Do Carriers Internalize Congestion Costs? Empirical Evidence on the Internalization Question

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Abstract

Economists have long suggested overhauling the existing U.S. airport landing/departure fees to reflect market valuations of scarce runway capacity. Economists, however, do not agree on the optimal congestion-based pricing scheme. While some researchers advocate for a uniform congestion fee regardless of a carrier's airport market share, others suggest that airport tolls only reflect the congestion costs imposed on other carriers. This paper uses ten years of ontime performance data to empirically determine if carriers internalize congestion costs. We find that the answer to the internalization question depends upon the flight delay measure used since highly concentrated airports have shorter excess travel times, while the converse holds for departure and arrival delays.

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"We've got a problem. We understand there's a problem. And we're going to address the problem." – President George W. Bush speaking to Transportation Secretary Mary Peters on how to reduce flight delays (Office of the Press Secretary, 27 September 2007).

1 Introduction

One of the critical questions confronting the airline industry in the 21st century is how to handle a growing and costly problem of airport and air traffic congestion.[1] Between 2000 and 2007 twenty percent of all U.S. commercial flights were delayed (arriving 15+ minutes late) with delays averaging nearly 30% during the first six months of 2007. Given that 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,[2] and more business aviation flights, while the supply of airport runway capacity will likely remain constant, it is important to find ways to address this problem. Airport runways and facilities suffer from the "tragedy of the commons" since runway capacity is a public good there is an incentive to over use this resource because the current weight-based landing (and take-off) fees do not reflect the market value assigned to this scarce resource.

Even before airline deregulation, economists suggested congestion-based pricing to allocate landings and takeoffs at the nation's busiest airports (for example, Levine 1969; Carlin and Park 1970; Borins 1978). More recently, congestion pricing (Daniel and Pahwa, 2000) and the welfare gains associated with congestion pricing have been examined (Daniel, 2001; Morrison and Winston 2007a). Selecting the optimal congestion-based pricing scheme, however, is not clear cut. Public policy makers must decide whether to charge all carriers the same congestion fee or whether to adjust this fee to reflect only the congestion costs imposed on other carriers.

[1] Delta's executive Vice President, Joe Kolshak, told a Senate panel "delays cost our airline more than $700 million a year" (Geewax, 2007).

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

Daniel (1995) was the first to raise this internalization question in the context of airline congestion. His analysis of Minneapolis-St. Paul airport flights suggested the potential for dominant carriers to internalize congestion costs, however, Daniel concludes that if the dominant carrier fully accounted for congestion costs and reduced its flight offerings, then competitors would likely fill the void with new flight offerings. More recently, Daniel and Harback (2007) examine a week of flights during the summer of 2003 at twenty-seven major U.S. airports and use specification tests to reject the internalization hypothesis at most airports. Morrison and Winston (2007a) find similar results in their data of 74 U.S. airports as the authors find that most airport delays are not internalized. The above studies suggest atomistic congestion pricing since the researchers find that most airport delays are not being internalized.

On the other hand, Brueckner (2002, 2005), Brueckner and Van Dender (2007), and Pels and Verhoef (2004) argue that carriers are not atomistic, since scheduling an additional flight at a congested airport imposes congestion costs on the other flights operated by the same airline. Hence they suggest a reduction in congestion fees for carriers with larger airport market share to reflect the internalization of congestion costs. Brueckner (2002) also presents empirical evidence from the 25 busiest U.S. airports to show that more concentrated airports have shorter delays, a finding consistent with the internalization hypothesis. Using a larger data set, Mayer and Sinai (2003a) report similar findings of fewer delays at highly concentrated airports.

Zhang and Zhang (2006) offer an explanation for this apparent "inconsistency" in the internalization debate as they find an airport's objective (profit maximizing or welfare-maximizing) affects capacity investment and hence congestion. Given the lack of agreement on whether carriers internalize flight delay costs, this paper uses recent empirical evidence to answer the internalization question. The first novel aspect of this paper is that we use very detailed individual flight level data which enable us to estimate the airport concentration effects while controlling for important economic, logistical, and weather variables that likely influence flight delays. The second novelty of this paper is that we address the internalization question from both the carrier and passenger viewpoints.

The importance of including passenger delay experience is underscored by Morrison and Winston (2007b), who show that flight delays are more costly for airline passengers than for carriers.[3] The value that passengers assign to waiting times has been explored in other transportation areas as well.[4] For example, Small (1982) shows that urban commuters change their schedule to avoid congested highways, Mohring, et al. (1987) finds that higher income bus travelers have a higher value of waiting times, while Vansteenwegen and Van Oudheusden (2007) show that railway passengers are more concerned about arriving late rather than longer waiting times to depart the station or waiting while seated on a train.

In addition to the high passenger and airline costs associated with flight delays, poor on-time performance has also 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.[5]

Our empirical test of the internalization hypothesis comes from examining ten years of domestic Bureau of Transportation Statistics on-time performance flight data (1995-2004) from commercial airports in the U.S. to determine the statistical relationship between actual flight de-

[3] Morrison and Winston (2007b) estimate that on a per-minute basis the median cost of flight delays are $98.94 (in 2000 dollars). This figure is comprised of three components, median aircraft operating costs per minute ($40.16), flight attendant costs per minute ($2.52), and median value of passenger time per minute ($55.42).

[4] For a thorough overview of the economics of transportation see Winston (1985).

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

lays and airport concentration. From the carrier perspective, we adopt Mayer and Sinai's (2003a) measure of flight delays: excess travel time, which is the difference between actual travel time and the monthly minimum travel time by the carrier on the route. Excess travel time provides an accurate depiction of travel time sans congestion.

Passenger welfare, and hence a substantial portion of the "costs" of delay, however, are not directly related to this airline measure of congestion. It is highly unlikely that passengers make "excess travel time" calculations when determining the length of delay.[6] Instead, passengers likely perceive delays as the difference between actual arrival (and departure) time and scheduled arrival (and departure). In fact, in the railroad literature Wardman (2004) reports that the value of waiting an additional minute for a train (i.e., departure delay) is equivalent to driving 2.5 miles (i.e., excess travel time). Clearly passengers do not view departure/arrival delays and excess travel time as equivalent delay measures. Moreover, large adverse deviations from posted flight schedules can cause substantial costs for passengers (e.g., missed passenger connections, arriving late for business meetings/conferences, or delaying the onset of a vacation).[7]

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 (2007b) suggest that the FAA increase its spending on air traffic control facilities in order to reduce air travel delays. Morrison and Winston (1989) estimate that an optimal congestion pricing system would increase total welfare by approximately $4 billion (1988) dollars annually due to a reduction in carrier operating costs and lower passenger

[6] A simple example illustrates the shortcoming of using excess travel time to measure flight delays. If dinner is served at 6 pm, then how do you know if you are late? Excess travel time compares the actual commuting time with the monthly minimum to determine tardiness. Suppose the typical evening weekday commute takes 45 minutes, while the weekend commute lasts just 15 minutes. Those arriving promptly at 6 pm (after a 45 minute weekday commute) experience 30 minutes of excess travel time. Whereas, from the passenger perspective, those arriving at 6pm after a 45 minute weekday commute are considered "on-time" (rather than 30 minutes late).

[7] Moreover, arrival delays also impose costs of those waiting to meet arriving passengers at the airport.

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 the most congested U.S. airports (e.g., New York LaGuardia Airport).

We find very different answers to the internalization question based on which perspective (carrier or passenger) one uses to examine flight delays. Controlling for hub airports and other important factors like weather, we find that from the carrier perspective, shorter excess travel times occur at highly concentrated airports. This suggests that carriers internalize airport congestion. From the passenger perspective, however, we find the opposite result as departure and arrival delays are more likely at highly concentrated airports. This finding indicates that carriers are not internalizing delays and are hence behaving more like atomistic competitors. This paper is organized as follows. The next section discusses the causes of flight delays, our choice of delay measures, and data. We then introduce our econometric model, propose some hypotheses, present the estimation results, and conclude with some comments on the potential effectiveness of congestion-based pricing.

2 The Causes of Flight Delays

During the ten year period 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). In June 2003, domestic carriers began reporting 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): local 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 by ranking the monthly flight delay averages for the 147 months between 1995 and 2007 (through March). We find that the top decile (the 15 months in our sample with the 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 (the 15 sample months with the most delays) are December, January, and June while five months never appeared (March, April, September, October, and November).

Before elaborating on the causes of flight delays, we first must define the difference between carrier's and passenger's perspectives on flight delays.[8] 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 (e.g., seating capacity, yield, monopoly route, etc.), and random influences ϵ (e.g., weather, maintenance issue, equipment failure, etc.). Hence flight time is represented as:

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

[8] I thank Jan Brueckner for his modelling suggestions in this section.

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.

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 on-time performance data. We use Bureau of Transportation Statistics (BTS) data for every domestic flight between January 1995 and December

2004 by mainline carriers.[9] 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 to gauge both carrier and passenger perspectives on flight delays. The advantage of the excess travel time is this variable is not subject to manipulation or schedule padding[10] by carriers. In addition, excess travel time provides an accurate measure of how quickly carriers could transport passengers between airports absent of any air traffic congestion. One caveat of 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). 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.[11] 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. Differences in aircraft cruising speeds can cause modest fluctuations in travel times along the same route.[12] These travel time differences are most apparent on routes

[9] Regional and commuter flights (i.e., American Eagle or Comair) are excluded since for most of the sample period, regional carriers did not report on-time performance.

[10] 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 and increase consumer welfare.

[11] 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.

[12] 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 differed based on aircraft manufacturer 1:45 for Airbus A321 and

served by both turboprop and regional jets.[13] In sum, excess travel time captures both speed differences between aircraft models *and* airport congestion effects.

While passengers maybe apathetic toward excess travel time, on the other hand, consumers are keenly aware of arrival and departure delays. Flights that significantly differ from flight schedules are likely deemed "late" by consumers. Passenger perceptions of delays is important for a variety of reasons, foremost, passengers who experience repeated delays may be more inclined to switch carriers when making future travel plans (Suzuki, 2000). In addition, 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[14] (the difference between scheduled and actual time leaving the gate).[15] These two delay measures are based on the U.S. Department of Transportation definition of flight delay and are widely reported by the media. A caveat of calculating delays from flight schedules is that carriers can account for airport congestion by scheduling additional travel time.

The differences between carrier and passenger views on congestion and flight delays 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) served by three 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

1:53 for Candian Regional Jet.

[13] 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.

[14] 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.

[15] 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.

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. Clearly carriers anticipate peak congestion periods (8 a.m., 12 p.m., and 6 p.m.) by adding time to the scheduled flight.

Finally, Figure 1 reveals notable differences among the three 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. Hence from the passenger's perspective, there are only minimal air traffic delays; whereas, from the carrier's perspective excess travel time (the difference between actual and minimum travel time) 8 a.m. departures experienced 34 minutes of air traffic delays. In sum, one can arrive at very different flight delay conclusions based on which perspective (carrier or passenger) one uses to examine flight delays.

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. [16]

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

[16] For an in-depth look at schedule padding, see Mayer and Sinai (2003b).

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 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 travelers has caused airport congestion to resurface in 2004 as the proportion of late arrivals (20 percent) has returned to its historical average.[17]

A majority of our variables are constructed from BTS flight data. We match aircraft tail numbers provided by the BTS to the FAA Aircraft Registry database to determine aircraft *seating capacity*.[18] 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.[19] The average yield is $0.36 per mile (in 2004 dollars). Another economic measure is *load factor* which is the proportion of total seats occupied by passengers. This variable is obtained from the T-100 domestic market data. In our sample of domestic flights between 1995 and 2004, the average load factor is 67 percent.

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

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

[18] 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).

[19] 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).

to maintaining flight networks and may also have revenue implications since consumer demand 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.[20]

We also examine the effect of route competition on schedule reliability.[21] 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[22] from the U.S. National Oceanic & Atmospheric Administration (NOAA).[23] Given that the BTS finds that weather is the leading cause of flight delay, we include controls for daily weather events at both origination and destination airports when examining the link between airport concentration and delays.

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 that influence flight delays. For example, since airport congestion tends to build throughout the day, we can control for the scheduled

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

[21] 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.

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

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

departure time of each flight. We normalize the scheduled departure time to a continuous variable ranging from 0 (midnight) to 1 (11:59 p.m.). In addition, we control for aircraft *seating capacity* since flight delays of larger aircraft affect more travelers and hence cause greater passenger inconvenience.

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 over-scheduling flights at peak travel times is increased airport congestion and more 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 (2007b) estimate that the median cost (in 2000 dollars) 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 overburdening airport facilities and creating longer delays.

In addition to airport concentration, other factors contribute to airport congestion. These factors include whether an airport (or airline) is a hub since these airports experience greater congestion due to the clustering or "peaking" of flights by the hub airline. Congestion problems are also especially acute at larger hub airports. If the internalization hypothesis holds we expect to see dominant carriers internalizing congestion costs and hence having fewer delays at more concentrated airports.

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

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

The subscripts *orig* and *dest* represent origination and destination airports, respectively. We use Mayer and Sinai's (2003a) definition for *hub airport* (and *hub airline*) on the basis of an airport's connectivity. For example, airports (airlines) that serve between 26 and 45 destinations are considered *small hub airports* (*hub airline*); 46-70 destinations are *medium hub airports* (*hub airline*); and, 71+ destinations are *large hub airports* (*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 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 $\times$ month $\times$ year (for example, Delta, August, 2002).

We control for the variation in local airport demand that could contribute to flight delays. The *demand* variable represents Metropolitan Statistical Area (MSA) annual population, per capita income, and employment at both origination and destination airports.[24] 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. For non-MSA airports, we interact a non-MSA dummy variable with national demand averages. To address the seasonal demand fluctuations all estimations include *month* indicator variables. 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

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

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 summarizes 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, 10 of the 35 airports experience a hub size change while 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, competitive, logistical, and weather variables. In addition to *seating capacity*, other economic factors that may also 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 control for important logistical factors such as *normalized departure time* and flight *distance* since longer flights give carriers more opportunities to make-up time while airborne. Our preferred flight delay specification is:

$$\begin{aligned} Delay_{ijt} = \; & f(hub\ airport_{orig}, hub\ airport_{dest}, airport\ concent_{orig}, airport\ concent_{dest} \\ & hub\ airline_{orig}, hub\ airline_{dest}, demand_{orig}, demand_{dest}, economic_i, \\ & logistical_i, weather_{orig}, weather_{dest}, carrier_j, month_t, year_t, \\ & airport_{orig}, airport_{dest}) \qquad (6) \end{aligned}$$

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 four 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.[25] Second, since each of our delay measures are "nominal" values of waiting times, a passenger may view a ten minute delay on a short-haul flight differently from a ten minute delay on a cross-country flight. Hence we construct a relative flight delay measure termed "delay per mile". Third, 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.[26] 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[27] for each takeoff or landing during a specified 60 minute period.

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 over-scheduling 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 an FAA meeting with the two hub airlines (American

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

[26] 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.

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

and United) who "voluntarily" agreed to reduce the number of scheduled flight offerings.

Fourth and finally, due to within-day fluctuations of airport congestion, at many hub airports during peak-travel times scheduled operations exceed the maximum airport capacity. Hence, 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. Each delay measure is estimated both including and excluding airport fixed effects. First, we consider flight delays from the carrier's perspective and find longer excess travel times for larger hub airports at both origination and destination. Model 1 reveals that flights originating from small, medium, and large hubs experience approximately four minutes (small hubs) and eight minutes (medium and large hubs) longer excess travel time, compared to non-hub originating flights. Therefore airport hubbing effects are between four and eight times larger than the airport concentration effects since 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) and Brueckner (2002) we also find evidence that carriers internalize flight delays since more concentrated airports (at both origination and destination) have shorter excess travel times.

Both the hub and airport concentration effects, however, are considerably reduced after controlling for airport fixed effects (see model 2). 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 is that *airport concentration at destination* (in model 2) loses its explanatory power with the inclusion of airport fixed effects. Next, we examine flight delays from the passenger perspective.

Departure and arrival delay results appear in models 3-6. Due to the important time invariant airport effects (and for the sake of brevity), we limit our discussion of results to models that control for airport fixed effects. Similar to the excess travel time estimations, both departure (model 4) and arrival delays (model 6) 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). Airport congestion appears to a slightly larger problem for flights originating from hubs compared to flights destined for hubs since departure and arrival delays are modestly longer (about one-half a minute) for hub originations.

The most noticeable difference when comparing flight delays from the airline versus consumer perspective occurs for airport concentration. After controlling for airport fixed effects, we find that passengers experience significantly longer departure and arrival delays at more concentrated airports (at both origination and destination). Hence from the passenger perspective it appears that carriers are behaving like atomistic competitors who are not internalizing the costs of flight delays. Moreover, 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. Similarly, 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. Given that this internalization relationship is sensitive to the flight delay measure (excess travel time versus arrival/departure delays), we next examine whether this relationship has been affected by the events on 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. Our first robustness check appears on Table 4, which 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 from 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 hub airport 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 is sensitive to one's perspective (carrier or passenger) since we get different results based on which delay measure is used. From the airline's viewpoint, there is evidence supporting the internalization hypothesis since highly concentrated origination airports have significantly shorter excess travel times, however, from the passenger's vantage point there is evidence to reject internalization since airport concentration at destination is positively (and significantly) associated with longer departure and arrival delays. More specifically, we find that 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. How do we explain these different internalization findings?

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, the demand for airline tickets is higher for 8 a.m. departures than any other morning departure time (Borenstein and Netz, 1999). 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 on-time flight schedule. Therefore we now turn to our preferred specification, which controls for potentially important economic, competitive, and logistical factors.

4.4 Preferred Specification

Estimations from our preferred specification for all three delay measures for 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, after controlling for economic, logistical, and weather factors we find no empirical evidence to support the internalization hypothesis from the carrier's viewpoint since airport concentration at both origination and destination has no effect on excess travel time. Moreover, from the passenger perspective, we once again find longer arrival and departure delays at more concentrated airports. Hence in our preferred specification we find some evidence which suggests that dominant airport carriers do not internalize congestion delays. These results are consistent with previous work by Daniel (1995), Daniel and Harback (2007), and Morrison and Winston (2007a).

Second, we find that economic, logistical, and weather factors[28] 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). The relationship between monopoly routes and delays depends on which delay measure is considered. From the airline's viewpoint, monopoly routes have significantly shorter delays (excess travel time); however, passengers' delay experience suggests the opposite with longer departure and arrival delays on monopoly routes. How can both of these 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.

For all three delay measures, we find significantly longer delays for later in the day departures. This propagation of flight delays has been well documented in the literature (Mazzeo 2003, Ahmadbeygi et al. 2007). Hence it is important to control for the schedule departure time when examining air travel delays. Long-haul flights are subject to longer excess travel times, however,

[28] 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.

we find shorter departure and arrival delays for longer flights. This result is consistent with the belief that longer flights provide the pilots with more opportunities to "make-up time" while airborne.

As a robustness check, since our three delay measures are nominal values of waiting times, we construct a relative flight delay measure of "delay per mile" by dividing the minutes of delay by flight distance (in 100s of miles). In our sample period, the length of delays were 6.3, 1.7, and 1.6 minutes of excess travel time, departure, and arrival delays per 100 flight miles, respectively. We re-estimate the six models from Table 3 using these three relative delay measures and find that most estimations have a positive and significant correlation between airport concentration (at both origination and destination) and relative flight delay.[29]

As a further robustness check, we also examine the set of flights to and from 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 further evidence to reject the internalization hypothesis as airport concentration at destination is now positively and significantly correlated with excess travel time. This result had been previously documented for only departure and arrival delays. These findings suggest that at airports where carriers are free to set their own schedule, more concentrated airports have longer travel times regardless of the delay measure. In sum, at non-slot restricted airports, we find no evidence to support the claim that carriers internalize the costs of flight delays.

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

[29] I thank the University of California Irvine transportation group for offering this relative travel time suggestion. These estimation results are available upon request.

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

Previous research has presented conflicting views on whether carriers internalize flight delay costs. This paper examines the on-time performance of approximately 50 million flights between 1995 and 2004 to address this internalization question. We find that the answer to the internalization question depends on how flight delays are measured. If one uses excess travel time (i.e., the number of minutes exceeding the route's monthly minimum), then most estimations suggest that delays are inversely correlated with airport concentration, a finding consistent with internalizing flight delay costs. On the other hand, we find the opposite result for departure and arrival delays since these delay measures are positively correlated with airport concentration. The passenger's perspective on delays are important for two reasons. First, passengers bear a larger burden of delay costs than airlines (Morrison and Winston, 2007a). And second, borrowing a finding from the railroad literature, passengers experience significant disutility from arrival and departure delays since they value a minute of waiting time as equivalent to 2.5 minutes of additional travel time

(Wardman, 2004).

In our preferred specification, which controls for important economic, logistical, and weather factors, we find no evidence to support the internalization hypothesis. More specifically, we find no statistical relationship between excess travel times and airport concentration while longer arrival and departure delays occur at more concentrated airports. After excluding the four U.S. slot restricted airports, we find stronger evidence to reject the internalization hypothesis as all three delay measures indicate longer delays at more concentrated airport destinations. What can public policy makers infer from these findings?

The recent increase in airport congestion and subsequent flight delays has fostered greater passenger discontent with airline service quality. Hence a congestion-based airport runway allocation scheme appears inevitable. Our empirical findings suggest that carrier are not internalizing the costs of flight delays (especially from the passenger's perspective). We show that carriers behave like atomistic competitors, which suggests that congestion-based tolls be determined regardless of a carrier's airport market share. Moreover, an additional benefit of adopting a congestion-based toll scheme in which all carriers pay the same fees is more politically appealing since smaller carriers are not penalized with higher landing fees (Morrison and Winston, 2007a). In addition, Morrison and Winston find only minimal welfare differences from charging atomistic congestion tolls instead of optimal tolls adjusted to reflect internalized congestion costs.

Our findings raise the question: why aren't carriers internalizing congestion costs? We believe that profit maximizing carriers have competing objectives when developing and implementing flight schedules. Flight schedules that minimizes flight delays may not be maximizing profits, and vice versa. Moreover, carriers with a dominant airport market share may jeopardize their market position if they do not satisfy consumer air travel demand by offering enough peak period flights on a route (Daniel, 1995). A reduction in flight offerings, while reducing congestion costs, leaves the door open for entry by competitors.

Beyond airport concentration, we also find significant airline hub size effects on U.S. flight delays. Due to the peaking of hub airline flights, hub airports are more congested and hence have longer flight delays. Hub congestion from flight peaking is more noticeable at origination, rather than destination airport. We attribute this result to two factors. First, hub carriers typically have a smoother distribution of flight arrivals compared to the spiking of departures at peak travel times. Second, hub carriers need on-time hub arrivals in order to maintain their hub-spoke network. In addition to delays, an additional consequence of peaked flight schedules is the lengthened "turnaround" times for hub carriers (the difference between aircraft arrival and next scheduled departure).[30]

Longer delays at hub airports between 1995 and 2004, combined with lengthened "turnaround" times for hub airlines may explain why several carriers have recently rescheduled their hub airport traffic to avoid peak congestion periods (e.g., American at DFW in November 2002; US Airways at PHL and CLT in February 2005; Delta at ATL in February 2005). De-peaking of hubs provides a great opportunity for carriers to reduce air travel delays. Congestion will improve, if competing carriers do not step-in and offer flights at peak travel times.

The current weight-based landing (and departure) fee structure in the U.S. has contributed to an increase in airport congestion. While economists agree that a congestion-based toll scheme would improve airport congestion, there is considerable debate on the optimal toll scheme. Particularly, whether carriers should be charged a uniform-fee or a fee that accounts for only the congestion costs imposed on other carriers. While the answer to this internalization question

[30] 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.

partially depends on how one measures flight delays, we find considerable empirical evidence to reject the internalization of congestion costs hypothesis. These results lend support for a uniform congestion fee structure that does not discriminate based on a carrier's airport market share.

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.

_____. 2005. 'Internalization of Airport Congestion: A Network Analysis', *International Journal of Industrial Organization,* 23, p. 599-614.

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.

Brueckner, Jan K. and Kurt Van Dender. 2007. 'Atomistic Congestion Tolls at Concentrated Airports? Seeking a Unified View in the Internalization Debate', CESifo working paper No. 2033, Category 1: Public Finance. June 2007.

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 Katherine Thomas Harback. 2007. '(When) Do Hub Airlines Internalize Their Self-Imposed Congestion Delays?', *Journal of Urban Economics*, forthcoming.

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

Geewax, Marilyn. 2007. 'Bush Says Search is On for Air Travel Delays,' Cox News Service, 28 September 2007, Washington D.C. Bureau.

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.

Mohring, Herbert, John Schroeter, and Paitoon Wiboonchutikula. 1987. 'The Values of Waiting Time, Travel Time, and a Seat on a Bus', *Rand Journal of Economics*, 18:1, p. 40-56.

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.

_____. 2007a. 'Another Look at Airport Congestion Pricing', forthcoming *American Economic Review.*

_____. 2007b. 'The Effect of FAA Expenditures on Air Travel Delays', forthcoming, *Journal of Urban Economics.*

Office of the Press Secretary, Oval Office. 'President Bush Meets with Secretary of Transportation Mary Peters and Federal Aviation Administration Acting Administrator Bobby Sturgell.' The White House press release, 27 September 2007.

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.

Small, Kenneth A. 1982. 'The Scheduling of Consumer Activities: Work Trips', *American Economic Review*, 72:3, p. 467-79.

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.

Vansteenwegen, P. and D. Van Oudheusden. 2007. 'Decreasing the Passenger Waiting Time for an Intercity Rail Network', *Transportation Research: Part B*, 41, p. 478-92.

Wardman, M. 2004. 'Public Transport Values of Time'. *Transport Policy*, 11:4, p. 363-77.

Winston, Clifford. 1985. 'Conceptual Developments in the Economics of Transportation: An Interpretative Study', *Journal of Economic Literature*, 23, p. 57-94.

Zhang, Anming and Yimin Zhang. 2006. 'Airport Capacity and Congestion when Carriers have Market Power.' *Journal of Urban Economics*, 60, p. 229-47.

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

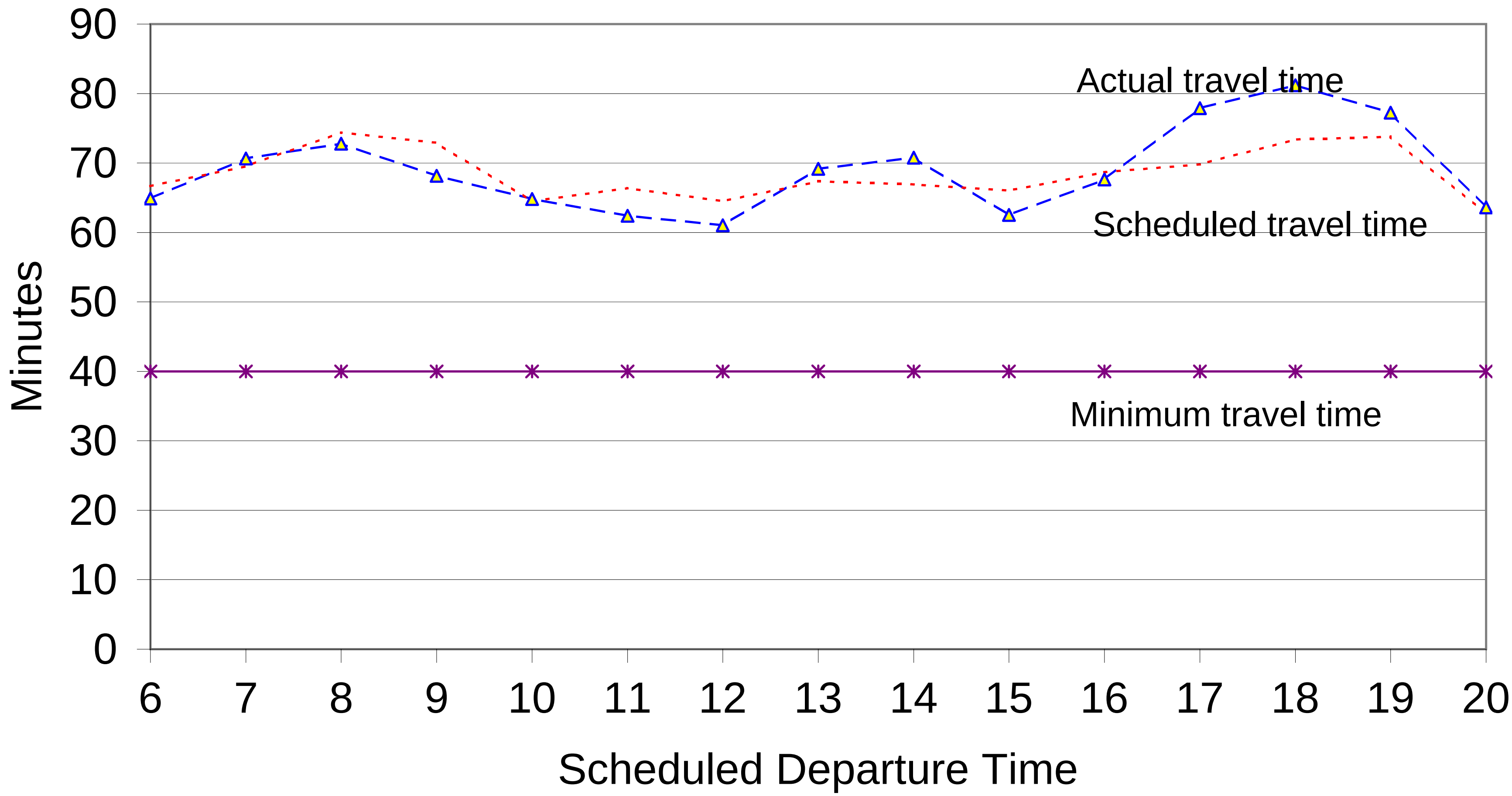

Figure 2: Minutes of Excess Travel Time, Departure and Arrival Delays, 1% sample U.S. Domestic Flights