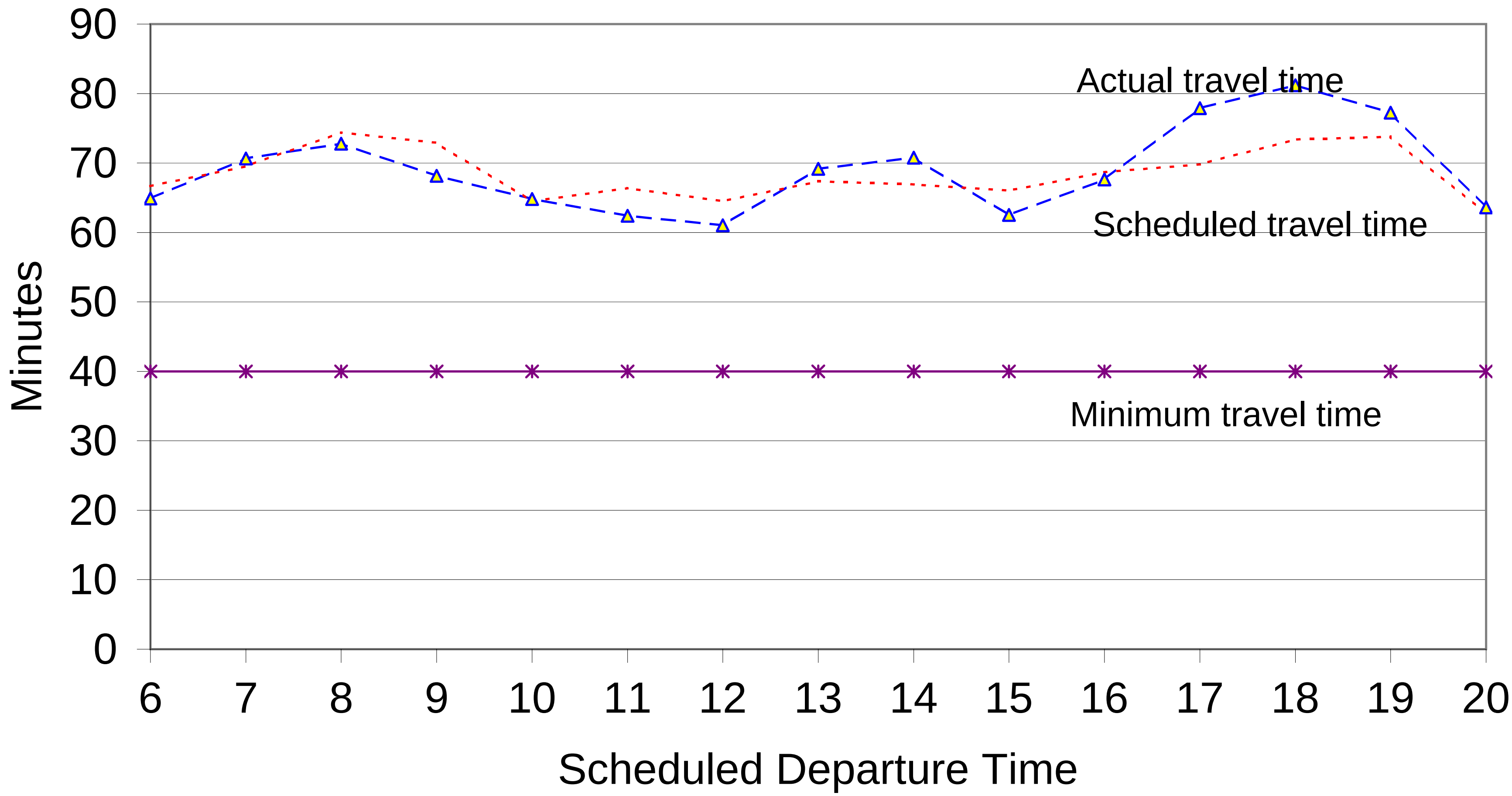

Figure 2: Minutes of Excess Travel Time, Departure and Arrival Delays, 1% sample U.S. Domestic Flights