Working Paper Series
Department of Economics
Alfred Lerner College of Business & Economics
University of Delaware

Working Paper No. 2005-09

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Do Airlines that Dominate Traffic at Hub Airports Experience Less Delay?

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The desirability of airport congestion pricing largely depends on whether dominant airlines otherwise fail to internalize their self-imposed congestion delays. Brueckner (2002) and Mayer and Sinai (2003) find (weak) statistically significant evidence of internalization. We replicate and extend these models by refining their measures of delay and controlling for fixed and random airport effects. For twenty-seven large US airports, we estimate every flight's congestion delay attributable to its operating time. These time-dependent queuing delays result from traffic rates temporarily exceeding airport capacity, and are precisely the delays susceptible to peak-load congestion pricing. As modified, the models reject the internalization hypothesis. (JEL H2, L5, L9, D6)

Forty years of conventional economic wisdom holds that replacing weight-based pricing of aircraft operations at major airports with congestion-based pricing would reduce delays and improve airport efficiency by internalizing the costs of delays that aircraft impose externally on one another. Now, just as the Federal Aviation Administration (FAA) finally seems ready to take this wisdom seriously, several recent articles question whether airlines with dominant shares of airport traffic already internalize their self-imposed congestion delays, making conventional congestion pricing proposals inappropriate for airports. The stakes involved in how we resolve this policy issue are large. According to the Federal Aviation Administration (FAA), twenty percent of flights were delayed by more than fifteen minutes in 2004. Air transport delays cost the United States economy $9.4 billion in the year 2000 and will cost $154 billion over the next ten years (Boeing, 2002). Building additional airports or substantially expanding existing airports can cost $10 billion each, and require at least a decade for planning and construction. Understanding internalization is essential to choosing the appropriate policy response to airport congestion. If dominant airlines internalize, then the congestion costs they impose on their own flights need not be included in congestion prices because they are already accounted for in airline scheduling decisions. If they do not internalize, however, then congestion fees should reflect costs that each flight imposes on all other flights—even flights by the same carrier.

Daniel (1995), Daniel and Harback (2005), and Morrison (2005) argue that the internalization effect is negligible, while Mayer and Sinai (2002) and Brueckner (2003) find significant (but weak) statistical relationships between airport concentration levels and the amount of delay dominant airlines experience. The latter authors infer from their results that dominant airlines do internalize self-imposed delays. Brueckner argues that congestion fees of dominant airlines should be reduced by their share of airport traffic. This paper replicates the models of Mayer and Sinai (2002) and Brueckner (2003) using a refined measure of delay and controlling for fixed and random airport and airline effects. Brueckner measures delay using the FAA's annual on-time arrival statistics that are aggregated by airport. The FAA measures delay as the percentage of flights that are over fifteen minutes later than their scheduled arrival times. While this statistic may be relevant to passengers who want to compare the likelihood of on-time arrivals across several airlines, it does not measure the extra flight time required due to congestion delay because it ignores any padding of flight times that airlines build into their schedules. Mayer and Sinai measure each flight's delay as the travel time in excess of the minimum observed travel time by any flight between the same city-pair during a given month. This measurement overstates airport congestion delay by including some of the normal flight time and other delays that are unrelated to regularly scheduled traffic exceeding airport capacity. We estimate the delay from queuing to land or takeoff by regressing each flight's travel time on dichotomous variables for each minute of the day at each airport while controlling for flight distance and speed. This measure includes the delays common to flights operating at an airport at a particular time, while it excludes delays of flights that are uncorrelated with those of other aircraft (with different origins or destinations) operating at the same airport at the same time. Coefficients on the dichotomous time variables represent the time spent waiting for a turn to use the runway. It is this regular diurnal pattern of queuing delay attributable to a particular airport that is susceptible to peak-load congestion pricing.

Accounting for temporal aspects of delay also enables us to take advantage of variation in the dominant airline's share of traffic at a particular airport over time. Traffic at large congested airports generally exhibits periodic peaks that are largely caused by dominant airlines coordinating arrivals and departures of their aircraft to facilitate rapid exchange of passengers at their hub airport. Airlines refer to such groups of aircraft as flight banks. Non-dominant aircraft also operate during peak periods associated with the dominant airline's flight banks because the banks are scheduled at travel times that are particularly convenient for passengers. The share of dominant flights varies from bank to bank, however, because the number of hub-airline operations is more constant than the number of non-dominant aircraft. The number and frequency of operations during a bank affect the delays of other aircraft operating during the same bank, but usually have negligible effects on delays experienced by aircraft operating during other banks because banks are separated by periods of relatively low traffic when the queues disappear. If dominant airlines internalize more delay when they have larger shares of traffic, then this should be true from bank to bank as well as from airport to airport. On the other hand, airlines have different strategies with respect to congestion. Some tightly schedule rapid passenger interchanges at hub airports to minimize layovers, while others schedule more relaxed interchanges to connect more city-pairs over longer periods. These strategies differ across airports with varying capacities and degrees of direct versus hub-and-spoke service. Panel data techniques can isolate the effects of market share on delay while controlling for airline and airport effects.

The purpose of this research is to investigate the empirical evidence of internalization to inform the choice of appropriate airport pricing policies. Section 1 places the internalization issue in the context of the recent literature. Section 2 details the data and econometric estimation of take off and landing queues. Section 3 fits dynamic-stochastic congestion functions to twenty-seven major hub airports and uses these functions to calculate the queuing times that aircraft experience directly, that they impose on other aircraft operated by their own airline, and that they impose on other aircraft operated other airlines. Section 4 presents the results of using our measure of delay with Brueckner's (2002) and Mayer and Sinai's (2003) econometric models. It also presents our own econometric models using panel data techniques. Section 5 presents a final summary of our results and conclusions.

Section 1—Literature Survey

While there is an extensive literature on congestion pricing, only five papers focus on whether dominant airlines internalize their self-imposed congestion at hub airports: Daniel (1995), Brueckner (2002), Mayer and Sinai (2003), Morrison (2005), and Daniel and Harback (2005). Of these, Brueckner (2002) and Mayer and Sinai (2003) find statistically significant relationships between airport dominance and decreased delay, while the remaining papers argue that whatever relationship exists is negligible. Morrison (2005) tests for the same relationship as Brueckner and Mayer and Sinai, while defining flight delay as excess flight time over the average—instead of minimal—observed flight times by city pair. This approach underestimates delay time by counting average delays as part of normal flight times. Morrison finds very little evidence that airport dominance reduces delays experienced by dominant airlines. Daniel (1995) and Daniel and Harback (2005) take a different approach based on specification tests of alternative optimizing models that determine the internal and external delays generated by each aircraft—rather than using a general regression model to test for relationships between airport dominance and delays experienced by each aircraft. These specification tests generally reject internalization in favor of non-internalization, under the assumption that the modeling framework is correct. We focus on Brueckner's and Mayer and Sinai's studies that support the internalization hypothesis to show that their results are not robust to alternative definitions of delay and/or panel data techniques that control for fixed or random effects of airlines or airports.

Brueckner (2002) developed an analytical model that characterizes airlines' incentives to internalize when they have significant market share. In Brueckner's model, travelers have uniformly distributed travel values. Profit maximizing airlines set prices to separate travelers between higher-valued periods with peak congestion and lower-valued periods with off-peak congestion. Airline congestion costs increase with the number of peak-period travelers. Brueckner considers cases of perfect price-discriminating monopoly, non-discriminating monopoly, Cournot duopoly, and perfect competition. The model predicts that more concentrated airports experience less congestion delay—controlling for the amount of hubbing activity—because dominant carriers internalize more congestion costs.

Brueckner tests this prediction using the FAA's data on aggregate annual delays at the twenty-five most congested US airports in 1999. His dependent variable is the FAA's standard measure of airport congestion—the number of flights that operate more than 15 minutes behind schedule. This measure strictly understates delay because it ignores the additional flight time airlines add to their schedules to allow for anticipated delays. Brueckner regresses delay counts by airport on a dichotomous slot-control variable, [1] a dichotomous major-hub variable, the amount of precipitation, the number of annual operations, and a measure of market concentration. He tries three different specifications of market concentration: the Herfindahl index, the market share of the largest airline, and a dichotomous variable that is equal to one when the dominant airline's share is greater than 65%. To support the internalization hypothesis, the estimated coefficients on the particular concentration measure must be significant and negative indicating that the more concentrated an airport is the greater share of congestion is internalized and thus the less delay the airline experiences, controlling for other factors.

The results of Brueckner's regressions consistently produce the predicted negative relationship between delay and concentration under all three measures of concentration. The significance of his coefficient estimates, however, is not consistent, and ranges from insignificant in most of the regressions, to significant in regressions omitting the intercept term. Brueckner attributes the lack of overwhelming statistical significance to the fact that his data set has only twenty-five observations on annual delays aggregated by airport. Brueckner's result that the incidence of delayed flights is lower at more concentrated airports could be due to less exposure to volatility of non-dominant operations (which is not the same as internalization). The primary thrust of Brueckner's article is his theoretical model and he makes rather modest claims for the basic econometric results on the internalization hypothesis, calling them "encouraging" rather than definitive evidence for the model.

Mayer and Sinai propose a model of hub-and-spoke airlines that face strong incentives to cluster flights at airports that serve as hubs for their route networks. Airlines achieve network economies by scheduling flights close together to facilitate connections between many origins and destinations. An additional spoke city in a network with N spokes creates $2N$ possible new itineraries, implying increasing returns to network connections. Non-dominant airlines that are not part of a network at the hub at the airport do not face the same incentives to cluster flights as the hub airline. Congestion is more of a problem at hub airports and increases with the number of spoke cities connected through a hub. Delay is primarily caused and experienced by the dominant hub airlines(s) at an airport. Mayer and Sinai argue that controlling for the level of hubbing activity, however, more concentrated airports will have less delay because the dominant airline will internalize its self-imposed delays.

Mayer and Sinai (2003) uses a significantly larger and more detailed data set to address the question of internalization, the U.S. Department of Transportation (DOT) Airline Service Quality Performance (ASQP) data and its somewhat more limited precursor cover 250 airports from 1988 through 2000. ASQP covers operations of airlines that account for at least 1% of domestic enplaned passengers. They avoid the FAA's biased measure of congestion delay based on on-time arrival statistics by using the excess flight time over the monthly minimum flight time between each directional city pair. There are still serious problems with this measure of delay because it implicitly assumes that random shocks only make flights longer. A flight with a favorable tail wind, however, can take substantially less time than a flight with no tail wind under otherwise identical conditions. Excess flight time over such a minimum overstates congestion delay. Using average travel time would not fix the problem—in that case delay is understated because flights that experience delay are included in the calculation of the average and thus pull the average travel time up.

Mayer and Sinai regress their measurement of delay on Herfindahl-Hirschman Indices (HHI) of airport concentration; the degree of hubbing by the dominant airline as measured by the number of spoke cities served at the origin, hub, and destination; interaction terms to differentiate flights of the dominant carrier at its hub airports; control variables for population, employment, and per capita income; dichotomous variables for the year and month of travel; and airport-level fixed effects. Their coefficient estimates are of the predicted signs and are significant. The sign on the concentration variable is negative, as was Brueckner's, indicating some degree of internalization when controlling for network effects. Unlike Brueckner's results, the Mayer and Sinai internalization result is usually statistically significant. However, the magnitude of the hubbing coefficients dwarf the effects of concentration on the predicted levels of congestion. Mayer and Sinai conclude that network effects associated with hub-and-spoke operations explain much of congestion delay, while there is a slight internalization effect associated with increased concentration.

Mayer and Sinai omit the effects of code sharing agreements under which some non-dominant airlines coordinate flights with dominant airlines and use its name. Code sharing agreements are numerous. Most regional code sharing airlines are small compared to their dominant partners and international code sharing airlines have a small domestic presence.[2] This means that a majority of code sharing airlines do not appear in the ASQP data which only include observations of airlines that fly at least 1% of the domestic passengers. Regional code share airlines fly smaller aircraft and play an important role in linking smaller communities to hubs. Ignoring them understates the size of the network and leads to misspecification of the dichotomous hubbing variables. This problem is exacerbated by large differences in the amount of code sharing across airlines and airports. Table 1 details the major carriers and their code share carriers, showing the disparate levels of code sharing by airlines. The middle columns of Table 2, labeled Share 1 and Share 2, illustrate the significant effect that including code sharing airlines has on dominant airlines' shares of airport traffic. The parties to the code sharing agreements should have the same incentives to internalize delays imposed on each other as dominant airlines have for their own aircraft because the agreements can divide revenues so that joint profit maximization dominates individual profit maximization.

As the literature stands, Daniel and Daniel and Harback test alternative models to determine whether dominant airlines treat delays their aircraft experience directly the same as delays their aircraft impose on their other flights. They reject the internalization hypothesis within a particular (bottleneck) modeling framework. Brueckner weakly confirms the internalization hypotheses using a small aggregated data set with a problematic measure of delay. Mayer and Sinai confirm a statistically significant internalization effect using a large disaggregated data set, but find the internalization effects are small. Their model does not account for code sharing relationships and their measurement of congestion delay includes any increase in flight times relative to the minimum, regardless of whether the increase is related to airport-specific delay. Morrison uses an approach similar Mayer and Sinai, but with an alternative measure of delay. He finds negligible evidence of internalization. The instant paper seeks to address problems in the literature associated with the measurement of delay and the treatment of code sharing airlines. It provides a general econometric specification using disaggregate data that distinguish between delays experienced by aircraft and delays imposed on other aircraft, while controlling for airline and airport effects.

Section 2- Data and Delay Measurement

This section develops an empirical model for determining the diurnal pattern of delay that is due to excessive airport traffic relative to capacity. Although many factors effect flight time, it is the systematic, recurring delay at airport landing and take off queues that is relevant to congestion pricing. Our approach improves on existing methodologies that use aggregated annual delay counts, or the excess of observed flight times over minimum or average flight times, to account for congestion delay. The estimates generated in this section are further refined in the next section by applying a dynamic-stochastic congestion function to separately identify the delays experienced by an aircraft, the delays it imposes on other aircraft of the same airline, and the fully external delays it imposes on other airlines.

Data from the Enhanced Traffic Management System (ETMS) for air traffic control and flow management include every flight using navigational instruments that files a flight plan, regardless of airline size—even including non-airline flights such as freight, general aviation, and military. ETMS data report airborne flight duration, take off and landing times, origin and destination, and type of aircraft. For departure queues, we supplement the ETMS data with additional data from the Airline Service Quality Performance (ASQP) data covering the same time period as the ETMS. The data sample consists of flights at the twenty-seven busiest airports in the United States from July 28 through August 3, 2003. We treat arrivals and departures separately to determine both the take off and landing queues. Table 2 contains a list of the airports, summary statistics, and three letter airport abbreviations of the airports used in this study.

Queue Estimation

Aircraft with different origins or destinations that operate at a particular time and airport share a common element of delay associated with waiting in the landing or takeoff queues. These queues are regular and predictable because they result from airlines scheduling too much traffic relative to airport capacity at certain peak intervals during the day. The queues depend on flight schedules that are highly stable from day to day. Queue estimates can be developed by regressing duration of travel on dichotomous variables representing the time of day that the aircraft lands or takes off, while controlling for flight distance and speed. To do this, we consider one airport at a time with arrivals and departures treated independently. Flights arriving at an airport experience airborne flight times that depend on several variables: the airport of origin, the distance of that airport from the destination airport, the type of plane used for the flight, time spent in the landing queue, and stochastic shocks from things like weather. Translating this statement into an equation yields:

Airborne time = uncongested time for destination *(1)*

+ adjustment for specific plane type

+ queuing time + random shock

A dichotomous variable equal to one when a particular airport is the origin and zero otherwise captures the portion of flight time that varies systematically by origin for a given destination airport. Likewise, dichotomous variables control for different aircraft types according to engine type, number of engines, and weight class. We interact these aircraft-type variables with the number of miles between the origin and destination airports to account for differences in speed and flight procedures for different kind of airplanes. If queuing time depends on scheduled traffic rates exceeding capacity and flight schedules are stable from day to day, then inclusion of dichotomous variables for each minute of the day captures the part of flight time that varies systematically with the time of arrival at the destination airport. We interpret the portion of airborne time that varies systematically by time of day and thus by schedule as an estimate of the queuing time. Rewriting the equation above as a regression equation produces:

$$airborne = \beta 1(city) + \beta 2(plane*distance) + \beta 3(minute) + e \qquad (2)$$

There is no need to account for the destination city because the equation is estimated for fixed destinations (e.g. all of the airborne times will be for flights arriving at the same airport and each of those airports will have its own regression). Each ß represents the vector of coefficient estimates. Each flight has a single city of origin, plane type, and minute of the day dummy (some aircraft operating during the entirely uncongested late night and early morning hours have no minute of the day dummy in order to allow the model to be full rank).[3] Using multiple days of data to estimate the queues in this way allows for minute-by-minute level of resolution.

This regression was carried out for each of the 27 airports individually, with the city, plane, and minute arrays being of dimensions unique to each airport. The results are better suited to graphical than tabular representation, as some airports have upwards of 800 minutes represented by dummy variables. Figures 1 and 2 illustrate the diurnal queuing patterns for six representative airports—ATL (Hartsfield Atlanta), DFW (Dallas/Fort Worth), EWR (Newark), LAX (Los Angeles), MSP (Minneapolis-St. Paul), and ORD (Chicago O'Hare)—that characterize the range of delay patterns exhibited by the twenty-seven major hub airports. The units on the horizontal axis are minutes of the operating day. Units on the vertical axis in each graph are minutes of queuing delay for the delay estimates.

A common pattern emerges from hub and spoke operations by strongly dominant hub airlines at congested airports. The graphs for ATL and MSP in Figures 1 and 2 typify such airports that exhibit well-defined peaks at regularly occurring intervals throughout the day separated by periods of very low levels of traffic. Airports with similar banking patterns include CLT (Charlotte), CVG (Cincinnati), DEN (Denver), DTW (Detroit Wayne County), IAH (Houston), PHL (Philadelphia), PHX (Phoenix), PIT (Pittsburgh), SLC (Salt Lake City), and STL (St. Louis). A few additional airports have similarly strong banking patterns, but fewer peaks in their operating day—these include MEM (Memphis), MIA (Miami), and IAD (Washington Dulles). Two particularly busy airports—ORD (Chicago) and DFW (Dallas-Ft. Worth) exhibit the same clear banks but have two strongly dominant carriers (American and United or American and Delta, respectively) whose banks typically do not overlap. While DFW exhibits banking, the magnitude of its arrival queues is quite small due to its ample capacity.

LAX (Los Angeles) and LGA (New York LaGuardia) have several dominant carriers, but unlike DFW and ORD, are not highly concentrated and exhibit a low degree of banking. Both LAX and LGA serve very large local populations and do not have sufficiently central locations as required to serve large volumes of connecting domestic passengers like ORD and DFW. There are additional airports that serve high levels of origin and destination traffic and have a low number of connecting flights. EWR, along with JFK (New York Kennedy) and SFO (San Francisco), exhibit even less banking behaviors, though they do have a clear diurnal delay pattern. These airports all have low queuing estimates for the early part of the day and high queuing estimates later in the day.

Several airports do not exhibit banking and have low levels of queuing, including BWI (Baltimore-Washington), BOS (Boston Logan), DCA (Washington National), and SEA (Seattle). BWI is unique in the set of airports in that it is the only Southwest hub represented that does not also have a high level of traffic from another carrier. Southwest is known for operating with a modified approach to hub and spoke networking that results in less peaked banks. SEA's is similar to BWI in that its dominant carrier, Alaska, also has less peaked banks. DCA was regulated by slot control under the High Density Rule, as was LGA and JFK.

The noisiness of the queue estimates evident in Figures 1 and 2 is largely due to the fact that the data is drawn from seven separate realizations of the diurnal queuing patterns. The queue estimates may also fold in some weather or other nonqueuing delays that either varied systematically by time of day or occurred during a period of time where observations from a particular day were significantly denser than observations from the unaffected days. With sufficient data, it would presumably be possible to estimate the entire distribution of queue lengths for each minute of the day, but instead we use a time-series filter to approximate the movement of the expected queue levels over time, as explained further below. The solid dark lines in Figures 1 and 2 represent the filtered value of the queue estimates.

Creating departure queues requires a slightly different framework. Flights experience time in the departure queue as taxiing after push back from the gate prior to taking off. There are not explicit components to this taxi time in the way that there are for airborne times used for estimating arrival queues. The departure queue taxi time regressions take the form:

$$\textit{taxi time} = \beta 1 + \beta 2(\textit{minute}) + e \qquad (3)$$

The $\beta 1$ constant represents the average taxi time it takes planes to get into position for take off excluding delay that varies systematically by time of day and stochastic shocks. The minute variables are defined in the same manner used for the arrival regressions. Some aggregating of minutes is necessary for minutes with few observed flights, as with the arrivals. While it takes different times to taxi from different gates at the airport, there were no data available for controlling for this in the way that city of origin is controlled for in the arrival regressions. This makes the R-squared values for the departure regressions significantly lower than for the arrivals.

The ETMS data only monitor air traffic flow management and do not capture taxi times, but the ASQP data do capture taxi times as an element of on-time performance. The ETMS data accounts for all the traffic, while the ASQP samples only flights by the larger carriers. Using ASQP data for the estimation of the departure queues is possible, however, because major airline flights are spread throughout the day and sample queue lengths during the relevant busy periods.

Figure 2 summarizes the coefficients on dichotomous variables for minute of departure, which, like those for arrivals, are estimates of queues at the same six airports detailed above. The output of departure queue estimates is qualitatively similar to the arrival queue estimation. Airports like ATL, DFW, MSP, and ORD that exhibit hub and spoke banking do so with respect to both departure and arrival queues. As with arrival queues, DFW and ORD have more departure peaks than ATL and MSP because of having multiple hub airlines. EWR's (non-hubbing) pattern of low morning delay and high afternoon delay also holds for the departures, as does LAX's pattern of many small peaks throughout the day. Departure queues generally peak more sharply than the arrival queues because time spent on the ground waiting to take off is less costly than time in the air circling the airport waiting to land, so airlines are willing to tradeoff more departure queue time to save a given amount of schedule delay time.

Section 3—The dynamic-stochastic congestion function

Brueckner and Mayer and Sinai look for econometric relationships between airport concentration and delay, without specifying any functional relationship between traffic levels and congestion. Similarly, our queue estimates derive directly from the data and are neutral with respect to any modeling assumptions associated with an explicit economic or queuing model. It is common practice in the congestion pricing literature, however, to fit a congestion function to traffic and delay data to facilitate calculation of the marginal congestion created by an additional unit of traffic. In addition to replicating Brueckner and Mayer and Sinai, we specify a congestion function so that we can calculate the marginal delays and distinguish between those experienced by each flight and those imposed by flights on other flights operated by the same or other airlines. Following Daniel and Pahwa (2000), we base the congestion function on an $M(t)/D/k/s$ queuing theoretic model that accounts for the dependence of the queuing system on current traffic rates and previous states of the queuing system as described by the probability distribution on queue lengths.

The function takes as inputs the observed traffic rates, $\lambda(t)$, for each service interval, t; the fixed service rate, d; and number of runways, s; and it outputs the state vector, $\boldsymbol{p(t)}$, that is the probability distribution on queue lengths in each service interval, t. For computational purposes, the queues have a finite maximum length k that is sufficiently large that the probability of approaching it is negligible. The queues evolve according to a transition matrix, $\boldsymbol{T(\lambda(t);d,s)}$, that determines the next period's state based on the current state, the probability distribution on number of arrivals given $\lambda(t)$, the number of available servers s, and the length of service d:[4]

$$\boldsymbol{p}(t+1)= \boldsymbol{T}(\lambda(t);d,s)\ \boldsymbol{p}(t). \tag{4}$$

In the initial period, the state vector has probability one of no queue, and probability zero of any positive queue lengths.

Figures 1 and 2 compare the queue estimates based on the regressions with the expected queue lengths from this congestion function to show that the diurnal patterns of estimated airport delays are highly consistent with those calculated from the dynamic-stochastic congestion function. To facilitate comparison, the queue estimates are filtered through a Hodrick-Prescott filter to eliminate noise in the estimates and approximate the expected queue levels over time. The dark solid lines in Figures 1 and 2 show the filtered delay estimates that are directly comparable to the lighter zig-zag lines representing the expected delays calculated from the congestion function.[5] The congestion function is clearly successful in reproducing the pattern and magnitude of the queue estimates at the various airports. This strongly supports the contention that the estimated delays are those caused by traffic rates exceeding the available capacity at a particular airport—in other words, the estimated delays are the relevant measure of delay for the purpose of congestion pricing.

Given the dynamic congestion function specified above, we can calculate the rate of change in the system state for each subsequent period with respect to the arrival rate $\lambda(t)$. Let $\boldsymbol{D}(t)$ be the matrix of derivatives of the elements of transition matrix $\boldsymbol{T}(t)$ with respect to $\lambda(t)$. The effect of $\lambda(t)$ on the queuing system in n periods hence is:

$$d\,\boldsymbol{q}(t+n)/d\lambda(t)=\boldsymbol{T}(t+n)\ \ldots\ \boldsymbol{T}(t+2)\ \boldsymbol{T}(t+1)\ \boldsymbol{D}(t)\ \boldsymbol{q}(t). \tag{5}$$

The ith element of the state vector, $q_i(t+n)$, denotes the change in probability that the queue is of length i in period $(t+n)$ as a result of an arrival at time t. To account for uncertainty over the actual arrival times, we weight the marginal queuing times by the probability that an aircraft scheduled to arrive at $t+n$ actually arrives at $(t+n+s)$:

$$\Sigma_s \{p(t+n+s)\ \Sigma_i\ i\ d\ q_i(t+n)/d\lambda(t)\}. \tag{6}$$

Summing the expressions in (6) for each aircraft over all other aircraft operated by the dominant airline gives the changes in indirect queuing times an aircraft arriving at time t imposes on other aircraft operated by its airline.

Section 4—Testing for internalization

We now use the delays calculated from the congestion function to conduct Brueckner-like tests with airport level observations, to conduct Mayer and Sinai-like tests with flight level observations while controlling for hubbing behavior, and to conduct an original panel data treatment with flight-level and bank-level observations.

Brueckner-Like Test

Brueckner (2002) develops a theoretical model in which airlines internalize the share of delay that their flights impose on one another, leading to the prediction that more concentrated airports experience lower levels of delay than less concentrated airports, holding everything else constant. Brueckner tests this hypothesis based on airport-level delay from FAA's count of flights that operate more than fifteen minutes late at the twenty-five busiest US airports during 1999. The use of annual airport-level data means he has twenty-five observations. His regression equation can be summarized:

$$\begin{aligned} \textit{delay count} = \beta 1 &+ \beta 2(\textit{annual airport operations count}) \\ &+ \beta 3(\textit{concentration}) + \beta 4(\textit{hub airport dummy}) \\ &+ \beta 5(\textit{slot constraint dummy}) \\ &+ \beta 6(\textit{ annual precipitation in inches}) + e \end{aligned} \tag{7}$$

Brueckner performs six versions of the regression including three standard regressions of Equation (7) with varying measures of concentration, one log specification, and two specifications without intercepts (one for each of two of the concentration measures). According to Brueckner's hypothesis, coefficients on counts of annual airport operations and dichotomous variables indicating hub airports and slot constraints should all be positive, while the concentration coefficient should be negative. His estimated operations-count coefficient is consistently positive and significant in all six versions of his regressions, confirming that airports with more traffic experience more delay. The hub-airport variable controls for airports that are hub-and-spoke network hubs. Its coefficient is always positive and significant in two of his regressions. The coefficient for slot constraints is positive and significant in all but one of his regressions. The precipitation variable attempts to control for effects of weather on delay, but precipitation at the airport is insufficient to capture important effects of weather on aircraft including wind, visibility, and convective action. Unsurprisingly, his coefficient on the precipitation variable is never significant.

Brueckner tries three measures of concentration in his alternative versions of the regressions. The Hirschman-Herfindahl Index achieves the highest significance (although still very weak) of the alternatives when he omits the intercept from the regression. The dominant airline's share of airport traffic and a dichotomous variable for airports with a dominant airline operating more than sixty-five percent of the traffic are either totally insignificant or marginally significant depending on the versions of the regression.

Brueckner acknowledges that the internalization problem really deserves a larger, more detailed data set. While our data set has flight-level observations, we initially aggregate it by airport to compare results using our measures of delay with Brueckner's. To this end, we use three versions of the dependent variable to measure the magnitude of airport delays during a typical day: the sum of delays that all flights directly experience themselves, the sum of delays that non-atomistic airlines impose indirectly on their own aircraft, and the sum of directly-experienced and indirectly-imposed delays. The queuing time each flight experiences plus the increase in queuing time the flight imposes on the airline's other flights is the incremental queuing time that an internalizing airline takes into consideration in optimizing the schedule. Brueckner measures delay using the FAA's count of aircraft operating more than fifteen minutes behind schedule because it is readily available, not because it is the most appropriate metric. To test the sensitivity of the results presented here, we also try FAA's count data for August, 2003 as a dependent variable (a measure directly comparable to Brueckner's).

We omit the precipitation variable in all our specifications because it is never significant in any of Brueckner's regressions and it is not a valid way to capture the complexity of weather effects, as noted above. We base our variable for traffic counts on the number of operations during the typical day for July 28 through August 3, 2003. We construct the same three concentration measures as Brueckner, while including code sharing airlines as part of the dominant firm.[6] Table 2 summarizes the airport level characteristics used in our regressions.

Table 3 presents the regression results that replicate Brueckner's six versions of the regression using our data including direct (average) and indirect (marginal) delays from our dynamic-stochastic congestion function. Standard errors appear in italics underneath the coefficient estimates. Our first nine modifications of Brueckner's regressions based on Equation (7) vary the dependent variable (total direct queuing, total indirect queuing, and the sum of the two) and switch the measure of concentration between the HHI, the dominant airline's share of traffic, and the dichotomous indicator that share exceeds 65%. These variations make little difference in the results—all estimate positive, insignificant coefficient on the concentration variables. Coefficient estimates that support internalization would be negative, indicating that when an airline controls a greater share of airport traffic, it takes greater account of the congestion it flights impose on one another, leading to less queuing time. The coefficients for the other variables (slot control airports, hub airports, and operations) are all of the predicted sign, although only the intercept and traffic-count coefficient are significant.

Dropping the intercept term does produce a negative coefficient on the concentration measure, whether using the share variable or the Herfindahl variable. These estimates, however, are insignificant, and the regressions without intercepts produce the incorrect signs on the hub and slot control dummy variables (they become negative). The natural log specification of the model produces the most significant coefficients on concentration, but they are positive, which does not support internalization.

Using the FAA's reported percentage of flights operating more than fifteen minutes behind schedule in August of 2003 (the reporting period that most closely resembles the period of the rest of that data) produces an interesting result. We include it as a dependent variable to see whether using a measure of congestion delay more similar to Brueckner's would more faithfully replicate his results. Like all of the results above, except the regressions that do not include an intercept, this specification produces a positive, insignificant estimate of the concentration coefficient, which does not support internalization. It also produces incorrect signs on the hub and slot coefficients, similar to the regressions with no intercept. It is unclear whether these contrary results from Brueckner's are due to differences in the dependent variable, inclusion of code sharing flights in the concentration measures, or significant changes in airline behavior between his 2000 data and our 2003 data. It is clear, however, that our airport-level analysis based on Brueckner's model overwhelmingly fails to support the internalization hypothesis.

Mayer and Sinai-Like Test

As described in Section 1, Mayer and Sinai (2003) focuses on hubbing (the clustering of flights to facilitate connections in a hub and spoke network) as an explanation for delays. They regress the excess of actual flight times over minimal flight times by city pairs on a list of independent variables including concentration levels and dichotomous variables controlling for level of hubbing activity. They average the dependent and independent variables by month and city pair because of the large scope of their dataset (250 airports from 1988 through 2000). Three dichotomous hubbing variables represent ranges of the number of cities the airport connects (26 to 45 cities, 46 to 70 cities, and 71 or more cities). They distinguish the effects of dominant and non-dominant airlines by interacting the hubbing variables with dichotomous variables for the dominant airline. The basic regression equation takes the form:

$$\begin{aligned} \textit{excess travel time} = {} & \beta 1(\textit{hub size}) + \beta 2(\textit{concentration}) \\ & + \beta 3(\textit{hub airline*hub size}) \\ & + \beta 4(\textit{year, month, demand variables}) + e \end{aligned} \tag{8}$$

where *ß1, ß3,* and *ß4* are vectors of coefficients on the vector of dichotomous variables in parentheses. Like Mayer and Sinai, we use HHI to measure concentration, but we also substitute the share of flights operated by the dominant airline and its code sharing affiliates. We omit Mayer and Sinai's income, population, and employment variables because our data represents observations on a typical day rather than over several years, so we do not need to control for variation in demand within airports over time.

Mayer and Sinai specify versions of their model with and without variables for the hub airline, slot control airports, and airport fixed effects. They perform separate regressions for arrivals and departures, but do not assign delays to the origin or destination so their delays include en route congestion. Mayer and Sinai also specify an instrumental variable model to address the possibility that the demand variables do not appropriately capture local demand conditions and may instead be correlated with the probability of an airport being a hub. We omit this version for our data set because it does not include variation in hubbing or local demand over time. Table 4 presents the number of airport links that we use to define the hubbing variables. These differ from Mayer and Sinai's ranges because ours include connections made through code share carriers and cover a different period of time.

Our modifications of Mayer and Sinai's regressions use more precise measures of delay than their original model. The three alternative dependent variables for each flight include; the queue in minutes experienced by the flight, the indirect minutes of queuing it imposes on other flights, and the sum direct and indirect delays. These are comparable to the dependent variables in our modifications of Brueckner's airport level regressions, but are at the flight level rather than aggregated by airport. We estimate airport-level effects for our data set by letting concentration and hubbing vary by *bank* instead of by *airport*, as discussed later in this section. In our modifications of Mayer and Sinai models, the significance of coefficients is aided by having more than 12,907 arrival observations and more than 14,501[7] departure observations—compared to only 27 observations at the airport level in the Brueckner models. Tables 5 and 6 present the regression results for arrivals and departures, respectively, based on our modifications of Mayer and Sinai's models.

Like those of Mayer and Sinai, our arrival regressions support the internalization hypothesis by consistently producing negative, significant coefficients on concentration—in all cases, regardless of the dependent variable or concentration measure. Likewise, our arrival regressions support the network hubbing hypothesis by producing positive, significant coefficients on the dichotomous hubbing variables that increase in the degree of hubbing. Estimates of concentration and hubbing coefficients are stable with respect to the inclusion or exclusion of the dominant-airline dichotomous variables. These coefficients have the correct sign, but the coefficient on hub classifications should decrease with hub size to be fully consistent with Mayer and Sinai's estimates. The R-squared values are lower than those of our modified Brueckner model, but with only 27 observations it has much less variability and many more explanatory variables.

The departure regressions in our modified Mayer and Sinai model tell a different story than the arrival regressions. The four specifications with aircraft's own queuing as the dependent variable produce the correct sign for coefficients on the concentration and hubbing variables. The hub-classification variables have the same problem as those in the arrival regressions, with smaller hub classifications displaying more delay. The effect of the concentration variables on indirect (internally-imposed) queuing is different for departures than it is for arrivals. The dependent variable in Regressions 5 through 8 of Table 6 is the indirect queuing that each flight generates at the margin. These models have significant, positive coefficients on the concentration measures for both the Herfindahl specification and the traffic-share specification. When the dependent variable is sum of direct and indirect queuing, the positive relationship between concentration and indirect delay is larger than the negative relationship between concentration and direct queuing (regressions 9 through 12). The significance levels for the departure models are generally more variable than for the arrival regressions.

The inclusion of indirect queuing also produces conflicting signs on the dichotomous hubbing variables when the dominant-airline indicator variables are present.

Regressions 6, 8, 10, and 12 estimate negative coefficient for the three ranges of hubbing, though some of them are insignificant or only marginally significant. In those regression models, therefore, flights at airports with low hubbing levels experience more delay than mid, moderate, or high hubbing levels, contrary to the Mayer and Sinai hypothesis. The robustness of the relationships in the arrival regressions with respect to the dependent variable and the inclusion or exclusion of the dominant carrier dummies makes them seem more trustworthy. The sensitivity of the departure results to inclusion of the dominant carrier variables and indirect queuing in the dependent variable (whether exclusively or as part of the sum) makes them seem less trustworthy. This is somewhat troubling for the Mayer and Sinai model because one of their predictions is that the relationship between hubbing and delay is even stronger for departures than arrivals.

Bank Level Panel Data Test

Daniel and Harback (2005) points to individual flight banks as the appropriate level of analysis in testing for internalization, because (according to its J-tests) dominant aircraft *do not* internalize delays they impose on one another during most flight banks, but *do* but internalize such delays during a few flight banks. Daniel's (1995) theory holds that the dominant airline acts as a Stackelberg leader in scheduling its aircraft by taking into account the reactions of non dominant airlines. The dominant airline realizes that reducing traffic and delay in the middle of a bank may prompt entry by non dominant aircraft. Different banks may have different potential for entry. As noted above, banking of flights is a common and crucial practice in connecting spoke cities across a hub and spoke network. Daily patterns of arrivals and departures exhibit significant variation in market shares within and across airports. For example, at Dallas/Ft. Worth (DFW), the second bank is highly concentrated, while the third has a large share of non dominant traffic. If the internalization hypothesis is correct, flights in the second bank should experience less delay, holding everything else constant. Setting the concentration variables at the airport level ignores this bank level variation. Table 7, for example, presents characteristics by bank for Hartsfield Atlanta (ATL) showing substantial variation in concentration between banks.

The hubbing variables in Table 7 are redefined to reflect potential city-pair connections by bank, as defined in Table 8. The thresholds for the four classes of hubbing are lower than the thresholds defined at the airport level because not all spoke cities served via the hub are served in every single bank (further emphasizing the relevance of bank-level variation). HHI's and the dominant airline's share of flights are also recalculated by bank. By adding bank-level variation to the Mayer and Sinai set up, the data now have 264 observations on concentration and hubbing for arrivals and 251 for departures.

We also perform fixed- and random-effects regressions to control for airport heterogeneity. Tables 9 and 10 show these results for arrivals and departures that are comparable to the results in Tables 5 and 6 except that dichotomous hubbing and concentration variables are defined at the bank level. The results from Tables 5 and 6 that support internalization with significant negative coefficients are largely reversed by the results in Tables 9 and 10 based on bank-level hubbing and concentration variables. Of the sixteen regressions (out of twenty-four) that produced negative coefficients, only five retain negative coefficients and only three of these are significant. Only one regression switched signs from positive to negative, and this coefficient was insignificant.

An F-test test confirms that the fixed effects model with airport level dichotomous variables is superior to the standard model. Hausman's chi-square test rejects the random effects models except when the dominant airline variables are excluded (these are regressions 6, 12, 18, 24, 30, and 36 for both the arrivals and departures). In all of these instances where the random effects model cannot be rejected, the coefficient on the concentration variable is positive and significant, not supporting internalization. In general, the signs and magnitude of the concentration coefficient estimates produced by the fixed effects model are similar to those produced in the model with a common intercept. The exceptions are those six coefficient estimates that were negative, supporting internalization. With the inclusion of airport fixed effects, these all switch from negative to positive, making every single fixed effects concentration coefficient estimate positive, dealing another blow to the internalization hypothesis. While support for internalization in the results of the modified Mayer and Sinai models was weak before, this addition of bank level variation weakens support for internalization considerably.

Because there are compelling reasons to think that bank-level characteristics are appropriate for looking for evidence of internalization, we extend the models to include specifications with bank-level observations—placing this treatment somewhere between Brueckner's approach with airport-level observations and Mayer and Sinai with flight-level observations. We maintain separate regressions for arrival and departures. Brueckner uses an operations count variable to measure for prevailing traffic levels in his model. Aggregation at the bank level allows for more detailed treatment of traffic levels to isolate the relationship between concentration and congestion delay. In addition to the flight count for the bank (comparable to Brueckner's annual flight count), we include the width of the bank in minutes (or spread) and average traffic rates by bank as potential explanatory variables. The three dependent variables for arrivals and departures are constructed by summing the queuing minutes for the bank, summing the indirect queuing minutes for the bank, and summing the two. We drop the dichotomous variable for dominant carriers out of necessity because it only applies at the flight level. The hubbing dummy variables are the same as in Table 8. The variables for bank-level HHI and dominant airline's traffic shares are also the same as in the flight-level regressions discussed previously, except that they apply to bank observations rather than flight observations.

Tables 11 and 12 report the results arrival and departure bank respectively. As was the case before, regressions that do not control for airport-level effects are rejected in favor of the fixed effects models. The Hausman test rejects all of the random-effects models for arrivals except for regressions 15, 18, 30, 33, and 45. It fails to reject all of the random-effects models for departures except 3, 6, 33, and 36. Five of fifteen fixed-effects arrival models estimate negative concentration coefficients, but they are all insignificant. Likewise, five of fifteen fixed-effects departures models produce negative, insignificant coefficients on the concentration variable. The five specifications that fail to reject the random-effects model for arrivals all produce negative but insignificant coefficient estimates on the concentration variables. Of the eleven specifications that fail to reject the random-effects models for departures, five produce negative coefficients, four of which are insignificant (regression 30).

The traffic variables—spread, flight count, and average traffic rate by bank—produce significant coefficients with the expected signs across all of the regressions. A negative coefficient on the spread variable indicates longer banks have less queuing delay, holding everything else constant. Positive coefficients on the flight count and average traffic rate by bank indicate that more traffic increases queuing in that bank. There is a pattern that emerges with the inclusions of these variables: the regression that includes traffic rates produces negative but insignificant coefficient on the concentration measure.

These results for bank-level observations are basically consistent with the other treatments (the modified models of Brueckner, Mayer and Sinai, and our panel model) presented in this chapter. While some specifications in each framework produce evidence of internalization—negative coefficient estimates on concentration variables—these are few and rarely significant.

Section 5--Conclusion

Two of the previous tests for internalization (Brueckner and Mayer and Sinai) find significant (but weak) negative relationships between congestion delay and airport concentration. A third (Morrison), using a similar approach, finds a negligible relationship between airport concentration and congestion. A fourth approach (Daniel and Daniel and Harback) relies on J-tests that explicitly account for scheduling behavior using a bottleneck model. It finds that dominant airlines do not schedule most of their aircraft in a way that internalizes the delays they impose on one another. The instant paper seeks to use a measure of delays similar to that of Daniel and Daniel and Harback to implement econometric models similar to Brueckner, Mayer and Sinai, and Morrison to account for the differing results. The regressions constructed in section 2 explicitly estimate takeoff and landing queues from the data. Econometric estimation of the queues provides a new unbiased measure of congestion delay. Section 3 fits a dynamic-stochastic congestion function to the time-dependent queuing estimates to separately calculate the additional delay each aircraft experiences directly, the delay it imposes on other aircraft operated by the same airline, and the delay it imposes on aircraft of other airlines. In Section 4, the queue values from Section 3 are used to carryout regressions comparable to previous treatments, as well as some new regressions controlling for bank level variation. Considered as whole, the regression results presented here do not support internalization— the negative sign on the concentration term required to illustrate internalization is not robust across inclusion different traffic variables or the different dependent queuing variables and is more often than not insignificant.

Results supporting internalization in the original Brueckner and Mayer and Sinai regressions may be spurious and sensitive to the flaws in the data and the specifications of the regressions. Extending the regression treatment to allow bank level variation in the Mayer and Sinai-like regression framework and constructing a new regression framework with bank level observations fail to find any consistent, robust evidence of internalization in the form of negative coefficients on concentration variables. Of the 195 regressions presented here, only 72 contain negative coefficient estimates on the concentration variables, regardless of significance. Only 27 are significant.

The results presented in this paper synthesize all of the previous treatments of internalization and find little evidence of internalization. The lack of internalization is an important result. Congestion pricing has greater impact on reducing delays if congestion is purely external. If carriers internalize some congestion, then the internalized portion should not be subject to congestion pricing—thereby reducing the welfare gains from imposing congestion prices. Congestion pricing is especially desirable as a solution to the runway capacity problem given the expense of expanding runways. Finding little evidence of internalization supports using congestion pricing to obviate the need for additional airport capacity.

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ENDNOTES

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[1] In 1999, these included O'Hare, Regan National, JFK, and LaGaurdia. These airports are regulated under the high density rule, which creates hourly take off and landing caps and rations them as rights to conduct operations to carriers operating at these airports, with special provisions to ensure service to small communities and access for competing carriers. In theory, definition of property rights over congestible airports resources should eliminate excess congestion and ensure allocation to the highest value users for each hourly interval. However, because carriers will not sell slot rights to competing carriers, provisions to ensure competition have resulted in the granting of waivers for new entrant operations and other problems that result in a misalignment of available "slots" with the actual number of operations that can be conducted. In practice, slot control is regarded as failure due to poor design.

[2] They are prohibited from serving passengers between cities in the US.

[3] The majority of minute dummy variables across the 27 airports correspond to a single minute of the day. Even with the additional arrivals per minute associated with using the entire week of data, some minutes were thin on observations. These thin minutes are minutes with 2 or fewer flights observed and are dealt with by including them with adjacent minutes in a common dummy. In the case when many "thin" minutes occur in

sequence they get aggregated into a common dummy variable or several aggregated dummy variables. The results in the small "flat" regions that appear in the results.

[4] The mathematical form of this transition matrix is derived and specified in Daniel (1995), Appendix A.

[5] The zig-zag is due to sampling the queue lengths at minute intervals that alternately fall just before or after the service completion intervals.

[6] All of the regression results presented here were also carried out using a specification of the concentration variables that does not include the code share carriers as part of the dominant carrier's operations. The results do not vary significantly on the verdict of internalization.

[7] In general, there are nearly the same number of arrivals and departures at an airport each day. The difference between the number of arrivals and departures in the typical day's data constructed from the week of ETMS observations and the Daniel queuing simulation comes from the definition of the relevant operating day—relative to departures, more flights came in the uncongested hours of the early morning and late night and were excluded from the operating day in the simulation framework.

Figure 1--Examples of Arrival Rates and Delay Data by Minute of the Day

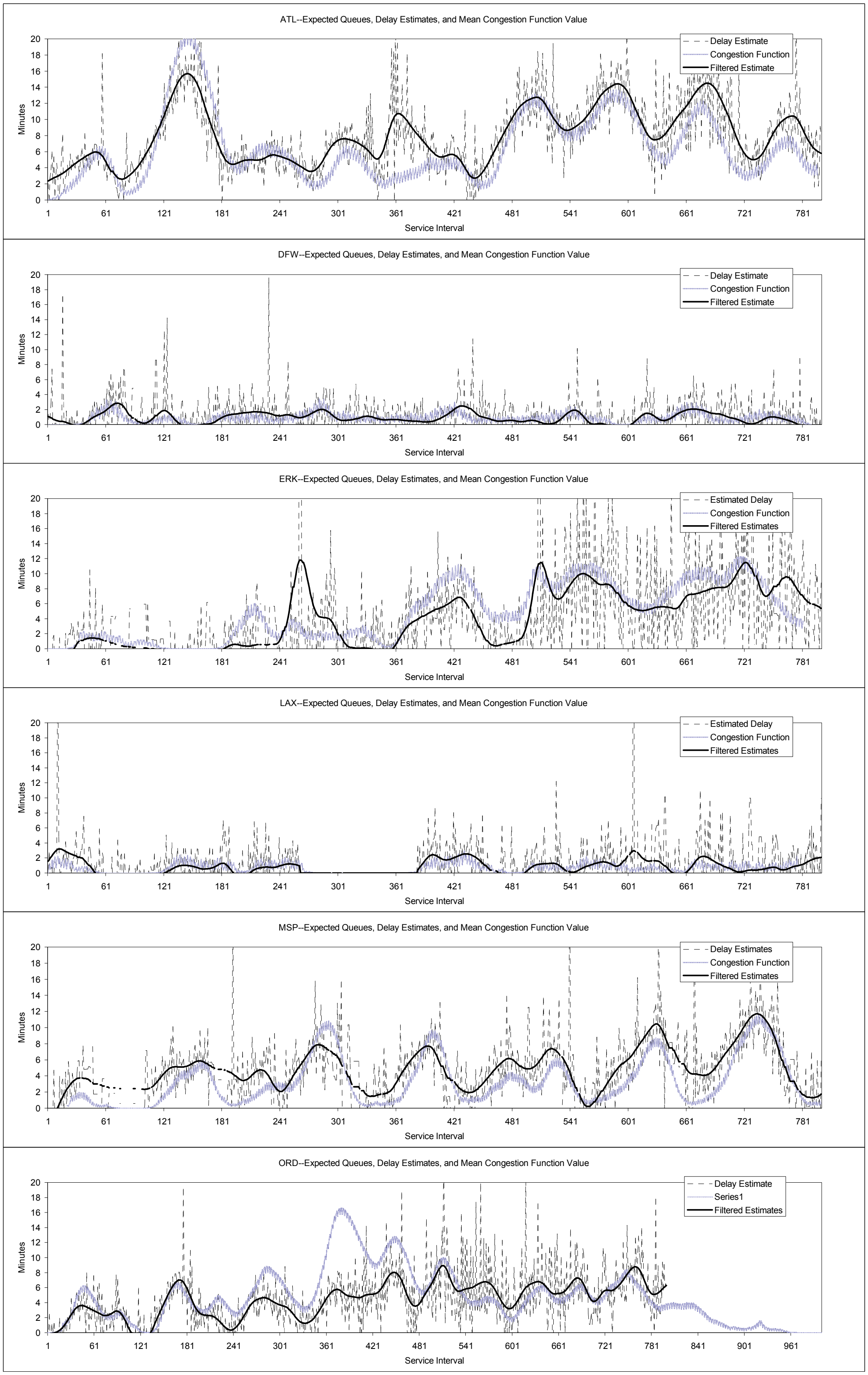

Figure 2--Examples of Departure Rates and Delay Data by Minute of the Day

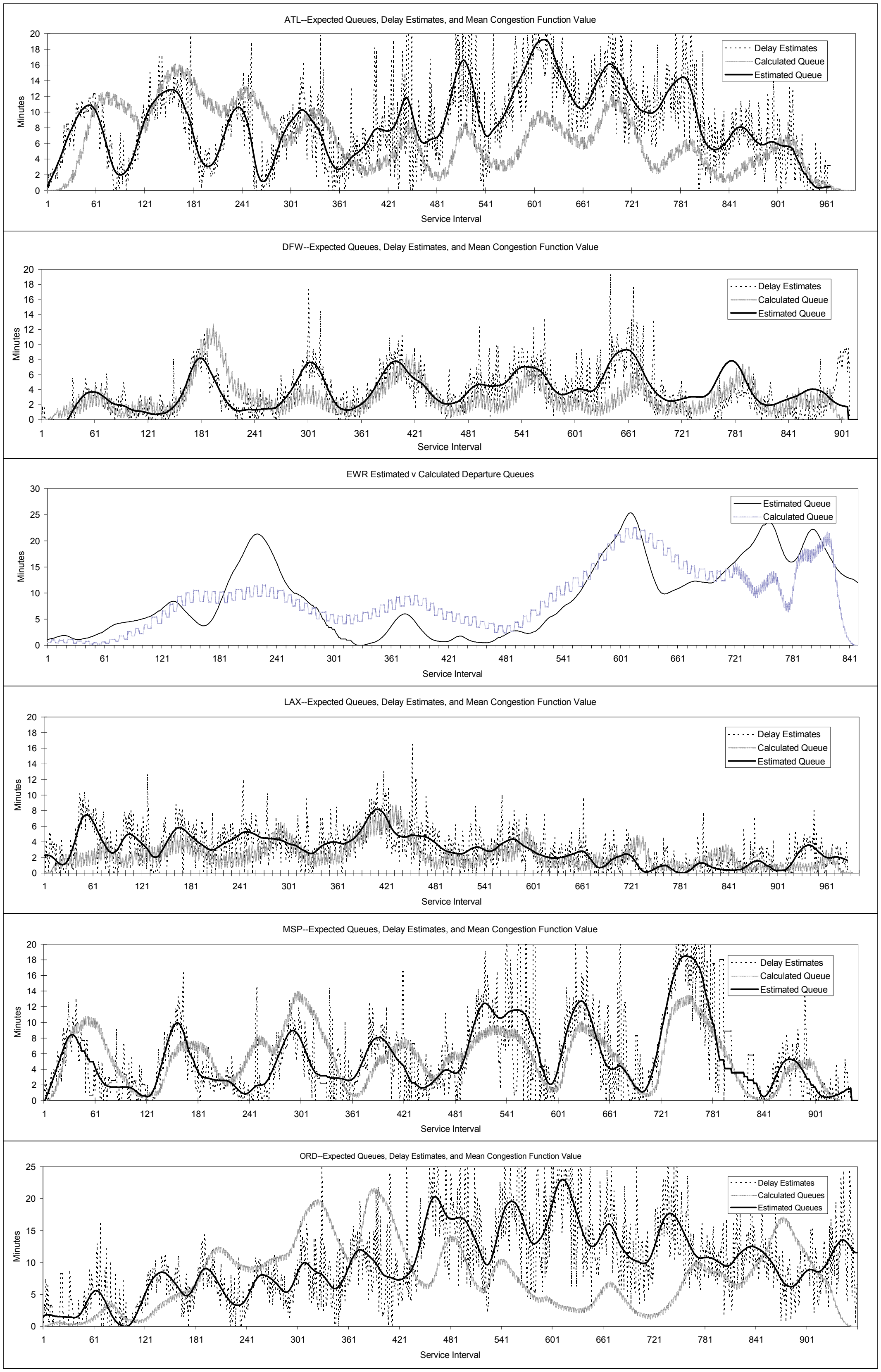

Table 1-- Code-Sharing Partners for Major Air Carriers

American Airlines (AAL)	**Alaska Airlines (ASA)**	**Delta Airlines (Con't)**	**United (Con't)**
American Trans Air (AMI)	Horizon Airlines (QXE)	Comair (COM)	Deutsche Lufthansa (DLH)
Alaska Airlines Inc. (ASA)		Japan Airlines (JAL)	Sky West (SKW)
British Airways (SAW)	**America West (A E)**	Korean Airlines (KAL)	
United Express (BLR)	Mesa Aviation Services (ASH)	Sky West (SKW)	**U.S. Air (USA)**
Big Sky Airlines (BSY)	Continental Express (BTA)		Pennsylvania Commuter Airlines (ALO)
Corporate Express (CEA)	Hawaiian Airlines (HAL)	**Northwest Airlines**	Air Midwest (AMW)
Chautauqua Airlines (CHQ)	Arizona Express Airlines (TMP)	Continental Express (BTA)	Mesa Aviation (ASH)
Comair, Inc. (COM)		Northwest Airlink (FLG)	Chautauqua Airlines (CHQ)
Cathay Pacific Airways (CPA)	**Continental Airlines (COA)**	Mesaba Aviation (MES)	Colgan AIR (CJC)
American Eagle (EGF)	Continental Express (BTA)		Deutsche Lufthansa (DLH)
Aer Lingus (EIN)	Virgin Atlantic (VIR)	**United Airlines (UAL)**	Jetstream International (JIA)
EVA Airways (EVA)		Asiana Airlines (AAR)	Trans World Express (LOF)
Japan Airlines (JAL)	**Delta Airlines (PAL)**	Air Canada (ACA)	Midway Airlines (MOW)
Trans World Express (LOF)	Air France (AFR)	Air Wisconsin Airlines (AWI)	Mid-West Express (MEP)
LOT-Polskie (LOT)	Aerovias De Mexi o (AMX)	United Express (BLR)	USAir Express (PDT)
Swissair (SWR)	Alitalia (AZA)	British Midland Airways (BMA)	Shuttle America (TCF)
Taca International Airlines (TAI)	Atlantic Southeast Airlines (CAA)	Katitta Air (CKS)	

Table 2 Airport Characteristics for July 28 through August 3, 2003

Name	Symbol	Location	Parallel Runways	Sharel1	Share22	HHI3	Average Daily Arrivals	% of Arrivals Delayed > 15 min	Dominant Carrler(s)
Hartsfield Atlanta International	ATL	Atlanta, GA	4	0.708	0.446	0.519	1188	25	Delta
Boston Logan International	BOS	Boston, MA	2	0.208	0.08	0.094	575	17.5	American, US Air, United
Baltimore-Washington International	BWI	Washington, DC	2	0.391	0.391	0.149	386	20	Southwest
Charlotte Douglas International	CLT	Charlotte, NC	2	0.749	0.749	0.615	556	17.2	US Air
Cincinnati/Northern Kentucky International	CVG	Covington, KY	2	0.699	0.219	0.487	685	15.4	Delta
Ronald Reagan Washington National	DCA	Washington, DC	1	0.429	0.181	0.247	343	11.6	US Air, Delta, American
Denver International	DEN	Denver, CO	4	0.504	0.355	0.276	713	27.6	United
Dallas/Ft. Worth International	DFW	Dallas, TX	5	0.639	0.435	0.456	1060	22.4	American, Delta
Detroit Metropolitan Wayne County	DTW	Detroit, MI	4	0.746	0.474	0.559	677	19.5	Northwest
Newark International	EWR	Newark, NJ	2	0.599	0.345	0.37	566	23	Continental
Washington Dulles International	IAD	Washington, DC	2	0.494	0.156	0.263	469	16.6	United
George Bush Intercontinental/ Houston	IAH	Houston, TX	3	0.764	0.455	0.658	646	21	Continental
John F Kennedy International	JFK	New York, NY	2	0.285	0.2	0.15	390	27.6	American, Jet Blue, Delta
Las Vegas McCarran International	LAS	Las Vegas, NV	2	0.321	0.321	0.123	540	13.4	Southwest, America West
Los Angeles International	LAX	Los Angeles, CA	4	0.316	0.128	0.157	827	13.5	United, American, Southwest
LaGuardia	LGA	New York, NY	1	0.324	0.13	0.198	546	17.2	American, Delta, US Air
Memphis International	MEM	Memphis, TN	3	0.44	0.181	0.3	533	15.5	Northwest
Miami International	MIA	Miami, FL	3	0.493	0.368	0.223	505	12.4	American, United
Minneapolis-St. Paul International	MSP	Minneapolis, MN	2	0.739	0.485	0.558	718	22.7	Northwest
Chicago O'Hare International	ORD	Chicago, IL	2	0.483	0.286	0.359	1222	17.7	United, American
Philadelphia International	PHL	Philadelphia, PA	3	0.606	0.309	0.373	611	29.8	US Air
Phoenix Sky Harbor International	PHX	Phoenix, AZ	3	0.45	0.299	0.277	678	20.7	Southwest, America West
Pittsburgh International	PIT	Pittsburgh, PA	3	0.758	0.258	0.582	488	26.5	US Air
Seattle-Tacoma International	SEA	Seattle, WA	2	0.642	0.279	0.413	545	23.4	Alaska Airlines
San Francisco International	SFO	San Francisco, CA	2	0.547	0.325	0.279	455	26.8	United
Salt Lake City International	SLC	Salt Lake City, UT	3	0.659	0.252	0.426	453	12.1	Delta, Southwest
Lambert-St. Louis International	STL	St. Louts, MO	2	0.698	0.365	0.512	559	14.3	American

1 - Share1 is the market share in flights counts of the dominant carrier including its code share partners.

2 - Share2 is the market share of the dominant carrier in flight counts not including its code sharing partners.

3 - HHI is the Hirschman-Herfindahl Index calculated for share by flight counts including code major carriers and code sharing partners as one entity.

TABLE 3-Brueckner-like regressions

Dependent Variable:	Total Minutes Spent Queuing	Total Indirect Queuing	Total Queuing Plus Indirect Queuing					Log of Total Queuing Plus Indirect Queuing	FAA Share of Arrivals Delayed
Regression	1	2	3	4	5	6	7	8	9
Variable:									
Herfindahl	3652	12175	15826			-160			0.07923
	2900	*10682*	*13475*			*17391*			*0.07241*
Share				17288			-12611	2.14027	
				13098			*14790*	*0.58159*	
Share > 65%					7578				
					4235				
Operations	18	50	68	70	70	43	47		0.00002629
	2	*8*	*10*	*10*	*9*	*11*	*11*		*0.00005239*
Log Operations								2.67783	
								0.30914	
Hub Airport	372	1789	2161	1406	1737	-13687	-9348	0.04226	-0.04493
	1433	*5277*	*6656*	*6714*	*6359*	*7500*	*8293*	*0.29723*	*0.03577*
Slot-control	2778	8217	10995	12025	11189	-8960	-7980	0.82667	-0.01597
	1641	*6045*	*7626*	*7689*	*7319*	*8214*	*8165*	*0.35028*	*0.04098*
Intercept	-8920	-30360	-39279	-43457	-36915			-9.55274	0.19176
	1923	*7084*	*8936*	*10055*	*8291*			*1.99925*	*0.04802*
R-squared	0.798	0.6979	0.7271	0.7313	0.7468	0.6538	0.6644	0.8262	0.1124

Table 4 Definition of airport-level hubbing dummy variables

Hubing Dummy Variable	Connections	Airports
Hub1	>115	ATL, CVG, DFW, DTW, IAH, MSP, ORD
Hub2	86-115	CLT, EWR, PHL, PIT, STL
Hub3	56-85	DEN, IAD, MEM, MIA, PHX, SEA, SLC
Hub4	<56	BOS, BWI, DCA, JFK, LAS, LAX, LGA, SFO

Table 5 Meyer and Sinai-like regressions for arrivals

Dependent Variable:	Queuing Experienced by Arriving Flight				Indirect Queuing caused by Arriving Flight				Experienced + Indirect Queuing for Arriving Flight			
Concentration measure	Herfindahl-Hirschman Index		Share		Herfindahl-Hirschman Index		Share		Herfindahl-Hirschman Index		Share	
Regression	1	2	3	4	5	6	7	8	9	10	11	12
Variable:												
Herfindahl	-5.762	-5.819			-32.292	-32.712			-38.054	-38.532		
	0.379	*0.377*			*0.939*	*0.900*			*1.146*	*1.104*		
Share			-6.044	-6.009			-36.327	-36.223			-42.371	-42.232
			0.321	*0.321*			*0.773*	*0.743*			*0.947*	*0.916*
Hub 1	5.390	4.680	5.524	4.893	16.796	10.873	18.351	12.949	22.186	15.553	23.874	17.842
	0.146	*0.180*	*0.132*	*0.173*	*0.361*	*0.430*	*0.318*	*0.399*	*0.441*	*0.528*	*0.390*	*0.492*
Hub 2	3.245	2.828	3.568	3.215	11.961	9.888	14.662	12.947	15.206	12.717	18.231	16.162
	0.158	*0.210*	*0.153*	*0.210*	*0.392*	*0.501*	*0.368*	*0.485*	*0.479*	*0.615*	*0.451*	*0.597*
Hub 3	2.233	1.416	2.579	1.827	7.373	5.222	9.809	8.078	9.606	6.637	12.389	9.904
	0.106	*0.143*	*0.110*	*0.148*	*0.263*	*0.342*	*0.265*	*0.343*	*0.321*	*0.420*	*0.324*	*0.422*
Dominant Carrier Hub 1		1.035		0.967		8.646		8.228		9.680		9.195
		0.117		*0.116*		*0.278*		*0.269*		*0.342*		*0.331*
Dominant Carrier Hub 2		0.666		0.618		3.728		3.511		4.394		4.129
		0.180		*0.179*		*0.428*		*0.413*		*0.526*		*0.509*
Dominant Carrier Hub 3		1.426		1.391		4.516		4.298		5.942		5.689
		0.130		*0.130*		*0.311*		*0.300*		*0.382*		*0.370*
Dominant Carrier Hub 4		0.189		0.344		1.669		2.656		1.858		3.000
		0.130		*0.130*		*0.310*		*0.301*		*0.381*		*0.371*
Intercept	2.871	2.810	3.910	3.770	6.102	5.554	12.752	11.729	8.973	8.364	16.662	15.499
	0.091	*0.100*	*0.125*	*0.129*	*0.225*	*0.239*	*0.300*	*0.299*	*0.275*	*0.294*	*0.368*	*0.368*
R-squared	0.1543	0.1681	0.1621	0.1751	0.1562	0.2324	0.2137	0.2854	0.1887	0.2545	0.2377	0.2995

Table 6 Meyer and Sinai-like regressions for departures

Dependent Variable:	Queuing Experienced by Departing Flight				Indirect Queuing caused by Departing Flight				Experienced + Indirect Queuing for Departing Flight			
Concentration measure	Herfindahl-Hirschman Index		Share		Herfindahl-Hirschman Index		Share		Herfindahl-Hirschman Index		Share	
Regression	1	2	3	4	5	6	7	8	9	10	11	12
Variable:												
Herfindahl	-4.446	-4.831			11.917	11.159			7.471	6.329		
	0.384	*0.383*			*2.387*	*2.291*			*2.579*	*2.478*		
Share			-5.679	-5.786			11.062	12.799			5.383	7.013
			0.333	*0.332*			*2.081*	*1.997*			*2.249*	*2.162*
Hub 1	5.537	4.707	5.989	5.156	14.842	-3.052	15.032	-3.885	20.379	1.654	21.021	1.271
	0.150	*0.182*	*0.138*	*0.175*	*0.930*	*1.090*	*0.861*	*1.049*	*1.005*	*1.180*	*0.930*	*1.136*
Hub 2	1.947	0.711	2.581	1.327	0.910	-5.502	0.708	-6.726	2.857	-4.791	3.289	-5.399
	0.157	*0.199*	*0.155*	*0.201*	*0.977*	*1.193*	*0.971*	*1.209*	*1.055*	*1.290*	*1.049*	*1.309*
Hub 3	0.751	-0.021	1.207	0.456	0.066	-3.761	-0.375	-4.754	0.817	-3.782	0.832	-4.297
	0.105	*0.141*	*0.110*	*0.146*	*0.654*	*0.846*	*0.688*	*0.878*	*0.707*	*0.915*	*0.743*	*0.950*
Dominant Carrier Hub 1		1.204		1.148		24.509		24.630		25.713		25.778
		0.114		*0.114*		*0.683*		*0.683*		*0.739*		*0.739*
Dominant Carrier Hub 2		1.810		1.782		9.752		9.834		11.562		11.616
		0.170		*0.169*		*1.018*		*1.014*		*1.101*		*1.098*
Dominant Carrier Hub 3		1.260		1.245		7.035		7.075		8.295		8.320
		0.134		*0.133*		*0.800*		*0.799*		*0.865*		*0.844*
Dominant Carrier Hub 4		-0.121		0.001		1.142		0.881		1.021		0.882
		0.130		*0.130*		*0.778*		*0.780*		*0.841*		*0.844*
Intercept	3.800	3.909	4.930	4.965	0.930	0.635	-0.723	-1.624	4.730	4.544	4.206	3.341
	0.090	*0.100*	*0.127*	*0.131*	*0.562*	*0.600*	*0.793*	*0.790*	*0.607*	*0.649*	*0.856*	*0.855*
R-squared	0.2148	0.2315	0.2231	0.239	0.1187	0.1994	0.1189	0.2004	0.1467	0.2227	0.1465	0.2229

Table 7 Arrival bank characteristics for Hartsfield Atlanta

Bank	Hub Variable	Share	Herfindahl
1	Hub2	77.03	0.6196
2	Hub1	75.71	0.5917
3	Hub1	71.91	0.5353
4	Hub2	74.67	0.5719
5	Hub1	73.04	0.5554
6	Hub1	73.33	0.5534
7	Hub1	73.45	0.5571
8	Hub1	76.03	0.5864
9	Hub2	63.64	0.434
10	Hub1	70.34	0.5235

Table 8 Definition of bank-level hubbing dummy variables

Hubing Dummy Variable	Bank-level Connections	Number of Arrival Banks	Number of Departure Banks
Hub1	>60	20	38
Hub2	40-59	61	56
Hub3	20-39	76	68
Hub4	<20	107	89
Bank Totals		264	251

Table 9 Meyer and Sinai-like regressions with bank level variation in concentration and hubbing

Dependent Variable:	Queuing Experienced by Arriving Flight						Indirect Queuing caused by Arriving Flight						Experienced + Indirect Queuing for Arriving Flight					
Concentration measure	Share						Share						Share					
Regression	7	8	9	10	11	12	19	20	21	22	23	24	31	32	33	34	35	36
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Dominant Airline: Variable: Herfindahl	yes	yes	yes	no	no	no	yes	yes	yes	no	no	no	yes	yes	yes	no	no	no
Share	1.029	2.397	2.317	2.150	2.709	2.664	-0.722	6.280	6.048	5.055	8.571	8.465	0.306	8.677	8.416	7.205	11.280	11.160
	0.226	*0.338*	*0.331*	*0.221*	*0.335*	*0.330*	*0.549*	*0.777*	*0.766*	*0.571*	*0.792*	*0.786*	*0.687*	*0.951*	*0.939*	*0.709*	*0.965*	*0.958*
Hub 1	4.030	2.133	2.148	2.678	1.986	1.990	0.116	-1.099	-1.108	-3.294	-0.125	-0.138	4.145	1.034	1.034	-0.615	1.860	1.851
	0.213	*0.214*	*0.213*	*0.128*	*0.149*	*0.149*	*0.519*	*0.491*	*0.491*	*0.331*	*0.353*	*0.353*	*0.649*	*0.601*	*0.601*	*0.411*	*0.430*	*0.430*
Hub 2	1.468	1.426	1.423	0.514	1.518	1.512	0.361	-0.136	-0.147	-4.326	-0.779	-0.792	1.829	1.290	1.278	-3.812	0.738	0.724
	0.161	*0.152*	*0.152*	*0.110*	*0.108*	*0.108*	*0.391*	*0.349*	*0.348*	*0.284*	*0.256*	*0.256*	*0.489*	*0.427*	*0.426*	*0.353*	*0.312*	*0.312*
Hub 3	-0.141	0.702	0.688	-0.989	0.585	0.574	0.019	1.257	1.237	-5.142	-0.587	-0.602	-0.123	1.959	1.932	-6.131	-0.002	-0.021
	0.130	*0.127*	*0.126*	*0.090*		*0.093*	*0.316*	*0.291*	*0.290*	*0.233*	*0.221*	*0.221*	*0.396*	*0.356*	*0.356*	*0.289*	*0.269*	*0.269*
Dominant Carrier Hub 1	0.100	0.267	0.266				5.550	5.641	5.642				5.650	5.909	5.908			
	0.210	*0.183*	*0.183*				*0.512*	*0.421*	*0.421*				*0.641*	*0.515*	*0.515*			
Dominant Carrier Hub 2	0.667	0.590	0.591				4.010	3.534	3.538				4.678	4.124	4.128			
	0.132	*0.115*	*0.115*				*0.321*	*0.265*	*0.265*				*0.402*	*0.325*	*0.325*			
Dominant Carrier Hub 3	0.660	0.312	0.316				2.482	1.826	1.832				3.142	2.138	2.146			
	0.126	*0.112*	*0.112*				*0.308*	*0.258*	*0.258*				*0.385*	*0.315*	*0.315*			
Dominant Carrier Hub 4	2.167	0.557	0.567				11.599	5.436	5.461				13.766	5.993	6.022			
	0.111	*0.112*	*0.111*				*0.271*	*0.256*	*0.256*				*0.339*	*0.314*	*0.313*			
Intercept	1.641		0.820	2.240		0.921	0.469		-3.376	3.769		-1.913	2.110		-2.588	6.009		-1.014
	0.115		*0.305*	*0.109*		*0.356*	*0.280*		*0.819*	*0.283*		*1.072*	*0.350*		*1.034*	*0.351*		*1.351*
R-squared	0.14053	0.34971		0.1124	0.34673		0.17384	0.44399		0.03741	0.40784		0.16632	0.46226		0.044	0.43361	
Hausman (Fixed vs. Random)			25.69			7.65			21.64			3.32			23.55			4.06
Degrees of Freedom			8			4			8			4			8			4

Table 10 Meyer and Sinai-like regressions with bank level variation in concentration and hubbing

Dependent Variable:	Queuing Experienced by Departing Flight						Indirect Queuing caused by Arriving Flight						Experienced + Indirect Queuing for Arriving Flight					
Concentration measure	Share						Share						Share					
Regression	7	8	9	10	11	12	19	20	21	22	23	24	31	32	33	34	35	36
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Dominant Airline:	yes	yes	yes	no	no	no	yes	yes	yes	no	no	no	yes	yes	yes	no	no	no
Variable: Herfindahl																		
Share	-2.578	1.670	1.537	-1.930	2.383	2.307	1.860	0.401	0.541	8.036	10.351	10.318	-0.718	2.070	1.995	6.105	12.734	12.539
	0.229	*0.315*	*0.311*	*0.225*	*0.311*	*0.309*	*1.327*	*1.961*	*1.926*	*1.359*	*2.041*	*2.004*	*1.439*	*2.093*	*2.062*	*1.473*	*2.174*	*2.145*
Hub 1	4.009	4.072	4.046	5.121	4.486	4.477	0.930	-7.057	-6.835	19.066	10.177	10.358	4.940	-2.986	-2.838	24.187	14.664	14.778
	0.166	*0.178*	*0.177*	*0.123*	*0.144*	*0.143*	*0.964*	*1.109*	*1.101*	*0.742*	*0.943*	*0.936*	*1.045*	*1.183*	*1.177*	*0.805*	*1.005*	*0.999*
Hub 2	1.639	1.892	1.874	3.002	2.611	2.604	-1.985	-0.356	-0.319	5.384	5.041	5.083	-0.347	1.536	1.541	8.386	7.652	7.669
	0.167	*0.159*	*0.159*	*0.121*	*0.123*	*0.123*	*0.970*	*0.991*	*0.988*	*0.732*	*0.806*	*0.802*	*1.052*	*1.058*	*1.055*	*0.794*	*0.859*	*0.856*
Hub 3	0.559	0.927	0.917	0.965	0.957	0.952	-0.806	0.922	0.898	1.429	2.181	2.168	-0.247	1.849	1.815	2.393	3.138	3.117
	0.134	*0.123*	*0.123*	*0.103*	*0.101*	*0.101*	*0.776*	*0.768*	*0.767*	*0.619*	*0.662*	*0.660*	*0.842*	*0.820*	*0.818*	*0.671*	*0.706*	*0.704*
Dominant Carrier Hub 1	1.730	1.013	1.021				28.022	27.290	27.285				29.753	28.302	28.310			
	0.131	*0.113*	*0.113*				*0.762*	*0.704*	*0.704*				*0.827*	*0.751*	*0.751*			
Dominant Carrier Hub 2	2.008	1.435	1.439				12.782	11.954	11.966				14.790	13.389	13.405			
	0.137	*0.118*	*0.118*				*0.796*	*0.734*	*0.734*				*0.863*	*0.784*	*0.783*			
Dominant Carrier Hub 3	0.736	0.456	0.452				5.704	6.041	6.041				6.440	6.498	6.492			
	0.122	*0.109*	*0.108*				*0.708*	*0.676*	*0.676*				*0.768*	*0.722*	*0.721*			
Dominant Carrier Hub 4	-0.188	0.326	0.320				0.621	2.184	2.158				0.433	2.510	2.479			
	0.160	*0.139*	*0.139*				*0.926*	*0.868*	*0.868*				*1.005*	*0.926*	*0.926*			
Intercept	3.647		1.024	3.340		0.823	1.347		1.706	-0.714		-1.675	4.994		2.788	2.626		-0.787
	0.123		*0.332*	*0.114*		*0.422*	*0.716*		*1.705*	*0.686*		*1.815*	*0.776*		*1.932*	*0.743*		*2.135*
R-squared	0.19475	0.41878		0.17139	0.40893		0.2119	0.34363		0.12169	0.26092		0.23081	0.37989		0.14361	0.30409	
Hausman (Fixed vs. Random)			30.29			5.34			14.84			6.05			14.93			4.39
Degrees of Freedom			8			4			8			4			8			4

Table 11a Regressions with bank level obervations

Dependent Variable:	Sum of Queuing Experienced by Arriving Flights in Each Bank														
Regression	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Variable:															
Herfindahl	-86.1	-8.3	-30.8												
	50.6	*48.7*	*46.3*												
Share				-241.2	-11.5	-108.5	143.6	169.1	142.7	83.0	37.1	48.7	-178.4	-135.8	-153.6
				79.3	*99.8*	*82.5*	*82.9*	*99.8*	*82.2*	*79.8*	*97.7*	*81.1*	*71.7*	*94.3*	*78.6*
Hub 1	623.4	464.3	512.1	672.3	464.6	535.5	-15.4	73.7	28.3	-3.6	76.9	40.9	465.4	373.4	397.8
	50.5	*52.7*	*48.6*	*53.6*	*53.7*	*50.3*	*92.5*	*87.6*	*84.7*	*88.1*	*82.9*	*80.5*	*54.7*	*51.7*	*50.0*
Hub 2	306.6	290.8	295.5	359.6	291.0	313.0	-61.5	39.9	-13.6	-44.2	48.6	7.8	217.2	210.0	212.5
	36.3	*36.2*	*33.8*	*41.6*	*38.2*	*36.9*	*60.9*	*58.3*	*56.1*	*58.1*	*55.2*	*53.4*	*41.4*	*37.5*	*36.7*
Hub 3	112.3	121.0	117.4	145.1	121.0	127.8	-82.4	-13.0	-49.5	-68.2	3.9	-28.1	64.6	78.8	74.5
	32.1	*30.7*	*29.3*	*34.2*	*31.9*	*30.8*	*40.0*	*38.8*	*37.2*	*38.2*	*36.9*	*35.5*	*32.3*	*30.2*	*29.5*
Spread										-1.7	-2.2	-2.0			
										0.33	*0.41*	*0.35*			
Flight Count							7.6	4.9	6.4	8.7	7.3	7.9			
							0.88	*0.90*	*0.84*	*0.86*	*0.96*	*0.86*			
Count/Spread													381.6	428.5	409.8
													48.0	67.2	55.9
Intercept	70.6		52.9	147.7		94.4	-229.8		-193.8	-116.6		-63.6	-58.6		-84.2
	22.9		*28.8*	*37.6*		*45.3*	*54.8*		*55.4*	*56.5*		*58.0*	*42.6*		*49.8*
R-squared	0.4339	0.6578		0.4473	0.6578		0.5716	0.6969		0.6129	0.7295		0.5474	0.7089	
Hausman (Fixed vs. Random)			16.59			21.8			23.79			18.3			8.71
Degrees of Freedom			4			4			5			6			5

Table 11b

Dependent Variable:	Sum of Indirect Queuing by Arriving Flights in Each Bank														
Regression	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Variable:															
Herfindahl	-202.1	23.6	-11.5												
	134.4	*117.6*	*114.3*												
Share				-700.0	65.5	-140.8	44.0	280.0	129.4	-117.0	55.9	-75.9	-538.1	-136.8	-284.6
				210.0	*241.1*	*213.3*	*233.8*	*252.4*	*220.0*	*226.4*	*255.3*	*221.4*	*190.9*	*238.4*	*208.1*
Hub 1	552.3	395.8	411.1	709.2	390.9	437.9	-620.6	-73.3	-237.1	-589.3	-67.7	-219.6	175.8	242.6	223.0
	134.3	*127.2*	*121.7*	*141.7*	*129.8*	*124.8*	*260.7*	*221.6*	*216.7*	*249.9*	*216.6*	*212.0*	*145.6*	*130.6*	*127.6*
Hub 2	471.0	411.3	413.8	641.8	405.7	439.2	-172.3	107.6	15.5	-126.6	122.2	45.2	274.8	273.9	268.2
	96.5	*87.4*	*84.1*	*110.0*	*92.2*	*90.4*	*171.8*	*147.6*	*143.9*	*164.9*	*144.3*	*140.9*	*110.2*	*94.8*	*93.4*
Hub 3	176.2	139.0	139.9	283.6	135.2	157.6	-156.3	-24.0	-67.3	-118.8	4.7	-31.8	76.0	66.5	66.2
	85.3	*74.1*	*72.3*	*90.5*	*77.0*	*75.5*	*112.8*	*98.1*	*95.6*	*108.4*	*96.3*	*93.9*	*86.1*	*76.3*	*75.1*
Spread										-4.6	-3.7	-4.1			
										0.94	*1.08*	*0.95*			
Flight Count							14.7	5.8	8.5	17.7	9.9	12.3			
							2.48	*2.27*	*2.18*	*2.45*	*2.52*	*2.31*			
Count/Spread													983.7	697.3	773.9
													127.8	*169.7*	*148.4*
Intercept	72.3		8.5	308.3		73.8	-421.6		-280.4	-121.2		-23.2	-223.6		-238.0
	60.9		*85.3*	*99.4*		*125.1*	*154.5*		*150.3*	*160.2*		*159.4*	*113.4*		*134.9*
R-squared	0.1137	0.5580		0.1428	0.5581		0.2457	0.5703		0.3102	0.5912		0.3029	0.5881	
Hausman (Fixed vs. Random)			3.09			9.41			22.78			17.17			2.74
Degrees of Freedom			4			4			5			6			5

Table 11c (Continued)

Dependent Variable:	Sum of All Experienced + Indirect Queuing by Arriving Flights in Each Bank														
Regression	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Variable:															
Herfindahl	-288.2	15.3	-34.8												
	172.7	*152.4*	*147.8*												
Share				-941.2	54.0	-228.2	187.7	449.2	265.7	-34.0	93.0	-36.9	-716.4	-272.6	-433.6
				269.6	*312.3*	*274.4*	*291.9*	*322.2*	*277.5*	*279.8*	*321.2*	*276.4*	*240.3*	*302.5*	*264.1*
Hub 1	1175.7	860.1	904.1	1381.5	855.5	949.6	-636.0	0.4	-214.2	-592.9	9.2	-180.1	641.2	616.0	613.1
	172.6	*164.8*	*157.2*	*181.9*	*168.1*	*161.2*	*325.5*	*282.8*	*276.0*	*308.8*	*272.6*	*266.5*	*183.3*	*165.8*	*161.9*
Hub 2	777.6	702.0	707.6	1001.3	696.7	746.0	-233.8	147.5	7.2	-170.8	170.8	58.2	492.1	483.8	479.9
	124.0	*113.2*	*108.6*	*141.2*	*119.4*	*116.9*	*214.5*	*188.3*	*183.2*	*203.8*	*181.6*	*177.1*	*138.7*	*120.3*	*118.5*
Hub 3	288.5	260.0	258.8	428.8	256.1	284.2	-238.7	-37.0	-111.1	-187.0	8.6	-54.5	140.6	145.3	142.0
	109.6	*96.0*	*93.5*	*116.2*	*99.7*	*97.6*	*140.9*	*125.2*	*121.6*	*134.0*	*121.1*	*117.9*	*108.4*	*96.9*	*95.3*
Spread										-6.4	-5.9	-6.1			
										1.17	*1.36*	*1.19*			
Flight Count							22.4	10.7	14.8	26.4	17.2	20.2			
							3.10	*2.90*	*2.76*	*3.03*	*3.17*	*2.89*			
Count/Spread													1365.2	1125.8	1188.6
													160.9	*215.4*	*188.3*
Intercept	142.9		59.2	456.0		159.2	-651.3		-467.9	-237.8		-77.8	-282.2		-327.1
	78.3		*108.1*	*127.7*		*159.6*	*192.9*		*188.9*	*198.0*		*198.8*	*142.7*		*171.2*
R-squared	0.2165	0.6031		0.2437	0.6032		0.3705	0.6254		0.4360	0.6535		0.4088	0.6450	
Hausman (Fixed vs. Random)			5.05			11.68			24.63			17.07			2.06
Degrees of Freedom			4			4			5			6			5

Table 12a Regressions with bank level obervations

Dependent Variable:	Sum of Queuing Experienced by Departing Flights in Each Bank														
Regression	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no			
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes			
Variable:															
Herfindahl	-209.3	217.8	72.6												
	594.6	*725.2*	*624.9*												
Share				-325.0	141.4	-10.8	1378.3	1292.7	1391.1	1128.4	484.6	877.1	332.8	-608.5	-62.4
				593.9	*760.9*	*645.5*	*722.6*	*819.9*	*738.3*	*687.8*	*834.5*	*719.3*	*560.0*	*757.5*	*602.6*
Hub 1	2603.8	1448.3	1967.6	2644.1	1459.9	1988.7	232.6	-411.4	-138.1	106.1	-525.5	-196.5	1118.1	667.3	967.2
	335.1	*421.4*	*360.9*	*336.5*	*426.4*	*365.9*	*696.8*	*698.4*	*665.9*	*662.1*	*682.7*	*645.8*	*392.2*	*455.2*	*397.7*
Hub 2	729.5	633.0	697.7	768.9	642.1	718.3	-790.5	-680.1	-709.6	-739.9	-770.0	-711.4	-243.8	-50.9	-79.9
	307.6	*322.3*	*300.4*	*308.9*	*330.6*	*307.9*	*498.5*	*511.1*	*486.5*	*473.4*	*499.7*	*470.9*	*327.0*	*361.5*	*326.5*
Hub 3	254.8	241.0	244.0	279.6	243.4	253.7	-736.9	-596.9	-652.7	-681.7	-566.6	-598.8	-416.3	-170.6	-261.9
	241.9	*258.0*	*241.6*	*246.9*	*261.9*	*246.6*	*353.3*	*359.0*	*342.7*	*335.7*	*350.6*	*332.2*	*253.3*	*272.5*	*252.1*
Spread										-15.0	-15.0	-14.8			
										2.85	*4.37*	*3.30*			
Flight Count							22.6	19.2	20.7	36.0	37.8	36.9			
							5.76	*5.76*	*5.53*	*6.03*	*7.80*	*6.44*			
Count/Spread													2498.7	2622.1	2551.9
													389.2	*640.7*	*457.5*
Intercept	107.5		68.7	184.9		92.8	-1069.5		-987.4	-384.9		-304.5	-1157.9		-1032.1
	197.5		*260.5*	*269.8*		*339.5*	*413.7*		*445.4*	*413.9*		*451.4*	*326.0*		*368.4*
R-squared	0.2794	0.4965		0.2800	0.4964		0.3224	0.5208		0.3915	0.5453		0.3837	0.5322	
Hausman (Fixed vs. Random)			10.86			10.75			7.6			6.57			8.16
Degrees of Freedom			4			4			5			6			5

Table 12b (Continued)

Dependent Variable:	Sum of Indirect Queuing by Departing Flights in Each Bank														
Regression	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Variable:															
Herfindahl	-340.3	-43.5	-129.2												
	100.4	*110.2*	*101.4*												
Share				-444.4	-76.6	-186.1	24.7	262.7	201.2	-38.6	76.5	26.0	-269.3	-261.2	-287.1
				98.7	*115.5*	*104.7*	*113.3*	*115.4*	*109.2*	*97.4*	*112.0*	*100.2*	*79.8*	*107.6*	*87.4*
Hub 1	810.6	696.5	705.0	847.5	703.3	720.0	183.4	151.8	143.9	151.3	125.5	121.0	441.2	508.1	470.1
	56.6	*64.0*	*58.8*	*55.9*	*64.7*	*59.2*	*109.2*	*98.3*	*95.9*	*93.8*	*91.6*	*88.0*	*55.9*	*64.6*	*57.2*
Hub 2	396.0	376.5	368.4	432.1	383.4	382.0	2.6	-6.3	-14.9	15.4	-27.0	-21.1	162.4	212.8	187.2
	52.0	*49.0*	*47.1*	*51.3*	*50.2*	*48.2*	*78.1*	*71.9*	*70.2*	*67.1*	*67.0*	*64.3*	*46.6*	*51.3*	*46.8*
Hub 3	177.7	168.9	163.5	203.3	172.6	171.8	-76.6	-75.0	-80.1	-62.6	-68.0	-68.1	18.0	70.7	47.9
	40.9	*39.2*	*37.9*	*41.0*	*39.8*	*38.5*	*55.4*	*50.5*	*49.4*	*47.6*	*47.0*	*45.3*	*36.1*	*38.7*	*36.1*
Spread										-3.8	-3.5	-3.5			
										0.40	*0.59*	*0.48*			
Flight Count							6.2	5.7	5.8	9.6	9.9	9.8			
							0.90	*0.81*	*0.79*	*0.85*	*1.05*	*0.91*			
Count/Spread													665.3	645.5	650.9
													55.5	*91.0*	*67.1*
Intercept	146.4		73.3	240.3		119.7	-105.2		-183.1	68.3		6.5	-117.2		-119.7
	33.4		*48.9*	*44.8*		*59.9*	*64.9*		*70.2*	*58.6*		*64.5*	*46.5*		*53.9*
R-squared	0.5140	0.7252		0.5301	0.7255		0.6063	0.7757		0.7112	0.8064		0.7040	0.7768	
Hausman (Fixed vs. Random)			5.54			7.07			3.44			4.47			4.1
Degrees of Freedom			4			4			5			6			5

Table 12c (Continued)

Dependent Variable:	Sum of All Experienced + Indirect Queuing by Departing Flights in Each Bank														
Regression	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
Airport Fixed Effects:	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no
Random Effects:	no	no	yes	no	no	yes	no	no	yes	no	no	yes	no	no	yes
Variable:															
Herfindahl	-549.6	174.3	-84.0												
	669.5	*804.4*	*703.5*												
Share				-769.4	64.7	-227.7	1403.0	1555.4	1547.9	1089.8	561.2	872.0	63.5	-869.7	-367.6
				668.0	*844.0*	*727.3*	*805.5*	*901.0*	*820.6*	*755.1*	*910.8*	*792.0*	*615.6*	*831.8*	*666.8*
Hub 1	3414.4	2144.8	2632.6	3491.7	2163.2	2673.8	416.0	-259.6	-23.6	257.4	-400.1	-93.0	1559.3	1175.4	1426.6
	377.3	*467.4*	*406.7*	*378.5*	*473.0*	*412.0*	*776.7*	*767.4*	*735.7*	*726.9*	*745.1*	*707.4*	*431.1*	*499.8*	*438.8*
Hub 2	1125.5	1009.5	1060.8	1201.0	1025.4	1098.2	-787.9	-686.4	-721.4	-724.4	-797.0	-729.5	-81.4	162.0	110.4
	346.4	*357.5*	*335.6*	*347.5*	*366.7*	*344.0*	*555.7*	*561.6*	*538.0*	*519.8*	*545.4*	*516.3*	*359.4*	*396.9*	*359.7*
Hub 3	432.5	409.9	406.3	482.9	416.0	426.5	-813.6	-671.9	-727.8	-744.3	-634.7	-662.6	-398.3	-99.9	-210.2
	272.4	*286.2*	*270.0*	*277.7*	*290.5*	*275.4*	*393.9*	*394.5*	*378.8*	*368.6*	*382.7*	*364.0*	*278.4*	*299.2*	*277.7*
Spread										-18.8	-18.4	-18.3			
										3.13	*4.77*	*3.66*			
Flight Count							28.8	24.9	26.3	45.6	47.7	46.7			
							6.42	*6.33*	*6.10*	*6.62*	*8.52*	*7.11*			
Count/Spread													3164.1	3267.6	3205.3
													427.8	*703.5*	*508.3*
Intercept	253.9		161.5	425.2		236.3	-1174.7		-1136.4	-316.6		-277.0	-1275.1		-1143.0
	222.4		*301.1*	*303.4*		*388.9*	*461.2*		*500.0*	*454.4*		*499.5*	*358.4*		*408.9*
R-squared	0.3311	0.5463		0.3328	0.5463		0.3835	0.5762		0.4629	0.6033		0.4546	0.5869	
Hausman (Fixed vs. Random)			9.44			9.55			6.09			5.11			6.69
Degrees of Freedom			4			4			5			6			5