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

Working Paper No. 2005-08

(When) Do Hub Airlines Internalize Their Self-Imposed Congestion Delays?

Katherine Thomas Harback and Joseph I. Daniel

(When) Do Hub Airlines Internalize Their Self-Imposed Congestion Delays?

By JOSEPH I DANIEL AND KATHERINE THOMAS HARBACK[*]

We develop theoretical models of airport congestion with non-atomistic traffic and implement them empirically using data from twenty-seven major US airports to determine whether dominant airlines internalize or ignore self-imposed congestion. Estimates of minute-by-minute delay patterns at each airport calibrate structural models of landing and takeoff queues as dynamic functions of traffic rates and airport capacities. These functions determine the internal and external congestion that aircraft impose on one another. Specification tests largely reject the internalization model. Optimal pricing values all time using non-dominant aircraft cost coefficients and treats all delays as external—i.e., fees equal opportunity costs of allocating peak capacity to dominant airlines. (*JEL* H2, L5, L9, D6)

- Daniel: Department of Economics, Purnell Hall, University of Delaware, Newark, DE 19716, (e-mail: Joseph.Daniel@verizon.net);
- Harback: Department of Economics, Purnell Hall, University of Delaware, Newark, DE 19716.

(When) Do Hub Airlines Internalize Their Self-Imposed Congestion Delays?

By JOSEPH I DANIEL AND KATHERINE THOMAS HARBACK*

We develop theoretical models of airport congestion with non-atomistic traffic and implement them empirically using data from twenty-seven major US airports to determine whether dominant airlines internalize or ignore self-imposed congestion. Estimates of minute-by-minute delay patterns at each airport calibrate structural models of landing and takeoff queues as dynamic functions of traffic rates and airport capacities. These functions determine the internal and external congestion that aircraft impose on one another. Specification tests largely reject the internalization model. Optimal pricing values all time using non-dominant aircraft cost coefficients and treats all delays as external—i.e., fees equal opportunity costs of allocating peak capacity to dominant airlines. (*JEL* H2, L5, L9, D6)

Airport congestion reasserted itself as a significant policy issue during the summer of 2004, after disappearing for several years following the highjacking attacks of September 11th, 2001 on the World Trade Center and the Pentagon. The highly congested airports are now at or above their pre 2001 traffic levels. Congestion is nearly certain to remain the industry's primary long-term nemesis, even more serious than recent airline concerns over bankruptcy, labor disputes, and fuel prices. According to the Federal Aviation Administration (FAA), twenty percent of flights in 2004 were delayed more than fifteen minutes. The industry estimates such delays will cost 154 billion dollars cumulatively over the next ten years even with the FAA's current modernization plans.[1] Historically, we have attempted to build our way out of the airport capacity problem, but planning and construction can take decades and cost over ten billion dollars per major airport. At best, airport construction offers a distant solution to an immediate problem—at worst, it is politically and financially infeasible in the foreseeable future.

For over forty years, economists have argued that congestion pricing of scarce airport capacity is an inexpensive way to achieve efficient use of existing resources. During that time, economic modeling of the airport-pricing problem has undergone numerous refinements, but nearly all of the research is based on models adapted from the highway congestion-pricing literature. Recently, however, several authors have questioned the practice of applying highway-pricing models to airports. In highway models, travelers are individual (atomistic) decision-makers whose travel decisions are unaffected by the congestion they impose on other travelers—a classic instance of externality. Authors who question this framework argue that a dominant airline at a hub airport schedules many flights that impose congestion on one another. Rather than facing a classic externality problem, these dominant airlines may already internalize their self-imposed congestion. The optimal pricing solution for purely external congestion entails charging a fee equivalent to the additional congestion burden one flight imposes on all other flights. Imposition of atomistic congestion prices would cause dominant carriers to react inefficiently because such fees would overcharge for already internalized congestion. If dominant carriers internalize their self-imposed congestion, optimal pricing would only charge them for the purely external congestion they impose on other airlines. Understanding if and when carriers internalize their self-imposed congestion delays, therefore, is critical to determining optimal congestion prices.

This article presents a theoretical model of a dominant airline's decision regarding whether it should internalize self-imposed delays and provides detailed empirical evidence from disaggregate data on every flight at twenty-seven major hub airports between July 28th and August 3rd, 2003. The theory and empirical results indicate that in most cases dominant airlines do not internalize—they ignore self-imposed congestion in the manner of highway models. If dominant airlines attempt to reduce self-imposed delays by rescheduling some flights away from the peak traffic periods, then non-dominant airlines will respond by shifting flights into peak periods—thereby counteracting the dominant airline's efforts to reduce peak traffic rates. Dominant airlines behave like Stackleberg leaders by anticipating such reactions by non-dominant aircraft and schedule their flights to preempt other aircraft from operating during their peak-period service intervals—even though this means that dominant aircraft impose delays on one another. The resulting Stackleberg equilibrium is similar to that of an atomistic model in which dominant aircraft act as if they have the (lower) time values of the non-dominant aircraft that they preempt.

Section I places our model in the context of the recent research literature. Section II extends the deterministic bottleneck model of William S Vickrey (1969) and Richard Arnott, Andre DePalma, and

Robin Lindsey (1990) to include a dominant airline that must decide whether or not to internalize its self-imposed delays. We show that atomistic, Stackleberg, or internalizing behavior can result—depending on traffic levels, airport capacity, costs of queuing delay, and costs of deviation from preferred operating times. Section III develops an empirical model for estimating minute-by-minute landing and takeoff delays using data on every flight at twenty-seven major US airports for a peak-demand week during Summer 2003. Section IV fits congestion functions based on dynamic, stochastic queuing theory to our airport delay estimates. These congestion functions embody the structural relationship between congestion delays and airport service (landing and takeoff) rates, number of parallel runways, and time-varying arrival and departure rates. The congestion functions enable us to calculate each flight's own (directly experienced) delay, the (indirect internal) delay it imposes on other aircraft of its own airline, and the (fully external) delay it imposes on aircraft of other airlines. Section V presents j-tests of the hypothesis that dominant airlines minimize queuing-and schedule-delay costs of each aircraft individually against the hypothesis that they internalize self-imposed delays to minimize such costs of all their aircraft jointly. Section VI concludes with a discussion of the policy implications of our finding that dominant airlines do not internalize most of their self-imposed delays.

I. The Literature

Joseph I Daniel (1995) initially noted that dominant airlines might internalize their self-imposed delays and discussed the implications of this possibility for congestion pricing. Proliferation of hub-and-spoke route networks following deregulation of the airline industry caused dominant airlines to obtain control over large shares of traffic at many major airports. According to Daniel, this creates three important distinctions between the problems of airport and highway congestion pricing. First, dominant airlines can strategically coordinate their aircraft operations to influence aggregate traffic patterns, so it is important to explicitly model the dynamic scheduling decisions of the airlines. Second, dominant airlines coordinate arrivals and departures at hub airports to facilitate passenger connections, leading to rapid fluctuations in traffic rates. Models with static on-peak and off-peak periods with steady-state traffic and delays ignore important dynamic aspects of intertemporal traffic adjustment. Third, dominant airlines may face incentives to internalize their own delays. To address the first issue, Daniel adapts a bottleneck model from the highway congestion literature in which dominant airlines schedule their aircraft to minimize connection costs at their hub airports. To address the second, he uses a time-inhomogeneous stochastic queuing model as a dynamic congestion function. Together, the bottleneck and queuing models are capable of distinguishing between internalizing and non-internalizing behavior on the part of dominant airlines. For the third issue, he performs a series of empirical tests using tower log data from Minneapolis-St. Paul (Minneapolis-St Paul) airport that reject the hypothesis that Northwest Airlines fully internalizes its self-imposed delay.

In spite of Daniel's empirical rejection of the internalization hypothesis, subsequent researchers find the theoretical position that dominant airlines internalize their self-imposed delays to be a compelling argument. They note that Daniel's empirical data is limited to a single airport and airline. His simulation model does not have a closed-form solution, so it is not transparent what drives the non-internalization result. Moreover, he does not have direct observations on actual delays—so he is unable to validate his simulation model of queuing delays against observed delays. To address these issues we develop a closed-form theoretical model showing when a dominant firm internalizes its delays and when it does not. We also extend Daniel's empirical analysis to include all major US airports and to estimate their diurnal delay patterns from data on aircraft flight times so that we can calibrate and verify our dynamic congestion function against time-dependent airport delay patterns that are implicit in the data.

Recent articles by Jan K Brueckner (2002) and Christopher Mayer and Todd Sinai (2003) use newly available data on flight delays from a broad range of major airports to test for econometric relationships between airline dominance of airports and the levels of delays. Brueckner relies on aggregated annual counts of flights delayed more than 15 minute from their scheduled operating time (the FAA's primary measurement of delay). Mayer and Sinai use disaggregated, flight-level data, with delay measured as the deviation from the minimum observed flight time between each city pair. Both find statistically significant—although weak—relationships showing that delays decrease as airport dominance increases, ceteris paribus. The authors argue that the inverse relationship between airport concentration and delays is evidence of internalization by dominant airlines and that their congestion fees should reflect internalization of self-imposed delays. Brueckner proposes that a dominant airline's fees should be inversely proportional to its share of aircraft operations at the airport.

A third study, Anonymous (2004),[2] uses an econometric approach similar to Mayer and Sinai with an alternative definition of flight delay based on deviations of actual flight times from *average* flight times between city pairs. This alternative approach understates delays because it excludes average flight delays that are part of average flight times. Mayer and Sinai defines flight delay as the excess of actual flight time over *minimal* flight time between city pairs. Their approach overstates delays because it includes normal flight time in excess of atypical flight times resulting from unusual conditions such as high tailwinds or the most favorable flight path. Anonymous finds very small relationships between airline dominance and amount of delay, and the author(s) argue(s) that the effect is too small to be of practical significance.

The latter three econometric studies are more general than Daniel's—as they do not rely on a specific theoretical model of minute-by-minute scheduling of flights by airlines. As a consequence, however, they must infer internalization (or not) from the statistical relationship between airport concentration and delay *experienced* by each aircraft, rather than comparing the dominant airlines' treatment of additional delay *experienced* by an aircraft and the additional delay *imposed* by it on the airlines' other aircraft. Brueckner, Mayer and Sinai, and Anonymous test whether dominant aircraft experience less delay at more concentrated airports, while controlling for other effects. Daniel and the analysis presented here directly test whether dominant airlines schedule each aircraft to minimize the aircraft's individual delay or to minimize its contribution to all delays experienced by the dominant airline's aircraft.

II. The Theoretical Model

In this section, we present a deterministic bottleneck model characterizing cost-minimizing airlines that operate non-negligible shares of airport traffic, but may nevertheless choose to ignore their self-imposed delays. Although airlines would like to reduce self-imposed delays, air-traffic controllers allocate landing and takeoff times on a first-come first-served basis so that dominant airlines cannot prevent other aircraft from operating during peak periods unless they use the periods themselves. In Nash equilibria, dominant airlines do not expect other airlines to respond to their reduction of peak traffic rates; while in Stackleberg equilibria, dominant airlines anticipate that other airlines will respond by shifting traffic back towards the peak. So in Nash equilibria, dominant airlines internalize delays by spreading their operations out thereby tempting other aircraft to operate during their peaks. In Stackleberg equilibrium, however, dominant airlines appear to ignore their self-imposed congestion in order to preempt other aircraft from operating during their peaks.

The FAA's recent attempt to help United and American Airlines to reduce congestion at Chicago O'Hare Airport by coordinating their operating times provides anecdotal evidence supporting the Stackleberg interpretation. United and American each reduced their peak-period flights by seven and a half percent, only to have regional airlines shift traffic into the vacated operating times.[3] Such agreements by dominant airlines to reduce traffic and congestion during peak periods are inherently unstable because they create incentives for non-dominant airlines to unilaterally deviate from their previous operating times. Congestion pricing would solve the capacity allocation problem by confronting each aircraft with the true (time-dependent) social cost of its operation and allowing airlines to adjust their operating times accordingly. Dominant airlines could rely on higher fees to dissuade other aircraft from operating during their peak periods.

Peak traffic periods at hub airports arise because hub airlines schedule their aircraft from spoke cities to arrive at hub airports in groups of flights (arrival banks) in time to exchange passengers with groups of flights (departure banks) that pick up passengers and leave the hub bound for spoke cities. Suppose the hub airline operates n_d aircraft in an arrival bank. In the absence of capacity constraints, hub carriers would ideally schedule all incoming flights to land at the same time, provide an interchange period exactly long enough for passengers to transfer to connecting flights, then schedule all outgoing flights to departure at the same time. Airport capacity constrains the rate at which landings and takeoffs may occur, forcing carriers to spread out arrivals and departures around their most preferred operating times. Arriving and departing aircraft have separate queuing systems with independent bottleneck equilibria. The basic framework applies to both arrival and departure banks, but the equilibria are not exactly the same.[4] We derive the arrival equilibrium and discuss how the departure equilibrium differs. The behavioral implications and welfare results apply equally to both equilibria.

The airport has fixed capacity of k landings or takeoffs per minute. Non-dominant aircraft do not participate in the passenger exchange. Their most-preferred-operating times are uniformly distributed at the rate of $f\,k$ aircraft per minute, where f is the ratio of fringe operations to capacity, k. In deterministic bottleneck models, capacity is fully utilized during congested periods, regardless of whether congestion is priced or unpriced. It takes $n_d/(k(1\text{-}f))$ minutes to process all the aircraft in the congested period surrounding the hub airline's interchange period. It follows that the total number of aircraft operating during the congested period is $n_d + f\,k\,n_d/(k(1\text{-}f)) = n_d/(1\text{-}f)$.

The dominant airline's problem is to schedule its arrivals and departures to minimize the cost of its delays and deviations from preferred operating times resulting from the airport bottleneck. Because of limited capacity, it must schedule some aircraft to arrive before and some to arrive after the interchange begins. Early arrivals experience additional layover time that costs c_e dollars per minute. Arrivals after the beginning of the interchange, later than the most preferred operating time, increase the chance of missed connections and increase passenger and baggage handling costs at the rate of c_l dollars per minute. Aircraft in an arrival queue have longer flight times (departures have longer block[5] time waiting to takeoff) at the cost of c_q dollars per minute. Since non-dominant aircraft do not face the same time constraints for operations associated with connecting flights at the hub airport, the cost of deviating from their most-preferred-operating times is almost certainly lower than that of the dominant airline.[6] The costs per minute of early and late deviations by fringe aircraft from their most preferred operating time are $\hat{c}_e$ and $\hat{c}_l$. The time fringe aircraft spend in landing and takeoff queues costs $\hat{c}_q$ dollars per minute. Fringe queuing-time values should be no greater than those of dominant aircraft. The following inequalities summarize these assumptions about time values:

$\hat{c}_e \le c_e;\ \hat{c}_l \le c_l;\ \hat{c}_q \le c_q;\ \hat{c}_e,\ \hat{c}_l \le \hat{c}_q;\ c_e,\ c_l \le c_q;\ \hat{c}_e \le c_e;\ \hat{c}_e \le c_e;\ \hat{c}_e/\hat{c}_q \le c_e/c_q;\ \hat{c}_l/\hat{c}_q \le c_l/c_q.$

A. The Atomistic Equilibrium

First consider the fully-atomistic unpriced equilibrium, in which every aircraft operating at the airport is essentially independently governed as in highway-congestion models. Every aircraft chooses its operating time to minimize the sum of its early, late, and queuing time costs:

(1) $\hat{C}[t] = \hat{c}_q\, q[t] + \hat{c}_e\, max[0,\ t_i \text{-}(t + q[t])] + \hat{c}_l\, max[0,\ t + q[t] - t_i]$, $\forall$ fringe aircraft, i, and

$C[t] = c_q\, q[t] + c_e\, max[0,\ t_0 \text{-}(t + q[t])] + c_l\, max[0,\ t + q[t] - t_0]$, $\forall$ dominant aircraft.

For aircraft with identical cost parameters, the sum of costs in Expressions (1) must be identical over their arrival times—otherwise aircraft with higher cost would have incentive to shift to lower-cost periods, meaning equilibrium is not yet achieved. Differentiating (1) with respect to t and solving for the rate of change in $q[t]$ gives:

(2) $$q'[t] = \frac{\hat{c}_e}{\hat{c}_q - \hat{c}_e}, \ \ for \ \ t < t_o - q[t], \ \ and \ \ q'[t] = -\frac{\hat{c}_l}{\hat{c}_l + \hat{c}_q}, \ for \ t > t_o - q[t].$$

Equilibrium queues adjust so that queuing costs just offset changes in early or late time costs, adjusting for the effect of queuing times on service completion times. The rate of change in queues depends on the relationship between the arrival rate and the capacity of the deterministic queuing system:

(3) $$q'[t] = \frac{(r[t] - k)}{k}.$$

Setting these expressions for the rates of change in queues equal to each other and solving for the arrival rates gives:

(4) $$r[t] = k\left(1 + \frac{\hat{c}_e}{\hat{c}_q - \hat{c}_e}\right), \ \ for \ \ t < t_o - q[t], \ \ and \ \ r[t] = k\left(1 - \frac{\hat{c}_l}{\hat{c}_q + \hat{c}_l}\right), \ for \ t > t_o - q[t].$$

Clearly, the rates of change in queues and the arrival rates must be different for the periods in which dominant and fringe aircraft arrive. During the hub airline's arrival periods, the queues will change rapidly enough to shift the fringe aircraft away from the hub airline's preferred arrival time, establishing a separating equilibrium with the hub operations in the center of the congested period, and the fringe on the edges.

Let h_b and h_e be the beginning and ending of the $n_d/(k(1\text{-}f))$ minute period occupied by the hub airline's arrivals. There are $f\,k\,n_d/(k(1\text{-}f))$ fringe aircraft displaced from this period. Fringe airlines regard the cost of time deviations between h_b or h_e and their preferred operating times as fixed, so they only consider the additional time between h_b or h_e and their scheduled time. At the beginning and ending of the congested period, t_b *and* t_e, there are no aircraft in the queue. The change in queuing costs from t_b to h_b and from h_e to t_e must just offset the change in early or late costs. It follows that:

(5) $$\hat{c}_e\,(h_b\text{-}t_b) = \hat{c}_q\, q[h_b] = \hat{c}_q\, q[h_e] = \hat{c}_l\,(t_e\text{-}h_e) = \hat{c}[t].$$

Equation (5) implies that the lengths of the queues at the end of the early fringe arrivals and the beginning of the late fringe arrivals are the same. Using the rate of change in queues from Equation (2) we obtain the relative length of these periods.

$$(6) \qquad (t_e - h_e) = \frac{\hat{c}_e\,(\hat{c}_l + \hat{c}_q)}{\hat{c}_l\,(\hat{c}_q - \hat{c}_e)}\,(h_b - t_b).$$

All fringe aircraft must arrive during these periods, so

$$(7) \qquad k\left(1 + \frac{\hat{c}_e}{\hat{c}_q - \hat{c}_e}\right)(t_b - t_b') + k\left(1 - \frac{\hat{c}_l}{\hat{c}_q + \hat{c}_l}\right)(t_e - t_e') = \frac{f\,n_d}{(1-f)},$$

and the lengths of the fringe arrival periods are:

$$(8) \qquad (h_b - t_b) = \frac{f\,n_d\,(\hat{c}_q - \hat{c}_e)\,\hat{c}_l}{(1-f)\,k\,(\hat{c}_e + \hat{c}_l)\,\hat{c}_q} \text{ and } (t_e - h_e) = \frac{f\,n_d\,(\hat{c}_l - \hat{c}_q)\,\hat{c}_e}{(1-f)\,k\,(\hat{c}_e + \hat{c}_l)\,\hat{c}_q}.$$

The queues at h_b and h_e are:

$$(9) \qquad q[h_b] = q[h_e] = \frac{f\,n_d\,\hat{c}_e\,\hat{c}_l}{(1-f)\,k\,(\hat{c}_e + \hat{c}_l)\,\hat{c}_q}.$$

Hub airline traffic spreads out around the most preferred arrival time, t_o, so that aircraft have the same cost whether they have the longest layover, the longest queue, or the longest late time. Converting the costs per minute from Equation (8) to cost per aircraft by multiplying by the arrival rate—or using the queuing costs from Equation (9)—and then multiplying by the number of fringe aircraft gives equilibrium total cost for all fringe aircraft. The fringe aircraft experience additional schedule delay time associated with deviations from their most preferred times to t_b or t_e.

$$(10) \qquad \frac{f^2\,\hat{c}_e\,\hat{c}_l\,n_d^2}{(f-1)^2\,(\hat{c}_e + \hat{c}_l)\,k} + \frac{\hat{c}_e\,\hat{c}_l\,f\,k\,n_d^2}{2(\hat{c}_e + \hat{c}_l)}$$

Turning to the problem of dominant aircraft—assuming they behave atomistically—they face similar incentives as the fringe, so their arrival rates and queues have the same relationship to their cost parameters as previously derived:

$$(11) \qquad r[t] = k\left(1 + \frac{c_e}{c_q - c_e}\right), \text{ for } t < t_o - q[t], \text{ and } r[t] = k\left(1 - \frac{c_l}{c_q + \hat{c}_l}\right), \text{ for } t > t_o - q[t].$$

$$(12) \qquad q'[t] = \frac{c_e}{c_q - c_e}, \text{ for } t < t_o - q[t], \text{ and } q'[t] = -\frac{c_l}{c_l + c_q}, \text{ for } t > t_o - q[t].$$

The hub aircraft must also determine how to time their arrivals relative to their most preferred operating time, t_o. As indicated in (11), the arrival rate shifts from high to low just when an aircraft joining the queue will complete service at exactly t_o. The beginning and ending times of the hub's arrival bank is determined by the relative costs of early and late time, the total number of aircraft in the bank, and the condition that the queue be in the same state at t_b and t_e:

$$k\left(1+\frac{c_e}{c_q-c_e}\right)(t_p-h_b)+k\left(1-\frac{c_l}{c_q+c_l}\right)(t_e-h_p)=n_d, \tag{13}$$

$$\frac{c_e}{c_q-c_e}\; t_p-h_b\; = \frac{c_l}{c_q+c_l}\; h_e-t_p\,. \tag{14}$$

Solving for the beginning, ending, and peak times, we obtain:

$$t_b=t_o-\frac{c_l\,n_d}{(c_e+c_l)\,k};\quad t_e=t_o+\frac{c_e\,n_d}{(c_e+c_l)\,k};\quad t_p=t_o-\frac{c_e\,c_l\,n_d}{(c_e+c_l)\,c_q\,k}\,. \tag{15}$$

At $t_p = t_o - q[t_o]$, the queue attains a maximum of:

$$q\left[h_b+\frac{c_l\,n_d}{(c_e+c_l)\,k}\right]=\frac{f\,\hat{c}_e\,\hat{c}_l\,n_d}{(1-f)\,(\hat{c}_e+\hat{c}_l)\,c_q\,k}+\frac{c_e\,c_l\,n_d}{(c_e+c_l)\,c_q\,k} \tag{16}$$

The full cost of the dominant airline's arrivals when it acts atomistically is:

$$\frac{f\,c_q\,\hat{c}_e\,\hat{c}_l\,n_d^2}{(1-f)\,\hat{c}_q\,(\hat{c}_e+\hat{c}_l)\,k}+\frac{c_e\,c_l\,n_d^2}{(c_e+c_l)\,k}\,. \tag{17}$$

The first term of (17) represents the additional queuing cost imposed on the hub airline by the fringe aircraft. The second term is the self-imposed delay.

The solid lines in Figures 1-4 illustrate the fully atomistic equilibrium. In Figure 1, the fringe arrivals begin at time zero and cumulate at a linear rate until about time eight. This corresponds to the graph of the arrival rate that is just below six aircraft per time unit in Figure 2. The dashed horizontal line in Figure 2 represents the service capacity of five aircraft per time unit. Since the arrival rate exceeds the service capacity, a queue forms—as represented by the vertical distance between the cumulative arrivals and cumulative service completions (the dashed line) in Figure 1. The number of aircraft in the queue can also be seen in Figure 3. At about time eight, the fringe arrivals cease and the aircraft of the dominant hub airline (acting atomistically) begin arriving at a rate that causes the queue to increase more rapidly than before. The fringe queuing cost increases at a faster rate than its layover cost decreases, so fringe aircraft either operate before this time or they wait until later. The queue increases such that the queuing cost of dominant aircraft increases at a rate that just offsets the rate at which its layover time cost decreases. After about time seventeen, dominant aircraft that join the queue will finish service later than they prefer. The arrival rate must now fall below the service rate so that the rate of decrease in queuing costs just offsets the rate of increase in the dominant aircraft late-time cost. For fringe aircraft, the queuing time cost is falling faster than the increase in late time, so it pays for them to continue waiting. Finally at about time twenty-eight, all the dominant aircraft have completed service, and the fringe aircraft resume operations. Their arrival rate is faster than the late-arriving dominant aircraft (but below the service rate) so that the reduction in their queuing costs just equals the increase in their late-time costs. In this equilibrium, the dominant aircraft preempt their peak-period operating times by using the queuing cost to discourage fringe operations. The solid line in Figure 4 represents the cost of queuing for aircraft that are *completing* service at the time given on the horizontal axis. A congestion fee schedule equal to this queuing cost could replace queuing by providing the same incentives as the queuing cost and result in aircraft arriving at the deterministic queuing system at a rate exactly equal to the service rate throughout the entire peak period. There would be no queues, and the airport authority would capture all of the social welfare that would otherwise be lost to queuing delay.

Note that atomistic behavior by the dominant hub airline actually causes more queuing than necessary to dissuade the fringe from operating during the peak period. All that is necessary is that the queue increase and decrease at the rates given by the dotted line in Figure 3, or that the congestion fee vary as the dotted line in Figure 4. In the following sections, we calculate and compare equilibria in which the dominant airline spreads its operations out to completely eliminate queuing (full internalization) or behaves atomistically but adopts the fringe time costs so that it creates just enough queuing to preempt the peak period. This latter behavior arises from a Stackleberg equilibrium and may be thought of as partial internalization, but is indistinguishable from an atomistic equilibrium in which the dominant and fringe airlines have the same time costs.

B. The Nash-Dominant (full-internalization) equilibrium

The dominant airline may reduce total costs by coordinating its aircraft in ways that do not satisfy the atomistic optimization conditions for each individual aircraft. The deterministic queuing system allows the arrivals to equal capacity without creating any queuing delay. The Nash assumption specifies that the dominant airline always chooses its best response taking the fringe arrivals as given. The dominant airline shifts aircraft off the peak to take advantage of unused capacity before and after the peak period. Each individual aircraft that shifts experiences higher costs, but total queuing costs of the dominant airline diminish as long as the fringe arrival rates are unchanged. Out of equilibrium, the dominant airline's expectation that the fringe will not shift its operations is erroneous. The fringe aircraft shift into the peak towards their most preferred operating times. Since layover time is less expensive than queuing time, it is always better at the margin for the dominant airline to spread arrivals until the queue is eliminated. When the dominant and fringe arrivals are uniformly distributed at rates $k(1\text{-}f)$ and $f\,k$, there are no queues and no incentives for any aircraft to shift operating times assuming the other aircraft are fixed.

The remaining problem for the dominant airline is to choose the beginning and ending time for its arrival bank. The number of dominant aircraft and the residual capacity after serving the fringe aircraft, $k(1\text{-}f)$ determines the length of the bank. Solving the condition that the costs of the first and last aircraft are equal to obtain the optimal starting time gives:

(18) $$(t_o - t_b)\, c_e\, (k - d_f) = c_l\, (k - d_f) \left(\frac{n_d}{k - d_f} - (t_o - t_b) \right) \Longrightarrow t_o = t_b + \frac{c_l\, n_d}{(c_e + c_l)\,(k - d_f)} .$$

It follows that the total cost of the Nash dominant airline is:

(19) $$\int_0^{\frac{c_l\, n_d}{(c_e + c_l)\,(k - d_f)}} c_e\, t (k - d_f)\, d t + \int_0^{\frac{c_e\, n_d}{(c_e + c_l)\,(k - d_f)}} c_l\, t (k - d_f)\, d t = \frac{c_e\, c_l\, n_d^2}{2 (c_e + c_l)\,(1 - f)\, k} .$$

Figure 2 shows the fringe arrival rate just equal to the rate of distribution of preferred arrival times. The hub airline arrivals use up the remaining capacity by spreading out beyond the atomistic arrival bank period. In Figure 1, total Nash arrivals just equal the service rates, and in Figure 3 the Nash equilibrium queues are zero throughout. Given the fringe arrival pattern, any change in hub arrivals would either increase schedule delay without decreasing queuing or increase queuing and schedule delay simultaneously.

C. The Stackleberg-Dominant Equilibrium

If the dominant hub airline acts first and anticipates the optimal response of fringe aircraft to its own schedule, then an intermediate solution may be feasible. The dominant airline adopts the arrival rates of the atomistic fringe airlines to create a queuing pattern that will just pre-empt the fringe aircraft from operating during the hub's arrival bank. If the fringe is less sensitive to schedule delays, then equilibrium queues can be significantly lower than in the atomistic case. The resulting traffic pattern is not a Nash best response to the fringe's schedule because the hub airline could reduce its cost by moving towards the Nash solution—but only if the fringe arrivals were actually fixed. But now the hub airline anticipates that fringe aircraft will shift into the bank period whenever the arrival rates and queues fall below the fringe's atomistic levels. The hub airline accepts self-imposed delays as necessary to discourage fringe aircraft from operating during its arrival bank.

For fringe aircraft, the Stackleberg solution is exactly as in the atomistic case. Hub airlines, however, recognize that atomistic queuing levels are higher than necessary to discourage the fringe from interfering with their flight banks. High atomistic queues are only necessary to establish atomistic bottleneck equilibria for hub aircraft with relatively higher schedule-delay values than fringe aircraft. Stackleberg dominant airlines need only establish queuing patterns required for equilibria among atomistic fringe aircraft. They schedule their aircraft as if they were acting atomistically *and had the fringe time values*. When the hub airline's bank begins and ends, the queues are in the same states as in the atomistic case. Since the service completion times are completely determined by the service rate, the total early and late times are the same. The only difference in cost is due to queuing costs decreasing by:

$$(20) \qquad \left(\frac{c_l\ c_e}{2(c_e + c_l)}\left(\frac{n_d^2}{k}\right)\right) - \left(\frac{\hat{c}_l\ \hat{c}_e c_q}{2(\hat{c}_e + \hat{c}_l)\,\hat{c}_q}\left(\frac{n_d^2}{k}\right)\right) = \left(\frac{c_e c_l}{c_e + c_l} - \frac{\hat{c}_e\,\hat{c}_l\,c_q}{(\hat{c}_e + \hat{c}_l)\,\hat{c}_q}\right)\frac{n_d^2}{2k}\ .$$

The hub airlines' total cost for the Stackleberg dominant airline is the atomistic cost less the reduction in queuing cost:

(21) $$\frac{c_q \hat{c}_e \hat{c}_l n_d^{2}}{(1-f)\hat{c}_q (\hat{c}_e+\hat{c}_l) k}.$$

Figures (1)-(3) illustrate that Stackleberg equilibria arrival rates and queues are similar to atomistic equilibria in which dominant airlines act as if their aircraft were atomistic and they all had the fringe time values. There are, however, several important differences. Dominant airlines position the arrival-rate changes so that the fringe aircraft begin and end their arrivals to correspond with the hubs' optimal offsets from the hubs' most preferred operating times. The condition that the aircraft with the longest delay arrives exactly on time is generally not satisfied. Other marginal conditions for atomistic equilibria do not apply to dominant aircraft: individual hub aircraft could reduce their own costs by shifting towards the peak, while dominant airlines could reduce total costs by further spreading arrivals—but, again, only if the fringe would not react.

D. Cost Comparisons

Comparing the equilibrum costs from Equations (17), (19), and (21), the ratio of the Stackleberg-dominant airline costs to the Nash-dominant airline costs is:

(22) $$\frac{\dfrac{c_e c_l}{(c_e+c_l)c_q}}{\dfrac{\hat{c}_e \hat{c}_l}{\hat{c}_q(\hat{c}_e+\hat{c}_l)}} \begin{cases} <2 \Longrightarrow & \textit{Nash Dominant} \\ >2 \Longrightarrow & \textit{Stackelberg Dominant} \end{cases}$$

The difference between the atomistic and Stackleberg equilibria is positive as:

(23) $$\frac{\dfrac{c_e c_l}{(c_e+c_l)c_q}}{\dfrac{\hat{c}_e \hat{c}_l}{\hat{c}_q(\hat{c}_e+\hat{c}_l)}} \begin{cases} <1 \Longrightarrow & \textit{Atomistic} \\ >1 \Longrightarrow & \textit{Stackelberg Dominant} \end{cases}$$

It follows that Stackleberg behavior weakly dominates purely atomistic behavior[7] and that a sufficient condition for Stackleberg behavior to dominate Nash behavior is that the dominant airline values schedule delay (early and late time) more than twice as much relative to its queuing costs than the non-dominant airlines.[8] Schedule delay that affects a dominant hub airline's coordination of its passenger interchange is likely to be significantly more expensive than that of non-hub airlines or airlines operating hubs at other airports. This implies that airports with strong hub operations—like Atlanta, Denver, Dallas, Detroit, Minneapolis, and Chicago—are more likely to exhibit Stackleberg behavior than airports with less connecting traffic—like Boston, Baltimore, Washington-National, Miami, Philadelphia, Boston, and Seattle.

III. THE DATA AND EMPIRICAL MODEL

We use a combination of the FAA's Enhanced Traffic Management System (ETMS) data and Airline Service Quality Performance (ASQP) data on all departures and arrivals at 27 major airports from July 28 through August 3, 2003.[9] The data include scheduled and actual arrival and departure times, expected and actual flight distances, airborne time, taxi time, and aircraft type. The data do not include direct observations on time spent in arrival or departure queues—a problem in common with the other recent articles. Mayer and Sinai use the excess of airborne time over the minimum observed flight times for the given city pair by date cohorts. Measurements based on minimum observed flight times overstate the queue by using the best realization of random shocks (such as favorable tail winds or more direct flight paths) as the standard flight time. Alternatively, Anonymous uses deviation above average flight time to capture the magnitude of a flight's delay. Measurements based on average flight time understate the landing queue by including some queuing time in the average. To avoid these problems, we exploit the fact that airport-specific delays due to capacity limitations are correlated with times of arrival and departure and do not vary across aircraft with different origins or destinations that operate at the same time. Using data from multiple days with virtually identical flight schedules largely eliminates effects of airport-specific random effects that are not time dependent—such as weather. It is the component of travel time that is common to flights with similar operating times at an airport—delay due to heavy traffic demand—that is susceptible to congestion pricing.

To estimate landing queues, we assume there are four components to airborne times for flights: the average time it takes to fly from the origin to the destination; an aircraft type specific component that accounts for varying aircraft speeds; time spent in the landing queue; and the stochastic error associated with random shocks like weather. The airborne time is the time from "wheels off" the runway on takeoff to touchdown on landing. This excludes any taxi or gate access time. Because time spent in the landing queue varies with the number of operations being completed at the airport, the queuing time is related to flight schedules and thus varies systematically by time of day. To strip out the landing queue time from airborne times for a given airport, we regress the airborne time of each arriving aircraft on sets of dichotomous variables for each minute of the day, each city of origin, and each aircraft type[10] interacted with flight distances to account for different speeds. The regression equation can be stated:

(24) $Airborne\ time = \beta_1 * minute + \beta_2 * city + \beta_3 * distance * plane\ type + \varepsilon$.

The resulting vector, β_1, of coefficients on the minute of the day dummy variables is the component of the airborne time that is accounted for by the time of arrival at the airport—i.e., the landing queue estimates by time of arrival.

For departures, we regress taxi time on a set of dichotomous variables for each minute of the day and a constant representing the average time to reach the takeoff queue from a gate. The dependent variable is the time elapsed between push back from the gate and wheels off time. Some of this taxi time includes the actual time needed to get from the gate into position at a runway to take off, and some is due to time the flight spends waiting its turn in the departure queue. The regression equations used to estimate the departure queues at each airport is:

(25) $Taxi\ time = \gamma_1 * minute + \gamma_2$.

The coefficients γ_1, as with β_1 for arrivals, are vectors of estimates of the takeoff queues for each minute of the day.

ETMS data derives from air traffic control, and as such does not include detailed information on taxi times on the ground. The chief advantage of using ETMS data is that it includes all flights that conduct instrument operations, including those of small carriers,[11] cargo, and general aviation. This ETMS data was used for the arrival regressions above, and the traffic counts for both the arrival and departure queuing models that will follow. However, because ETMS does not include detailed taxi information, ASQP data for the same time periods was used for the departure regressions above. ASQP data includes many fewer flights, being restricted to the carriers that are individually responsible for more than one percent of total domestic enplanements of passengers. ASQP has the advantage that it is focused on delay performance. It has a more detail—specifically, it captures taxi time after a flight departs the gate up until it takes off. It is not necessary to have every flight in the regressions for estimating takeoff queues, because the regression does not involve the departure rate and there is no sample-bias issue. When the traffic rate is an issue, we use the ETMS data.

Figures 5 and 6 illustrate some representative cases of airport arrival and departure traffic and estimated queues, Appendix A contains graphs for the remaining airports. The dark lines show the actual number of arrivals or departures at the airport by minute of the day. The estimated queuing times are subtracted from the service-completion times recorded in the data to show the times that the aircraft joined the queue. The light lines represent these estimated queues by minute of the day.

The selected airports demonstrate several different traffic patterns that are common in the remaining cases. Atlanta and Minneapolis-St. Paul, for example have the clear, regular, and distinct peaks that are the result of a dominant hub-and-spoke airline's flight banks. The traffic rates peak sharply every couple hours at a rate that exceeds the airport capacity, so the estimated queuing delay closely follows the traffic fluctuations. Between flight banks, the traffic rates drop below the airport capacity—often to nearly zero. This pattern is the most common among the twenty-seven airports. In addition to Atlanta and Minneapolis, this hub-and-spoke pattern is exhibited by: Charlotte, NC; Cincinnati, OH; Denver, CO; Detroit, MI; Houston, TX; Philadelphia, PA; Phoenix, AZ, Pittsburgh, PA; Salt Lake City, UT; and St. Louis, MO. In addition, Memphis, TN; Miami, FL; and Washington (Dulles) have a similar pattern but with fewer peaks.

Another group of airports exemplified by Dallas-Ft. Worth—known for heavy traffic—exhibit significant fluctuation in traffic rates but not as clearly coordinated peaking as those above. They also exhibit (at least in August, 2003) fairly constant and modest queues. These include New York (LaGuardia) and Los Angeles. Dallas has unusually high capacity with 6 runways. It has two major airlines so the traffic peaks are not as distinct as the Atlanta group. New York and Los Angeles both have more than one dominant carrier and they have even less distinct peaking. These airports have traditionally suffered from capacity problems, however, so it is surprising that they have such modest queues.

Newark, NJ has a clear diurnal pattern to its traffic and queues with constant high traffic rates during the afternoon that generate significant queuing. New York (JFK) and San Francisco have similar patterns. Although they have heavy traffic, these airports are not strong hubs because they are not centrally located for passenger connections. Their traffic patterns do not exhibit as regular periodic peaking as the hubs with more connecting traffic. These airports might be good candidates for the traditional congestion pricing models with prices set by hour based on hourly arrival rates. Their traffic, however, is clearly atypical of the large hub airports.

Chicago serves the hub airlines with the most connecting traffic and it is the focus of particular concern as its delays often cascade through the entire national airline network, disrupting its connecting airports. Chicago's traffic pattern exhibits peaking from the two dominant airlines with hubs at O'Hare. The queues and traffic peaks are similar to other hub-and-spoke airports, but are more frequent and allow less time for the queues to recover between banks. The presence of two large hub operations makes strategic interaction between the airlines more likely. Interestingly, the bank operations of the two dominant airlines rarely—if ever—directly overlap. Dallas-Ft. Worth has a similar traffic pattern, but as noted above, does not have as high queuing levels.

The remaining airports, including Baltimore-Washington, Boston, Washington National, and Seattle do not exhibit significant peaking of traffic or queues. Baltimore-Washington is distinct in that it is a Southwest hub with no other dominant carrier. National is regulated under the High Density Rule, but this is not a distinction as JFK and LaGuardia are subject to the same regulation.

The theoretical bottleneck model has two implications that can be tested directly from the traffic data and estimated queues, without requiring estimation of a congestion function. Fringe traffic should shift away from the traffic peaks of the dominant airlines at airports with Stackleberg equilibria, and the dominant airline should behave as if it has the same time costs as the fringe. The theoretical model makes several simplifying assumptions that are not satisfied by the data—fringe time cost are not homogeneous; preferred operating times of the fringe are not uniformly distributed; and the queuing system is not deterministic. Nevertheless, the data is generally consistent the theoretical model at the airports where internalization of congestion is most at issue.

Table 1 lists the twenty-seven airports in our data set and shows the HHI index, the dominant airlines, their share of flights, and the amount of capacity used by fringe airlines. The sixth column of Table 1 shows the results of regressing the traffic counts of the fringe on those of the dominant airlines. The result is nearly always negative and significantly so for most of the largest airports with major hub operations—for example, Atlanta, Chicago, Dallas, Denver, Detroit, and Minneapolis. This indicates that the fringe tends to avoid periods in which the dominant airlines operate. The magnitude of the effect is typically between -0.05 and –0.1—reflecting the disproportionate number of dominant aircraft at these hubs. Random deviations in flight times prevent the fringe arrivals from clearly separating from dominant airline arrivals as in the theoretical model. Moreover, some fringe aircraft with high schedule delay costs may schedule their operations during the peak periods.

Figures 7 and 8 show the traffic patterns of the dominant and fringe airlines at representative airports, the remaining airports are included in Appendix B. The fringe avoidance of dominant-airline peak periods is most apparent at Atlanta, Minneapolis, and perhaps Newark. Fringe arrivals tend to peak during off-peak periods of the dominant airlines. Charlotte, Dallas, Denver, and Detroit have comparable traffic patterns. Chicago also exhibits this pattern statistically, but it is difficult to detect from the graph.

Boston, Las Vegas, New York LaGuardia, Seattle, and Washington National, exhibit a distinctly different traffic pattern characterized by more frequent and less extreme peaking and no apparent shifting of the fringe out of the peaks. JFK could be added to this group, except that it has a single extreme peak in the mid-afternoon. Of this group, Las Vegas and Seattle are the most consistent with an internalization equilibrium because they have the most uniformly distributed traffic patterns and fairly steady queues. The other airports in the group are not strongly dominated by any airline and lack regular periodic peaking associated with hub-and-spoke traffic. The airlines at these airports probably lack the degree of dominance needed to internalize delays.

The final column of Table 1 shows the ratio of cost coefficients as given in Inequality (22). We determine the value of the coefficients by solving Equation (1) for the queue length as an endogenous function of the equilibrium time cost ($\hat{C}[t]$ or $C[t]$), early time ($max[0, t_i-(t+q[t])]$), and late time ($max[0,t+q[t] - t_i]$):

(26) $q[t]=(\hat{C}[t] / \hat{c}_q)- (\hat{c}_e / \hat{c}_q)max[0, t_i-(t + q[t])] -(\hat{c}_l / \hat{c}_q)max[0, t + q[t] - t_i]$, $\forall$ fringe aircraft, i, and

$q[t]=(C[t]/ c_q)- (c_e/ c_q)max[0, t_0-(t + q[t])] -(c_l/ c_q)max[0, t + q[t] - t_0]$, $\forall$ dominant aircraft.

We estimate the constants and coefficients in equation (26) by regressing each aircraft's queuing delay on its early and late time and a bank-specific constant term. When the dominant airline behaves as if it has the same costs as the fringe, its estimated coefficients are these counter-factual values, not the true values. If the estimated ratio from Inequality (22) as show in Table 1 is equal to one, then the cost estimates are consistent with Stackleberg behavior. Notice that all of the airports (except Dulles) with statistically significant relationships between fringe traffic and the dominant-airline peaks have cost-ratio values between 0.90 and 1.10. All of the airports (except Washington National, Newark, and St. Louis) with non significant relationships between fringe traffic and the dominant peaks have a cost ratio outside of this interval. These two tests are consistent with Stackleberg equilibira at Atlanta, Denver, Dallas, Detroit, Houston, Las Vegas, Los Angeles, Minneapolis, Chicago, and Salt Lake City. The tests do not lend support to Stackleberg equilibria at Baltimore, Charlotte, Cincinnati, Memphis, Miami, Philadelphia, Pittsburgh, or San Fransisco.

IV. THE DYNAMIC CONGESTION FUNCTION

In this section we show that stochastic queuing theory provides a highly accurate dynamic model of congestion based on its structural relationship to traffic rates, number of runways, and length of service intervals. Most empirical work on airport pricing uses congestion functions for which delays are functions of current-period traffic rates that vary by hour. The primary purpose of congestion pricing in these models is to toll off traffic during peak-demand hours rather than to shift traffic inter temporally. Figures 5 and 6, however, clearly show that traffic rates and delays fluctuate rapidly within hourly periods and that inter temporal shifting of traffic has great potential for improving airport capacity utilization.

While we assume *deterministic* queuing in the theoretical model of Section I to obtain closed-form solutions, time-varying *stochastic* queuing models are much better at modeling delays over a wide range of arrival rates. (see, Daniel and Pahwa, 2000). Our empirical specification, therefore, uses a dynamic congestion function that is based on a stochastic queuing model with Poisson-distributed arrivals with time-varying traffic rates and multiple deterministic servers representing runways. The function takes the observed arrival rates, $\lambda(t)$, for each service interval as arguments and the fixed service rate, d, and number of runways, s, as parameters. The state vector in each service interval, $\boldsymbol{p}(t)$, is the probability distribution on queue lengths. For computational purposes, the queues have a finite maximum length 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:[12]

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

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

We could simply use the arrival rates depicted in Figures 5 and 6 as the $\lambda(t)$'s, to calculate the queues. In the next section, however, we want to attribute delays to particular aircraft and distinguish between delays imposed internally or externally to the dominant airline. We also want the delay costs to reflect uncertainty caused by random deviations of actual operating times from scheduled operating times. We use the mean of each flight's seven observed operating times as its intended operating time. For each airport, we determine the distribution of deviations of aircraft operating times about their means. The expected arrival rate in each period is the sum over all the aircraft of the probabilities that the aircraft operate within that period. This smoothes the variation in expected traffic rates over time more than the observed traffic fluctuations in our data, but the queuing model treats arrivals as a Poison process with mean (and variance) $\lambda(t)$, so it accounts for the whole distribution of traffic rates and queue lengths. The number-of-servers parameter in the queuing model is equal to the maximum number of non-intersecting runways at the airports. We set the service-rate parameter to calibrate the queuing model to fit the simulated queuing pattern to the delays estimated from the regression model.[13]

Figures 9 and 10 compare the expected delays from the dynamic congestion function with the regression estimates at representative airports—Appendix C shows the remaining airports. The congestion function only has two parameters, yet it is able to reproduce the delay patterns at airports with very different traffic patterns. The model is particularly good at matching hub-and-spoke queuing patterns. Since the congestion function embodies the structural relationship between traffic rates, capacity, and service intervals, these graphs represent an overwhelming case that airport delays are largely a consequence of regular traffic patterns—not, as the FAA sometimes maintains, an unavoidable consequence of bad weather. The congestion function also matches the more constant queuing patterns that Baltimore-Washington, Dallas-Ft. Worth, Las Vegas, and Los Angeles exhibit. The model does less well at airports with long steady periods of elevated demand—but such airports are the exception, not the rule. Of these airports, the congestion function successfully approximates delays at Newark, but is less successful with New York-JFK or San Francisco.

The empirical analysis of traffic rates and delays in this and the previous section demonstrates that the congestion problem at nearly all major airports is characterized by rapid fluctuation of queues caused by airlines scheduling arrivals and departures to coordinate passenger exchanges between origin and destination flights. Modeling of airport congestion, therefore, requires a dynamic model of airline scheduling and a congestion function that reproduces the observed fluctuations in queues. The dynamic congestion function developed above is generally successful in matching the regression estimates of minute-by-minute delays based on their structural relationship to time-varying arrival rates, service capacity, and service intervals. In the next section, we use the bottleneck theory to model airline scheduling and the congestion function to determine the internal and external delays generated by each aircraft.

V. SPECIFICATION TESTS

We base our specification tests directly on the model's cost minimization conditions by calculating internal and external delay times of each aircraft using the dynamic congestion function and disaggregate traffic data. Brueckner and Mayer and Sinai must infer whether airlines internalize based on relationships between airport concentration levels and the amount of direct delay experienced by aircraft. If the internalization hypothesis is correct, then dominant airlines should treat indirect delays their aircraft impose on one another the same as they treat delays each aircraft experiences directly. They will adjust the operating times of their aircraft to minimize the sum of direct and indirect delays. If dominant airlines behave atomistically or as Stackleberg leaders, then they will adjust the operating times of their aircraft to minimize only the direct costs each aircraft experiences—ignoring the indirect delays. In either equilibrium—assuming homogeneous aircraft—airlines schedule each aircraft such that it contributes the same amount to the relevant measure of additional delay. The equilibrium condition for each aircraft in either case can be written as:

(28) (queuing time)=C-c_e/c_q (early time) - c_l/c_q (late time),

where the time values are those experienced directly by the aircraft for the non internalization case or the sum of direct and indirect delays for the internalization case. Queuing time adjusts endogenously with the traffic rates so that Equation (28) is satisfied for all aircraft scheduled during a bank.

The fundamental idea of the specification tests is to treat Equation (28) as a regression equation for estimation under both hypotheses. We then enter the predicted value from each specification as an independent variable in the alternative model to test whether it has any explanatory power against the independent variables of that specification. If the coefficient on the predicted value from the alternative model is significantly different from zero, we reject the specification of the model to which the predicted values has been added.

Given the dynamic congestion function specified in the previous section, we can calculate the rate of change of the system state in 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:

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

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. It follows that the change in early time of an aircraft arriving at period $t+n$ with respect an arrival at t is:

(30) $d\,e(t+n)/d\lambda(t)=\Sigma_{i<t^*-(t+n)}\, q_i(t+n)\,\{t^*-[(t+n)+i]\}.$

Similarly, the change in late time of an aircraft arriving at period $t+n$ with respect an arrival at t is:

(31) $d\,l(t+n)/d\lambda(t)=\Sigma_{i>t^*-(t+n)}\, q_i(t+n)\,\{t^*-[(t+n)+i]\}.$

To account for uncertainty over the actual arrival times, we weight the marginal queuing, early, and late times by the probability that an aircraft scheduled to arrive at $t+n$ actually arrives at $(t+n+s)$:

(32) $\Sigma_s\,\{p(t+n+s)\;\Sigma_i\; i\; d\,q_i(t+n)/d\lambda(t)\},$

$\Sigma_s\,\{p(t+n+s)\; d\,e(t+n)/d\lambda(t)\}$, *and*

$\Sigma_s\,\{p(t+n+s)\; d\,l(t+n)/d\lambda(t)\}.$

Summing the expressions in (32) for each aircraft over all other aircraft operated by the dominant airline gives the changes in indirect queuing, early, and late times an aircraft arriving at time t imposes on other aircraft operated by its airline.

We estimate two versions of Equation 28—the non-internalization case uses the aircrafts' own (direct) queuing, early, and late times, and the internalization case uses the sum of the aircrafts' direct and indirect delay times. For the non internalization case, the bottleneck model implies that the most prefered operating time t^* is the service completion time of the aircraft expereincing the maximal queue. There is no equivalent simple rule for determining t^* for the internalization case, so we chose the best t^* from those spaced at five percent increments of the bank period. The "best" t^* is the one that leads to the strongest case for rejection of the non-internalization hypothesis from among those consistent with the internalization hypothesis.[14] While this approach is based directly on the bottleneck model, it also applies to a more general class of models. We are essentially testing the best model that is piecewise linear in time costs where the dominant airline tradesoff schedule delay against queuing delay to minimize the sum of delay costs. We further generalize the empirical model by adding a specification with squared schedule-delay terms to allow for non-linear delay costs that may vary disporportionately with very long schedule delays or as a result of inhomogeneous aircraft time values that airlines order by decreasing schedule delay.[15]

The dependent variable in the alternative versions of Equation 28 differs by the amount of the indirect queuing delay. We modify the standard j-test to account for this difference in dependent variables by adding the indirect queuing delay to the direct queuing delay predicted by the non internalization model before entering it as an additional regressor in the internalization model. Similarly, we subtract the indirect queuing delay from the queuing delay predicted by the internalization model before entering it in the non internalization model. The resulting test equations are:

(33) (direct & indirect queuing time) = C/c_q + c_e/c_q (direct & indirect early time) + c_l/c_q (direct & indirect late time) + c_{h0} (predicted direct + indirect queuing time) + ε,

(34) (direct queuing time) = C/c_q + c_e/c_q (direct early time) + c_l/c_q (direct late time) + c_{h1} (predicted direct & indirect - indirect queuing time) + ε,

where the observations are by dominant aircraft.

Equations 33 and 34 essentially pit each alternative set of regressors against eachother. The coefficients c_{h0} and c_{h1} indicate whether the alternative hypothesis has any effect on the dependent variable when the model's own independent variables are included. If the t-statistics indicate that these coefficients are significantly different from zero, then we reject the original model to which the predicted value was added. When c_{h0} is significantly positive, then the airline appears to be adjusting its aircrafts' operating times in response to their direct delay costs even when we are already accounting for their full internal costs. We reject the internalization model. When c_{h1} is significantly positive, then the airline appears to be adjusting its aircraft operating times to respond to the full internal delay costs even when we are accounting for their direct delay costs. We reject the non-internalization model.

We perform sets of j-tests for flight data pooled by bank and for data pooled across flight banks within airports. Pooling by bank implies that cost coefficients are the same for aircraft within each bank, but may vary across banks at each airport. Pooling across banks at each airport forces the delay cost coefficients to be identical across all the banks (each bank still has its own equilibrium cost level, *C*), while allowing variation across airports. Airport specific estimates are desirable if the cost coefficients are primarily determined by characteristics of the dominant aircraft that do not change from bank to bank. Bank-specific estimates are desirable if dominant airlines strategically preempt fringe operations during the banks by adopting fringe cost coefficients, as in the theoretical model of Section 1. The fringe cost coefficients may vary by bank as the composition of fringe aircraft changes. Fringe airlines' demand elasticities and their propensity to shift operations into the dominant airline's peak operating times may also vary by bank—thereby changing whether the dominant airline chooses to internalize its self-imposed delays from one bank to the next.

We also test versions of the models assuming costs vary either linearly or non-linearly with length of schedule delay times. While the theoretical model maintains the assumption of linear time costs for the sake of simplicity, there are several reasons to believe that schedule delay costs may not vary proportionately with the length of delay. Aircraft operating close to the beginning or ending of the interchange period may disrupt passenger connections disproportionately to their expected schedule delay times. Moreover, aircraft are not actually homogeneous in delay costs—so dominant airlines may schedule smaller low-cost aircraft further from their interchange periods, causing schedule delays to cost disproportionately less with length of delay. To control for these non-linear schedule delay effects, we add specifications of the internalizing and non-internalizing models that have both linear and squared schedule delay terms. As shown below, the j-tests for linear specifications of the models have many indeterminant results—where both or neither model is rejected—but the j-tests on non-linear specifications often resolve these cases in favor of the non-internalization model.

Table 2 displays the cost coefficients for the linear specification of the internalization and non-internalization versions of Equation (28) along with the coefficients c_{h0} and c_{h1} from Equations (33) and (34). The j-tests for linear versions with pooled banks reject the internalizing specifications at every airport, while failing to reject the non-internalizing specification for arrivals the following airports: Boston, Baltimore-Washington, Cinncinatti, Washington National, Detroit, Newark, Dulles, Las Vegas, New York-Laguardia, Miami, Philadelphia, Pittsburgh, Seattle, San Francisco, Salt Lake City, and St Louis. For departures, the tests fail to reject the atomistic specification at: Atlanta, Baltimore-Washington, Cinncinatti, Detroit, Dulles, Las Vegas, New York-Laguardia, Memphis, Miami, Minneapolis-St Paul, Philadelphia, Pittsburgh, Seattle, Salt Lake City, and St Louis. Both the internalizing and non-internalizing models are rejected for either arrival or departures by the pooled linear j-tests at the remaining airports: Atlanta, Charlotte, Denver, New York-JFK, Los Angeles, Memphis, Miami, Minneapolis-St Paul, Chicago, and Pheonix. In many of these cases, while the coefficient on the internalizing model is significant, it is close to zero. The non-linear j-tests resolve many of these indeterminant cases by rejecting the internalizing model. For arrivals, the pooled, non-linear j-tests only reject the non-internalizing model for New York-JFK, Los Angeles, Memphis, Miami, Minneapolis-St Paul, Chicago, and Pheonix, and for departures only at Boston, Cinncinatti, Dallas, Houston, New York-JFK, and Pheonix.

In summary, the j-tests for specifications with common cost coefficients across banks within airports never unambiguously support the internalization model, while they do support the non-internalization model for about three-fifths of the airports in the linear versions and about three-quarters of the airports in the non-linear versions. Nevertheless, the non-internalizing model is rejected at several airports that are most often suggested as candidates for congestion pricing, namely Boston, Dallas, New York-JFK, Minneapolis-St Paul, and Chicago. As we show next, the bank specific j-tests show that flights operating during typical large interchange banks at nearly all the highly congested airports do not internalize delays.

Table 3 summarizes the j-test results for the bank-specific non-linear j-tests for all banks of fifteen or more aircraft. Of these banks, 188 or 54.6% reject internalizing behavior while failing to reject non internalizing behavior; 27 banks or 7.8% reject non internalizing behavior while failing to reject internalizing behavior; and 128 banks or 37.5% are inconclusive. Airports with a high percentage of non internalizing banks and little or no internalizing banks include: Atlanta, Charlotte, Washington National, Denver, Dallas, Detroit, Newark, Houston, New York-JFK, Minneapolis-St Paul, Chicago, Pittsburgh, San Francisco, and St Louis.[16] This list includes all the airports that are usually thought to be candidates for congestion pricing, except for Los Angeles and New York-LaGuardia. Congestion pricing that is limited to periods with large interchange banks at the listed airports would be an appropriate policy for reducing congestion and would only price otherwise uninternalized delays. Traffic at Los Angeles and New York-LaGuardia is atypical of large hub airports because it is more uniformly high relative to capacity than traffic at airports that have rapidly fluctuating traffic associated with serving connecting passengers. Los Angeles and New York-LaGuardia are more suited to flat rate landing fees designed to toll off excess traffic rather than optimize the scheduling of operations. We believe our j-test results constitute overwhelming evidence favoring the non internalizing specification for traffic data across a wide spectrum of the major US airports.

VI. CONCLUSION

This article seeks to answer two basic questions. First, is it sensible to believe that an airline with a dominant share of an airport's traffic would ignore the indirect delays its aircraft impose on one another? Second, assuming that airlines adjust their aircraft operating times to minimize (some measure of) queuing and schedule delay costs, is the data on the timing of individual aircraft operations by dominant airlines consistent with the minimization of all internal costs or only the aircraft's direct costs? We answer the first question by providing a theoretical model in which dominant airlines act as if they ignore their self-imposed delays. They can only exclude fringe aircraft from their peak periods by scheduling their aircraft preemptively as if they were fringe aircraft. The resulting (Stackleberg) equilibrium has less delay than a fully atomistic equilibrium because fringe aircraft have relatively lower schedule-delay cost and more readily shift off peak than dominant aircraft. The appropriate fee schedule is identical to that for an atomistic bottleneck equilibrium in which all aircraft have the fringe time costs. The answer to the second question is that our specification tests of alternative versions of the model fail to reject the hypothesis that dominant airlines behave consistently with the Stackleberg and atomistic equilibria at nearly all the major airports. The specification tests usually reject the internalization specification. The data also indicate that dominant aircraft operations tend to deter fringe aircraft from operating during the peak periods. Estimates of the cost coefficients reveal that dominant airlines act as if they have similar delay-time values as the fringe at many airports—while these coefficients vary across airports indicating that dominant aircraft adjust to local conditions rather than using their aircrafts' true time values.

So, what should be done? We argue that any policy to reduce airport congestion should be seen part of a system-wide effort to improve hub airline efficiency and promote inter-hub competition. The result of any airport congestion policy should be to allocate airport capacity in a way that recognizes that hub airlines generally have higher values of schedule delay than other aircraft operating at their hubs. Properly implemented, congestion pricing would improve flight connection times for airlines at their own hub airport, while imposing only minor scheduling delays (often less than 15 minutes) from their most preferred operating times at their non hub airports. We believe that hub-and-spoke networks will continue to be the core components of the national air-traffic network due to their economies of scale and scope. Some direct-service airlines will continue to "cream" high-density city-pair markets—but when older airlines finally shake off the high-cost legacies of the regulated era, the natural advantages of hub-and-spoke operations will prevail. Hub airlines should support congestion pricing as a means of reducing self-imposed congestion while pricing other airlines out of their periods of peak bank operations. This approach is pro-competitive because—while it strengthens the local hub—it means that other airlines will be able to provide more rapid connections at competing hubs. By improving connecting service, there would be more viable competition or potential competition in many origin-destination markets—putting downward pressure on fares. Direct-service airlines can operate during off-peak periods (by shifting their schedules slightly) and have lower landing fees than they would under the weight-based system, or they can operate during peak periods with higher fees but less delay. Since there are real resource savings from reduced delay, it is possible in principle to make all parties better off. The airport will have additional revenues with which to enhance capacity.

Our empirical analysis shows that large hub airline operations like those at Atlanta, Denver, Dallas, Detroit, Newark, Minneapolis-St Paul, Chicago, San Francisco, Salt Lake City, St Louis, and

Washington National generally have traffic patterns that are consistent with the bottleneck model.[17] While they sometimes show some small degree of internalization, it is limited to a few atypical banks. Most of these airports also exhibit evidence that dominant operations deter fringe operation during peak periods. These are the airports that are usually considered candidates for congestion pricing, and it appears safe to treat them as instances of Stackleberg equilibria in which dominant airlines apparently ignore the delays they impose on themselves. It follows that there is a significant role for congestion pricing in reducing delay at most US airports.

We leave the determination of equilibrium congestion prices for future research. The external delays used in our j-tests are calculated form the congestion function given the actual unpriced traffic rates and are not the equilibrium external delays under congestion pricing. Unlike the deterministic model, stochastic queuing systems have positive expected queues even when the traffic rate is below the capacity rate. Consequently, the deterministic result that optimal fees equal the monetary value of the queuing time that an aircraft with a given service-completion time would experience in the unpriced equilibrium does not hold for the stochastic model. Because it is impractical to totally eliminate stochastic queues, the endogenous traffic rates must balance some queuing costs against early- and late-time costs even in the priced equilibria. Daniel (1995) provides an algorithm for calculating the equilibrium arrival pattern for the stochastic model. A fully satisfactory treatment of system-wide congestion pricing also requires endogenizing traffic flows across airports as fees at highly congested airports shift aircraft to less-congested airports. Addressing these issues is beyond the scope of this paper.[18]

REFERENCES

Arnott, R., A. de Palma, and R. Lindsey. "Economics of a Bottleneck." *Journal of Urban Economics*, January 1990, Vol. 27(1), 111-130.

________, ________, and ________. "A Structural Model of Peak-Period Congestion: A Traffic Bottleneck with Elastic Demand," June 1992, Vol. 83(1), 161-179.

Brueckner, Jan K. "Airport Congestion When Carriers Have Market Power," *American Economic Review*, December 2002, 92(5), pp.1357-75.

Daniel, Joseph I., “Congestion Pricing and Capacity of Large Hub Airports: A Bottleneck Model with Stochastic Queues,” *Econometrica,* March 1995, 63(2), pp. 327-70.

________ and Pahwa, Munish “Comparison of Three Empirical Models of Airport Congestion Pricing,” *Journal of Urban Economics,* January 2000, 47(1), pp. 1-38.

Mayer, Christopher and Sinai, Todd “Network Effects, Congestion Externalities, and Air Traffic Delays: Or Why Not All Delays Are Evil,” *American Economic Review*, September 2003, 93(4), pp.1194-215.

Vickery, William S., “Congestion Theory and Transport Investment,” *American Economic Review,* May 1969 (Papers and Proceedings), 59(2), pp. 251-6.

Endnotes

---

[*] Daniel: Department of Economics, Purnell Hall, University of Delaware, Newark, DE 19716, (e-mail: Joseph.Daniel@verizon.net); Harback: Department of Economics, Purnell Hall, University of Delaware, Newark, DE 19716.

[1] Current delay estimates are from the FAA as published at http://www.bts.gov/help/aviation.html. This measure understates "delay" by excluding systematic congestion delay that carriers anticipate and build into their scheduled flight times. Projected delay costs are from a study by Global Insight and the Campbell-Hill Aviation Group published at http://www.boeing.com/news/releases/2002/q3/nr_020930d.html.

[2] Although the paper has been distributed as a working paper, it is currently under review and the author(s) request it not be cited.

[3] "FAA Targets O'Hare Airport Congestion; United, American Begin Cutting Flights" *Facts on File World News Digest,* September 9, 2004, p. 694B1.

[4] The symmetry of the arrival and departure bottlenecks is not perfect because arriving aircraft do not begin their layover time until they complete service, while departing aircraft end their layover time as soon as they join the takeoff queue.

[5] "Block" time refers to the elapsed time between removal of the aircraft wheel blocks just before push back from the departure gate and placement of the blocks around the wheels at the arrival gate. Block time is the period during which the aircraft engines are running and it is used to calculate crew compensation.

[6] Lower time-deviation costs of the fringe are an essential condition for the dominant airline to benefit from strategically pre-empting fringe traffic during its arrival and departure banks.

[7] Stackleberg and Atomistic equilibria are identical in the limiting case where the dominant airline has the same cost ratios as the fringe.

[8] The ratio of the dominant airline's early-time to queuing-time values can be less than twice as high as the non-dominant airlines if its ratio of late-time to queuing-time values is sufficiently more than twice as high—and vice versa.

[9] Thanks to Robert Hoffman and Julia Korey at Metron Aviation, and Dipasis Bhadra and Brendan Hogan at MITRE for assistance obtaining the data. The analysis in this article is solely that of the authors and does not represent the position of Metron Aviation or MITRE or its employees.

[10] Aircraft types depend on type of engine, number of engines, and weight.

[11] Small carriers are extremely important for consideration of airport level concentration because many of them code share with the large dominant carriers, meaning they operate coordinated schedules because of fare cross marketing arrangements.

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

[13] The complete mathematical specification of the queuing model is provided in Daniel (1995). We adopt the same specification.

[14] Values of t^* very early or late in the bank often result in incorrect signs on the time coefficients, indicating that if the t^* value was valid the airline does not trade off queuing time against schedule delays. Occasionally, these regressions resulted in the strongest rejection of the alternative hypothesis. In the few cases where there was no t^* consist with non internalization, or all values were equally bad, we chose the one with the highest R-squared. In the vast majority of cases, however, there was a clearly best value somewhere in the middle of the bank.

[15] There are at least three factors that could contribute to non-linear schedule delay costs. Aircraft with short schedule delays may cause disproportionately more problems for passengers connecting with other flights. With inhomogeneous aircraft, airlines should schedule aircraft with lower schedule delay costs further from the interchange. Passengers may be proportionately more adverse to long schedule delays.

[16] The non-linear specification significantly affects the j-test results at Atlanta, Denver, Detroit, and Chicago by increasing the rejection of the internalizing specification. The other airports are not greatly affected by inclusion of squared schedule delay terms. Results of the linear specification are available from the authors upon request.

[17] Two notable exceptions, New York (JFK) and Boston, yield inconclusive results. Neither of these is dominated by a hub-and-spoke airline and their traffic patterns appear more typical of purely atomistic aircraft without the distinct peaking caused by coordinated banks of flights.

[18] Note to editors and referees: We can include the optimal congestion prices for all the airports given the existing demand and network traffic patterns, if you think it strengthens the paper. Since we sought to focus on the internalization issue, and the paper is already long, we felt it better to include these results in an upcoming paper on system-wide congestion pricing and optimal capacity of US airports.

Figure 1—Cumulative Atomistic, Stackleberg, and Nash arrivals and service completions

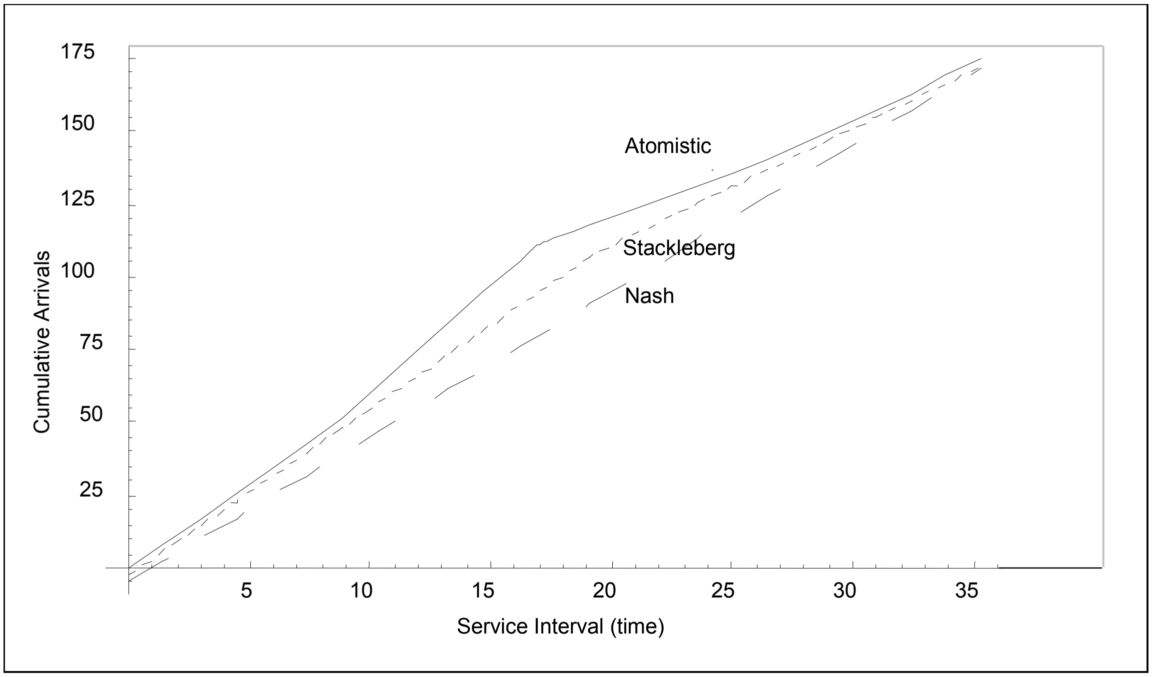


Figure 2—Atomistic, Stackleberg, and Nash arrival rates

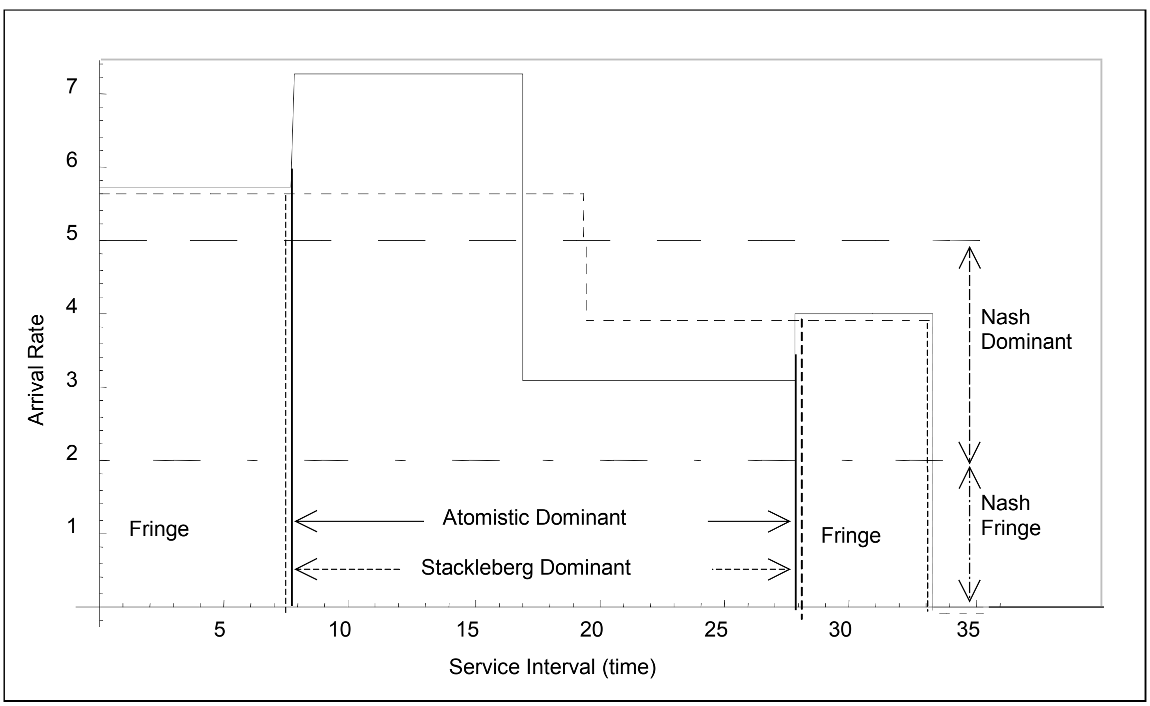


Figure 3—Atomistic and Stackleberg queue lengths

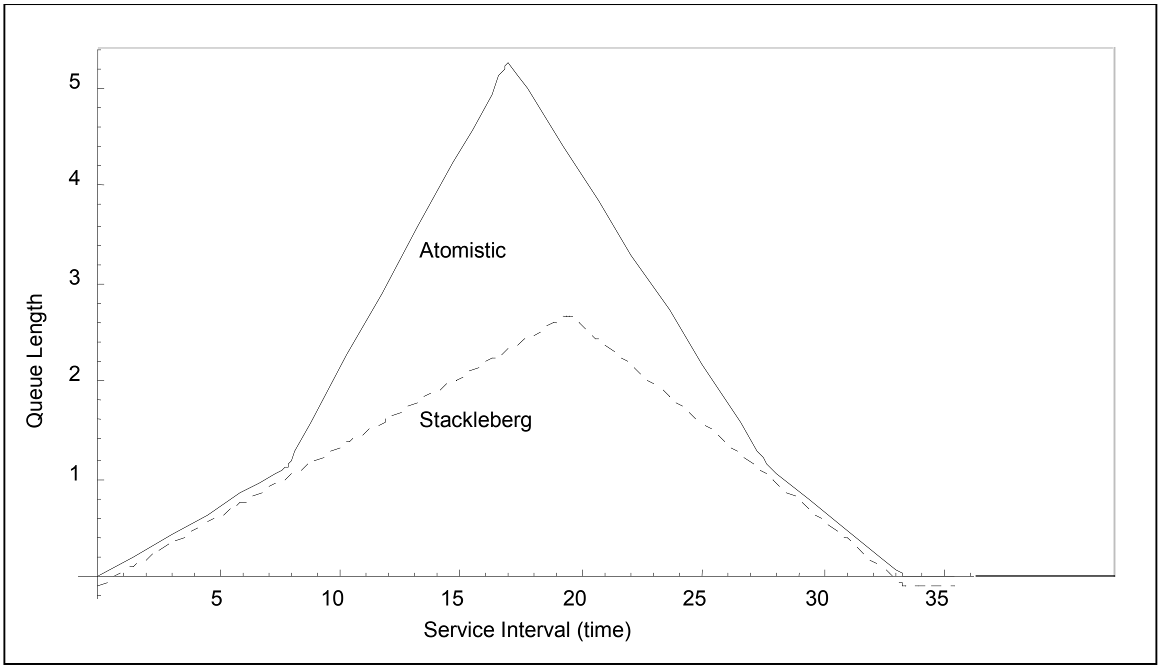


Figure 4—Atomistic and Stackleberg congestion fee schedules

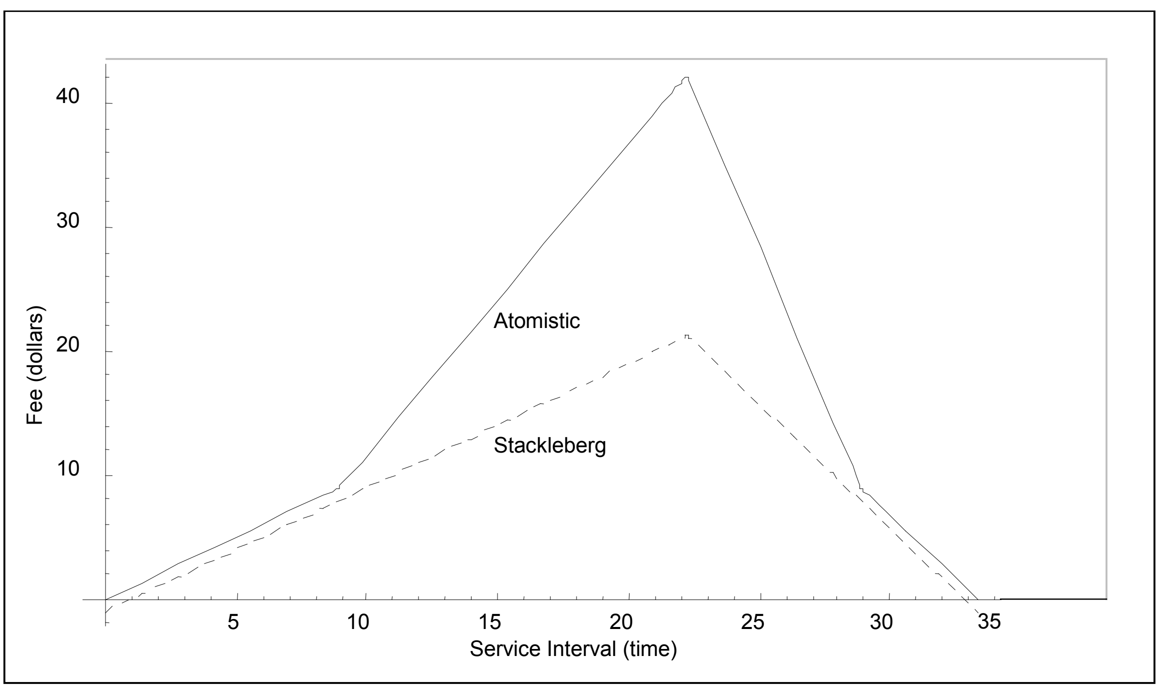


Figure 5--Examples of Arrival Rates and Delay Data by Minute of the Day

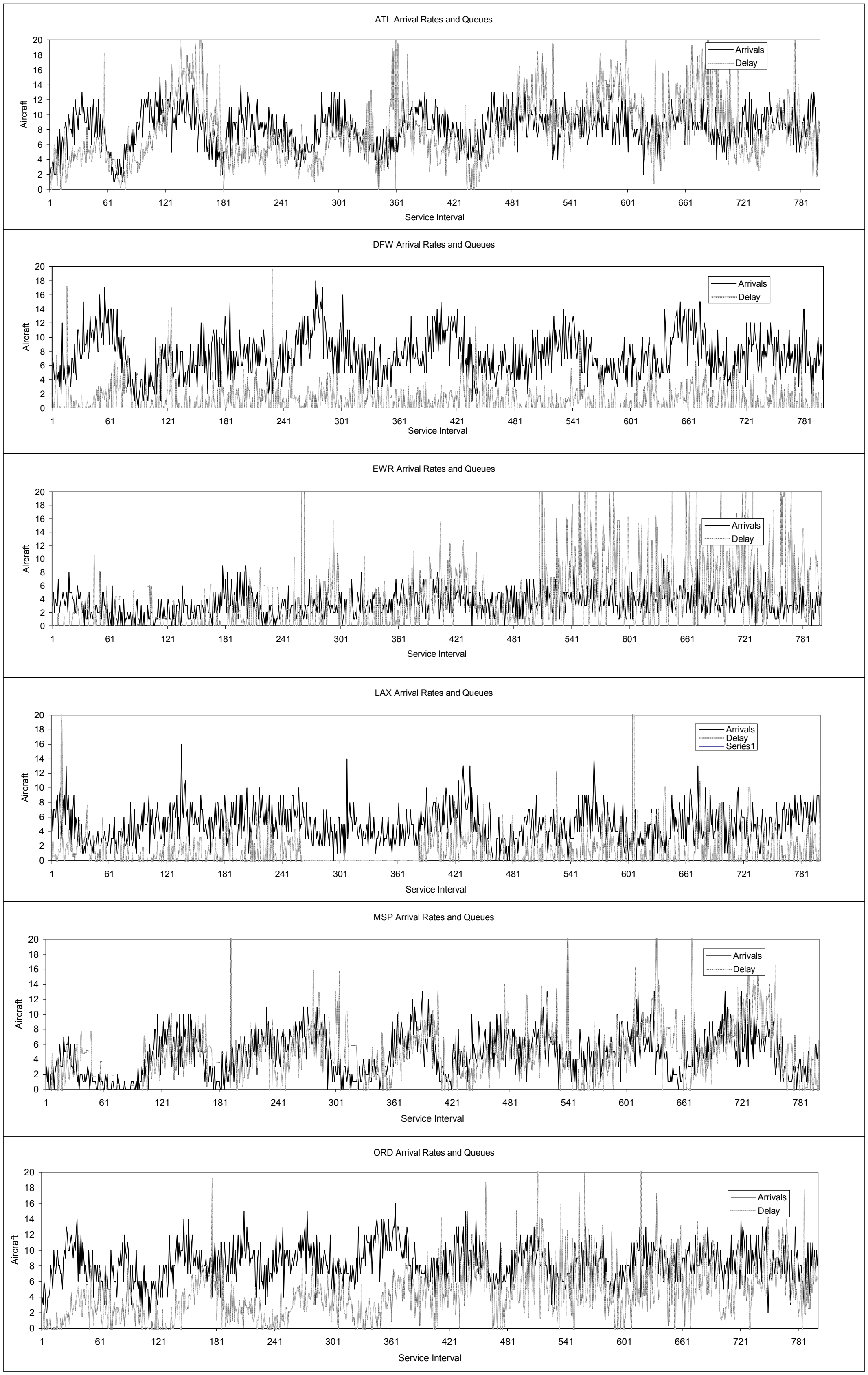
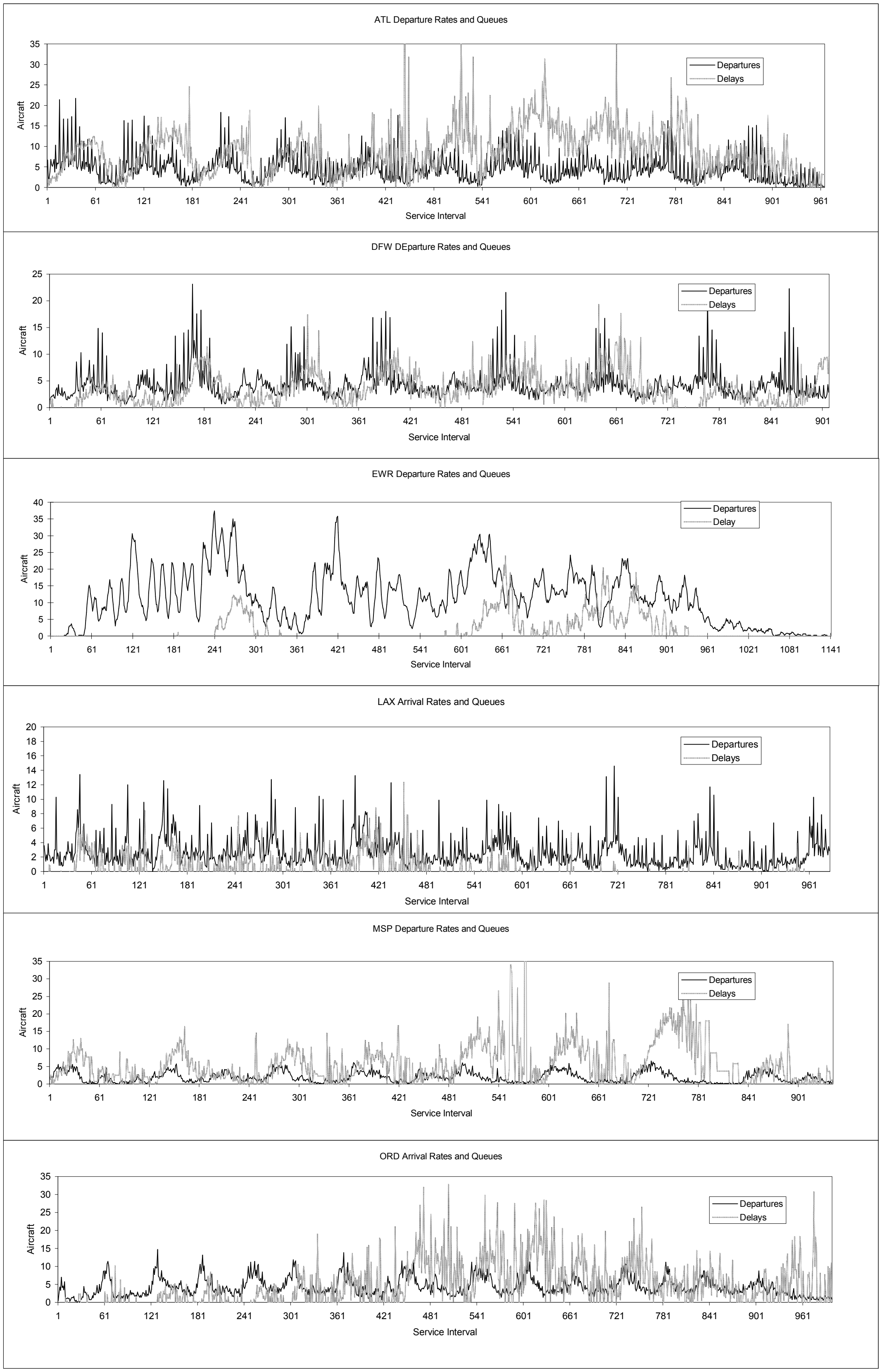
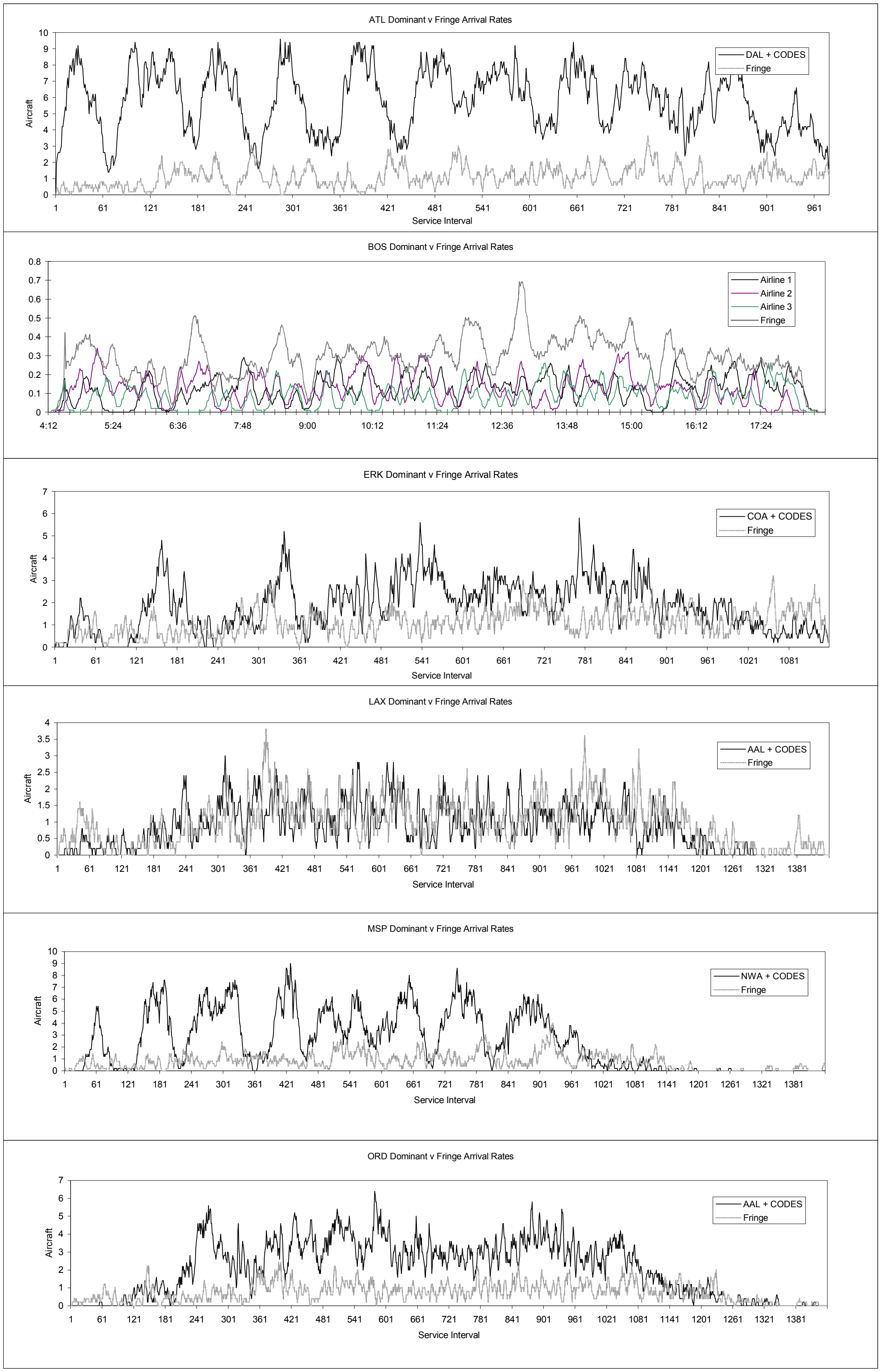


Figure 6--Examples of Departure Rates and Delay Data by Minute of the Day



Firgure 7--Selected Arrival Rates of Dominant and Fringe Airlines



Firgure 8--Selected Departure Rates of Dominant and Fringe Airlines

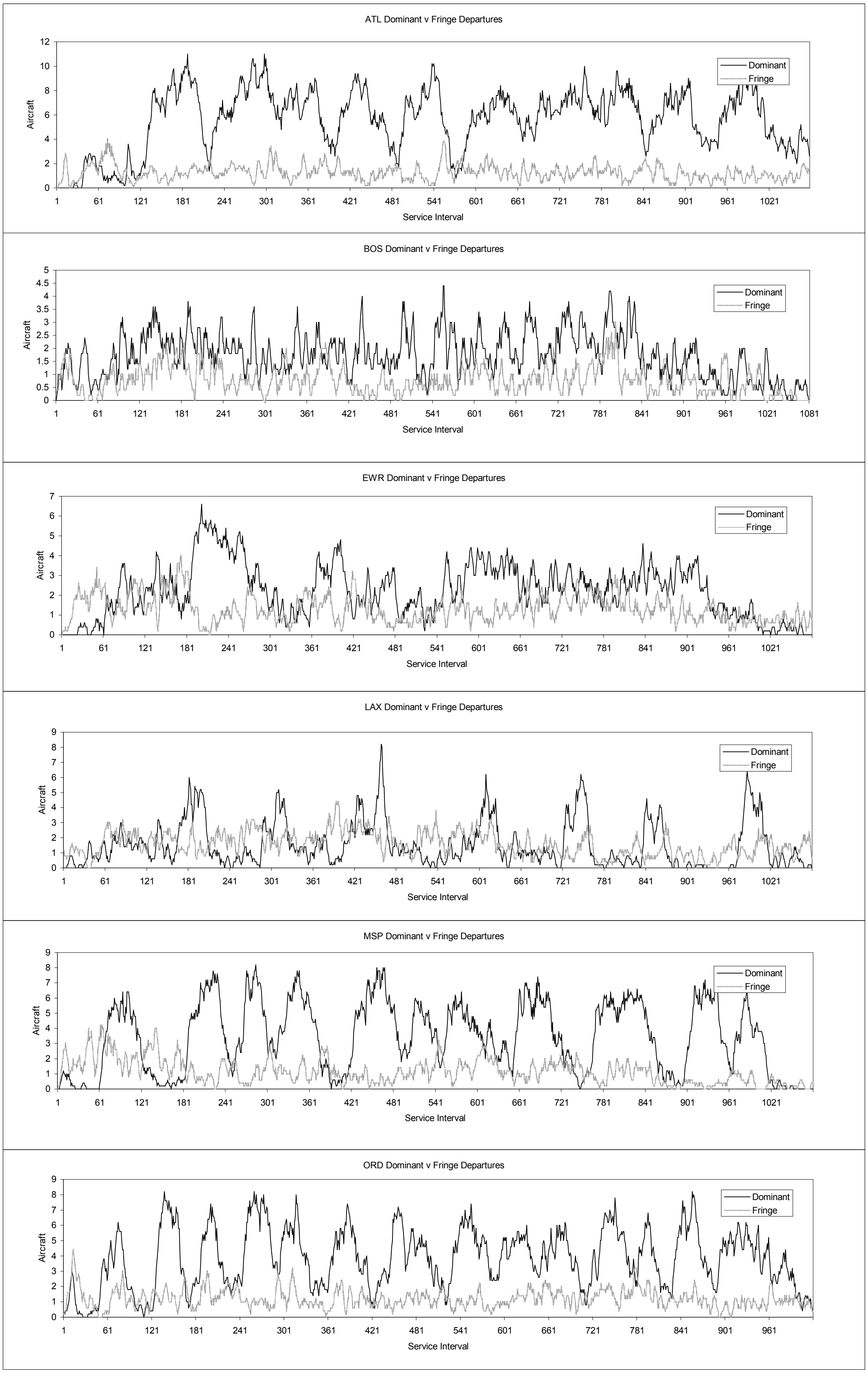


Figure 9--Examples of Delay Data by Minute of the Day, Compared with Delay from Queueing Model

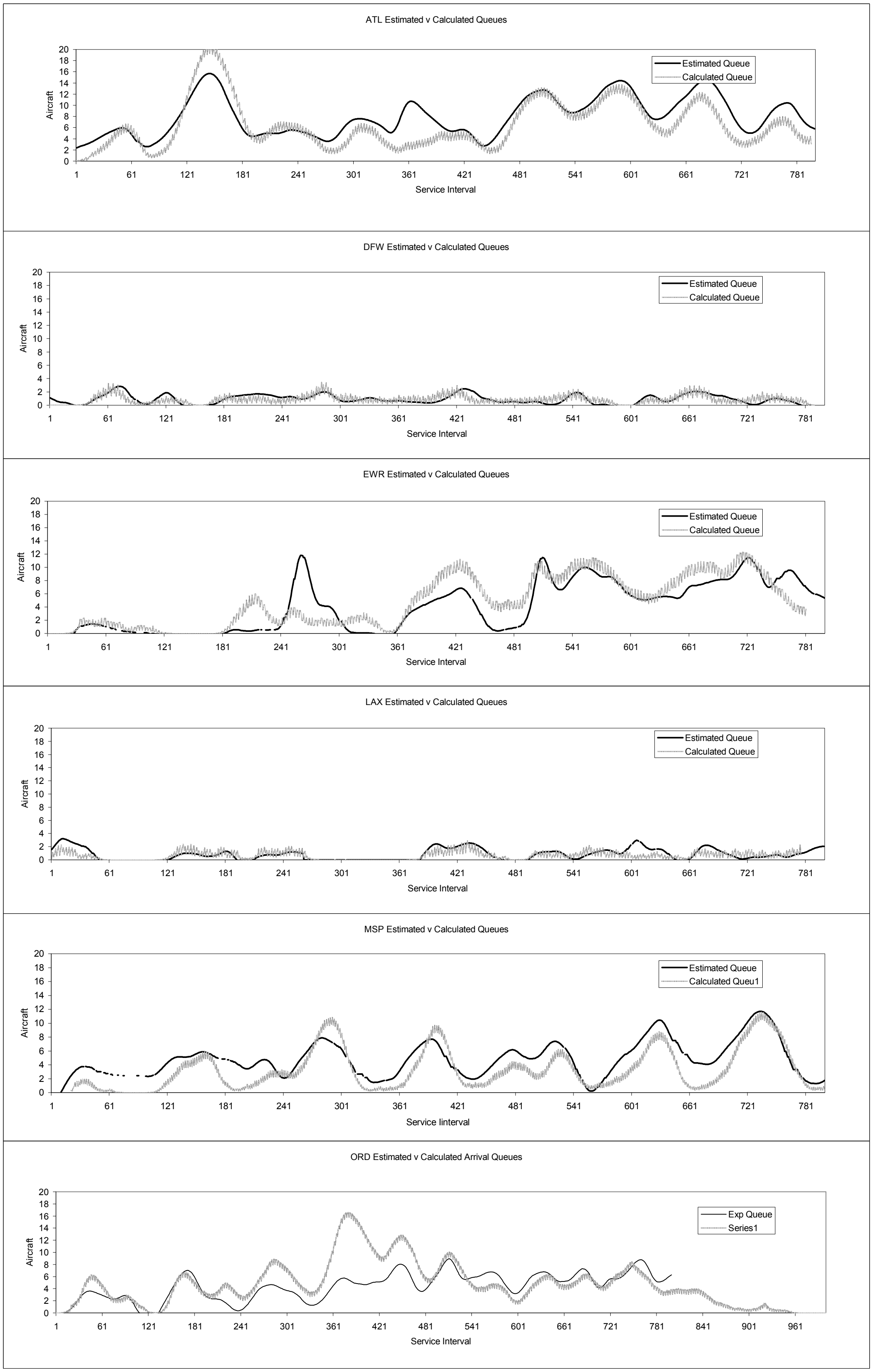


Figure 10--Examples of Delay Data by Minute of the Day, Compared with Delay from Queueing Model

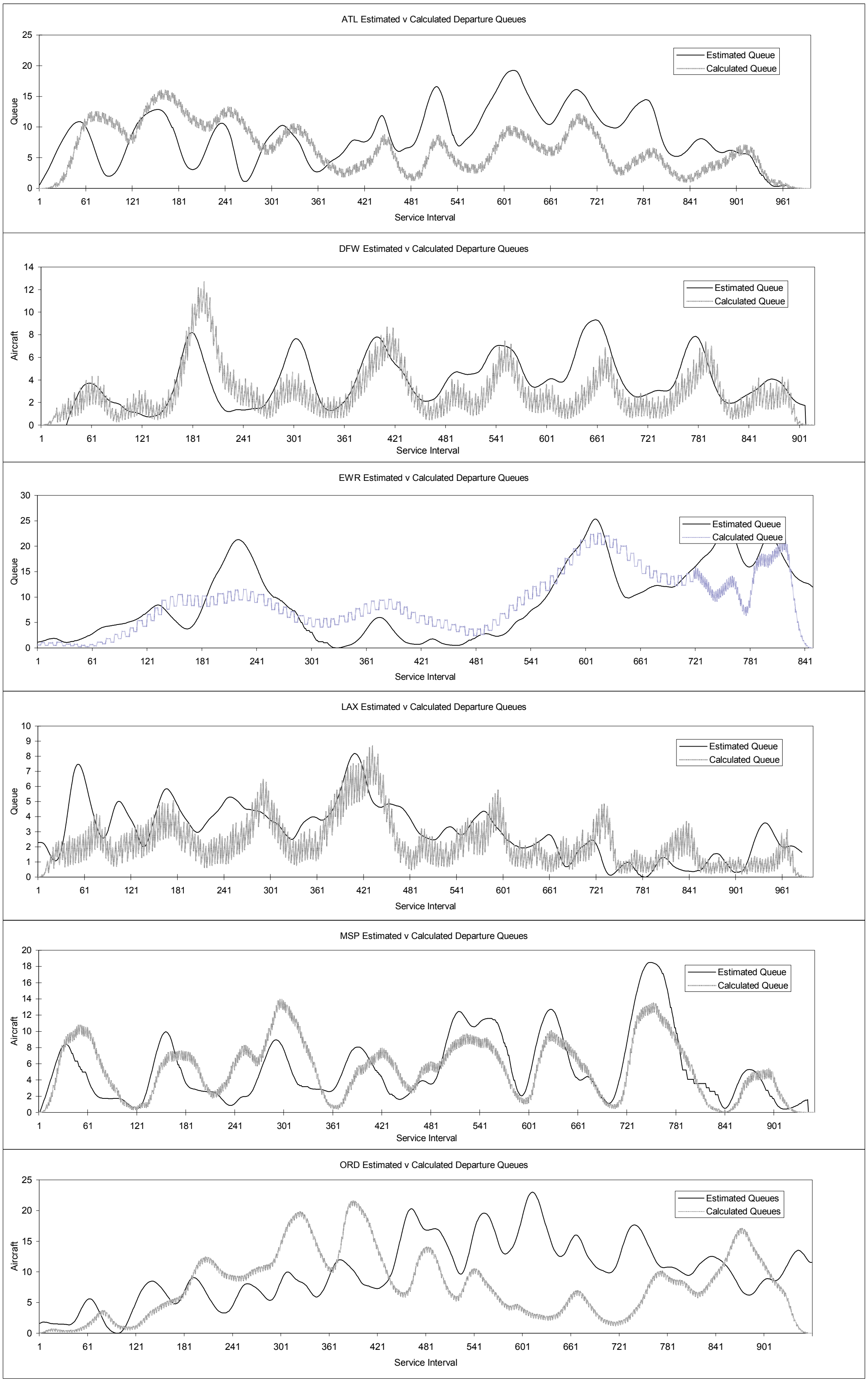


Table 1--Airport Concentration, Airline Shares, Dominant v Fringe Traffic Correlation, Cost Ratios

Airport	HHI	Carrier	Dominant Share	Fringe share of capacity	Dominant v Fringe Arrivals Correlation	Dominant v Fringe Departures Correlation	1/Ce+1/Cl	Cost ratio--Equals 1 for Stackleberg behvior
ATL	5036	DAL	70.8	0.217	**-0.098**	**-0.076**	11.53	1.00
BOS	816	AAL	20.8	0.389	0.023	**-0.155**	-86.46	1.21
		USA	14.5		0.059	**-0.116**	-64.28	0.90
		UAL	13.2		-0.024	**-0.142**	-150.77	2.11
BWI	1626	SWA	39.1	0.378	-0.030	**-0.127**	39.60	0.90
CLT	5640	USA	74.9	0.089	**-0.041**	-0.015	17.51	0.86
CVG	5059	DAL	69.9	0.112	0.029	-0.001	16.63	0.73
DCA	2513	USA	42.9	0.204	-0.019	-0.001	47.29	0.96
		DAL	18.7		-0.004	**-0.081**	45.98	0.94
		AAL	16.6		0.001	-0.064	50.24	1.03
DEN	2907	UAL	50.4	0.128	**-0.048**	**-0.134**	18.71	0.91
DFW	4560	AAL	63.6	0.068	-0.016	**-0.052**	43.87	0.91
		DAL	22.5		**-0.048**	**-0.083**	41.30	0.85
DTW	5609	NWA	74.6	0.091	**-0.042**	**-0.113**	25.35	0.99
ERW	3748	COA	59.9	0.182	-0.031	**-0.174**	16.76	1.07
IAD	2500	UAL	49.4	0.112	**-0.064**	**-0.145**	25.02	0.80
IAH	5843	COA	76.4	0.060	**-0.034**	**-0.071**	13.49	0.98
JFK	1494	JBU	20	0.564	0.033	-0.013	10.96	0.96
		AAL	28.5		0.010	-0.011	11.73	1.03
		DAL	16.8		0.014	-0.022	11.53	1.01
LAS	1441	SWA	32.1	0.193	**-0.064**	**-0.232**	47.34	1.04
		AWE	16.4		-0.063	-0.075	38.91	0.81
LAX	1882	UAL	31.6	0.158	0.030	**-0.071**	39.47	1.00
		AAL	24.6		-0.050	0.034	42.29	1.02
		SWA	14.6		**-0.124**	**0.114**	42.26	1.02
LGA	1978	AAL	21.7	0.353	-0.01	-0.053	45.98	1.00
		DAL	21.4		-0.01	**-0.085**	43.87	0.95
		USA	32.4		0.02	**-0.111**	51.48	1.12
MEM	2816	NWA	44.0	0.06	-0.020	**-0.059**	20.16	0.63
MIA	2703	AAL	49.3	0.159	-0.018	**-0.065**	33.08	0.87
		UAL	14.0		0.008	-0.024		
MSP	5488	NWA	73.9	0.109	**-0.057**	-0.030	11.95	1.04
ORD	3775	UAL	48.3	0.074	**-0.086**	**-0.038**	19.80	0.94
		AAL	37.8		**-0.100**	**-0.049**	20.39	1.00
PHL	3747	USA	60.6	0.150	-0.035	**-0.120**	14.41	0.89
PHX	2796	SWA	26.0	0.100	0.054	**-0.103**	22.79	0.99
		AWE	45.0		-0.015	**-0.170**	22.55	0.93
PIT	5775	USA	75.8	0.069	0.007	**-0.081**	27.32	0.90
SEA	5591	DAL	74.8	0.172	-0.026	**-0.169**	33.65	-1.63
SFO	3083	UAL	54.7	0.196	-0.042	**-0.119**	25.80	0.87
SLC	4424	DAL	65.9	0.113	**-0.033**	**-0.068**	17.00	1.08
		SWA	8.5		**-0.102**	-0.010		
STL	5032	AAL	69.8	0.121	**-0.032**	-0.028	14.81	0.96

Bold denotes significance at 95% level.

Table 2--J-Tests of Atomistic and Interalizing Behavioral Hypotheses, Flight Banks Pooled by Airport

	Atomistic Model					Internalizing Model				
	Early	Late	R-Squared/ Observations	Internalizing J-Test Coefficient	Significant in non-linear model?	Early	Late	R-Squared/ Observations	Atomistic J-Test Coefficient	in non-linear model?
Atlanta										
Arrivals	-0.105	-0.162	0.8353	***0.061***	no	-0.053	-0.118	0.9212	***0.953***	yes
	0.010	0.018	486	0.017		0.003	0.006	486	0.016	
Departures	0.290	0.010	0.9895	-0.026	no	-0.083	-0.089	0.9464	***1.029***	yes
	0.005	0.020	846	0.011		0.004	0.006	846	0.008	
Boston										
Arrivals	-0.064	-0.027	0.9411	-0.182	no	-0.040	-0.024	0.9381	1.182	yes
	0.011	0.005	237	0.117		0.009	0.004	237	0.117	
Departures	0.080	0.083	0.9232	*0.389*	yes	-0.029	-0.011	0.8445	*0.888*	yes
	0.013	0.012	132	0.092		0.010	0.011	132	0.081	
Baltimore/Washington										
Arrivals	-0.016	0.006	0.7871	-0.712	no	-0.008	-0.001	0.7624	1.711	yes
	0.014	0.006	112	0.122		0.009	0.004	112	0.121	
Departures	0.006	-0.012	0.9275	-0.292	no	0.000	-0.050	0.8915	*1.245*	yes
	0.020	0.018	131	0.071		0.009	0.017	131	0.062	
Charlotte										
Arrivals	-0.135	-0.212	0.8481	***0.051***	no	-0.073	-0.120	0.8408	***0.962***	yes
	0.019	0.015	400	0.024		0.007	0.007	400	0.023	
Departures	-0.023	-0.275	0.9297	***0.095***	no	-0.073	-0.064	0.8608	***0.906***	yes
	0.033	0.024	212	0.026		0.009	0.015	212	0.026	
Cinncinatti										
Arrivals	-0.068	-0.097	0.7307	-1.040	no	-0.065	-0.137	0.7375	2.037	yes
	0.012	0.015	452	0.110		0.010	0.014	452	0.107	
Departures	0.316	-0.051	0.9211	-0.031	yes	-0.085	-0.070	0.848	***1.066***	yes
	0.017	0.041	294	0.023		0.012	0.020	294	0.019	
Washington National										
Arrivals	-0.002	-0.032	0.9125	-0.061	no	-0.052	-0.027	0.9026	*1.114*	yes
	0.009	0.007	160	0.106		0.015	0.005	160	0.096	
Departures	1.815	1.516	0.9893	***0.046***	no	-0.067	-0.397	0.9756	***0.959***	yes
	0.123	0.037	175	0.007		0.022	0.044	175	0.006	
Denver										
Arrivals	-0.117	-0.107	0.901	*0.153*	no	-0.079	-0.044	0.8906	*1.022*	yes
	0.016	0.019	347	0.051		0.010	0.011	347	0.051	
Departures	-0.210	-0.232	0.9402	***0.091***	no	-0.098	-0.022	0.8824	***0.909***	yes
	0.022	0.018	192	0.035		0.010	0.008	192	0.035	
Dallas/Ft. Worth										
Arrivals	-0.018	-0.026	0.8931	***0.067***	no	0.001	-0.020	0.8231	***0.939***	yes
	0.006	0.004	453	0.047		0.004	0.003	453	0.047	
Departures	0.058	0.131	0.9146	***0.146***	yes	-0.032	0.007	0.7306	***0.946***	yes
	0.007	0.005	639	0.022		0.004	0.006	639	0.018	
Detroit										
Arrivals	-0.143	-0.079	0.8463	-0.039	no	-0.085	-0.066	0.8888	***1.040***	yes
	0.016	0.013	360	0.028		0.008	0.005	360	0.028	
Departures	0.316	-0.051	0.9211	-0.031	no	-0.085	-0.070	0.848	***1.066***	yes
	0.017	0.041	294	0.023		0.012	0.020	294	0.019	
Newark										
Arrivals	-0.596	-0.112	0.9264	-0.023	no	-0.097	-0.077	0.9738	***1.023***	yes
	0.039	0.020	241	0.022		0.007	0.007	241	0.022	
Departures	1.815	1.516	0.9893	***0.046***	no	-0.067	-0.397	0.9756	***0.959***	yes
	0.123	0.037	175	0.007		0.022	0.044	175	0.006	
Washington/Dulles										
Arrivals	-0.098	-0.058	0.8027	-0.337	no	-0.101	-0.101	0.863	*1.295*	yes
	0.018	0.015	196	0.088		0.011	0.012	196	0.069	
Departures	0.282	-0.296	0.9317	*0.034*	no	-0.012	-0.143	0.8854	*0.994*	yes
	0.068	0.065	66	0.068		0.025	0.031	66	0.064	
Houston										
Arrivals	-0.172	0.026	0.8155	***0.004***	no	-0.178	-0.101	0.8901	***0.998***	yes
	0.029	0.025	395	0.022		0.010	0.009	395	0.019	
Departures	-0.043	-0.254	0.9483	***0.371***	yes	-0.131	-0.308	0.8208	***0.765***	yes
	0.035	0.025	259	0.041		0.022	0.042	259	0.035	
New York/JFK										
Arrivals	-0.249	0.015	0.942	*0.747*	yes	-0.071	-0.009	0.8904	0.779	yes
	-0.051	0.013	227	0.083		0.016	0.018	227	0.131	
Departures	-0.065	-0.103	0.9584	*0.498*	yes	-0.065	0.049	0.8901	*0.619*	yes
	0.017	0.021	143	0.080		0.016	0.026	143	0.082	

Italics indicate significance at 90% and bold indicates significance at 95% confidence levels. P-values shown below coefficients.

Table 2--Continued

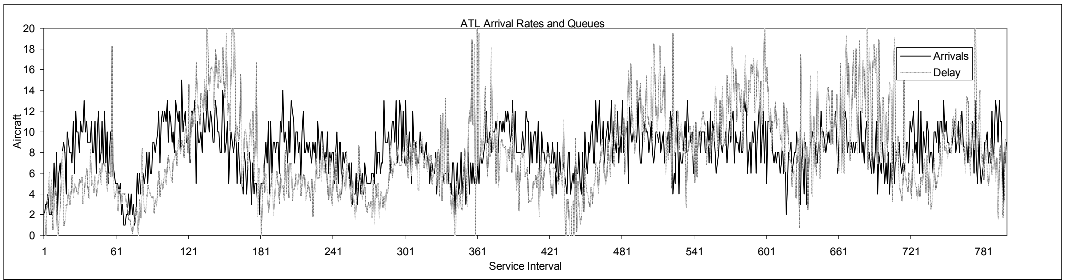
Las Vegas										
Arrivals	-0.023	0.016	0.8786	-0.210	no	-0.009	0.030	0.8606	*1.241*	yes
	0.013	0.012	194	0.053		0.006	0.009	194	0.050	
Departures	0.049	-0.024	0.6562	-0.629	no	-0.008	-0.089	0.6789	1.701	yes
	0.011	0.011	152	0.191		0.006	0.011	152	0.104	
Los Angeles										
Arrivals	-0.050	-0.018	0.8873	*0.062*	yes	-0.007	-0.025	0.8708	*1.004*	yes
	0.010	0.005	213	0.095		0.004	0.006	213	0.082	
Departures	-0.051	0.091	0.8348	***0.059***	no	-0.042	-0.039	0.8368	***1.016***	yes
	0.013	0.011	295	0.036		0.006	0.007	295	0.027	
New York/LGA										
Arrivals	-0.026	0.000	0.8952	-0.477	no	-0.004	-0.006	0.9163	*1.494*	yes
	0.009	0.005	154	0.089		0.003	0.005	154	0.086	
Departures	0.215	0.056	0.9516	-0.281	no	-0.047	0.031	0.9546	***1.256***	yes
	0.029	0.034	171	0.044		0.009	0.018	171	0.027	
Memphis										
Arrivals	-0.246	-0.087	0.9219	***0.389***	yes	-0.212	-0.079	0.9443	***0.891***	yes
	0.019	0.058	161	0.048		0.013	0.020	161	0.036	
Departures	0.198	-0.154	0.8611	-0.042	no	-0.060	0.034	0.7733	***1.070***	yes
	0.031	0.043	93	0.048		0.019	0.015	93	0.038	
Miami										
Arrivals	-0.208	-0.093	0.8666	*0.085*	yes	-0.073	-0.081	0.8918	*0.963*	yes
	0.044	0.038	95	0.066		0.015	0.021	95	0.058	
Departures	-0.197	-0.176	0.9333	-0.107	no	-0.037	0.033	0.8856	***1.120***	yes
	0.027	0.028	165	0.042		0.011	0.016	165	0.038	
Minneapolis										
Arrivals	-0.128	-0.128	0.8568	***0.057***	yes	-0.101	-0.163	0.919	***0.990***	yes
	0.009	0.012	466	0.029		0.005	0.007	466	0.026	
Departures	0.011	-0.319	0.904	-0.113	no	-0.092	-0.113	0.9428	***1.114***	yes
	0.032	0.030	328	0.010		0.006	0.009	328	0.010	
Chicago										
Arrivals	-0.114	0.004	0.9076	***0.162***	yes	-0.082	-0.057	0.9041	***0.857***	yes
	0.023	0.026	303	0.029		0.013	0.013	303	0.028	
Departures	-0.202	-0.294	525	***0.006***	no	-0.026	-0.180	0.9478	***1.003***	yes
	0.027	0.019	525	0.020		0.007	0.015	525	0.016	
Philadelphia										
Arrivals	-0.085	-0.109	0.7634	-0.013	no	-0.080	-0.095	0.8906	***1.017***	yes
	0.020	0.020	134	0.059		0.009	0.008	134	0.046	
Departures	-0.110	-0.376	0.8606	-0.039	no	-0.056	-0.090	0.7787	***1.100***	yes
	0.086	0.040	168	0.036		0.016	0.020	168	0.024	
Pheonix										
Arrivals	-0.075	-0.087	0.9124	0.299	yes	-0.035	-0.045	0.8836	0.889	yes
	0.010	0.011	171	0.103		0.008	0.008	171	0.109	
Departures	-0.254	-0.271	0.9582	***0.061***	yes	-0.052	-0.078	0.9336	***0.957***	yes
	0.044	0.015	191	0.034		0.009	0.009	191	0.031	
Pittsburgh										
Arrivals	-0.072	-0.068	0.8075	-0.076	no	-0.034	-0.017	0.8781	***1.116***	yes
	0.018	0.026	87	0.062		0.011	0.007	87	0.047	
Departures	-0.191	-0.214	0.8586	-0.044	no	-0.025	0.019	0.8247	***1.068***	yes
	0.022	0.033	97	0.041		0.013	0.007	97	0.035	
Seattle										
Arrivals	-0.009	-0.003	0.9289	-0.030	no	0.001	-0.004	0.8945	1.161	yes
	0.002	0.002	286	0.104		0.001	0.002	286	0.108	
Departures	0.027	0.034	0.9067	-0.079	no	-0.013	-0.025	0.8609	***1.140***	yes
	0.031	0.012	135	0.052		0.006	0.009	135	0.039	
San Fransisco										
Arrivals	-0.178	-0.040	0.849	-0.051	no	-0.035	-0.045	0.9059	***1.058***	yes
	0.031	0.019	207	0.035		0.008	0.008	207	0.032	
Departures	-0.060	-0.194	0.9069	***0.046***	no	-0.052	-0.048	0.9316	***0.971***	yes
	0.032	0.028	106	0.034		0.008	0.009	106	0.029	
Salt Lake City										
Arrivals	-0.054	-0.040	0.7895	-0.295	no	-0.032	-0.033	0.8318	*1.267*	yes
	0.025	0.036	89	0.089		0.015	0.016	89	0.085	
Departures	-0.049	-0.141	0.877	-0.113	no	-0.025	-0.069	0.8851	***1.124***	yes
	0.031	0.023	88	0.045		0.009	0.020	88	0.043	
St. Louis										
Arrivals	-0.058	-0.124	0.6996	-0.483	no	-0.025	-0.074	0.6666	*1.476*	yes
	0.018	0.020	350	0.057		0.010	0.014	350	0.057	
Departures	-0.458	-0.420	0.9559	-0.006	no	-0.083	-0.176	0.9398	***1.024***	yes
	0.062	0.018	188	0.030		0.010	0.013	188	0.028	

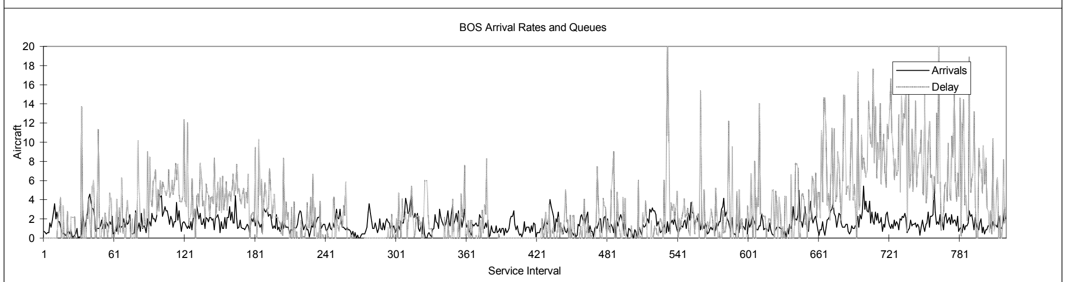
Italics indicate significance at 90% and bold indicates significance at 95% confidence levels. P-values shown below coefficients.

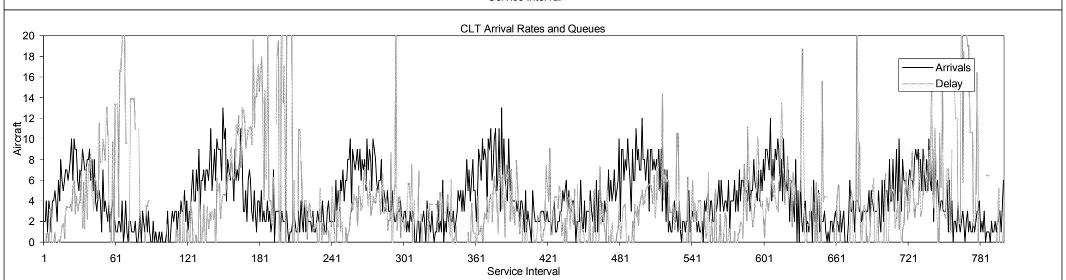
Table 3--Summary of J-test Results for Individual Arrival and Departure Banks with Non-linear Schedule Delay Effects

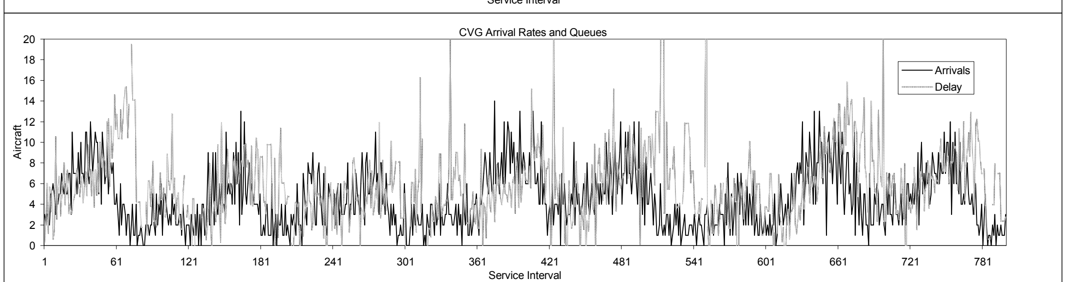
	Arrivals				Departures			
	# of Banks	% Atomistic	% Internalizing	% Inconclusive	# of Banks	% Atomistic	% Internalizing	% Inconclusive
ATL	**11**	**63.6**	**0.0**	**36.4**	**10**	**50.0**	**0.0**	**50.0**
BOS	6	66.7	33.3	0.0	2	0.0	50.0	50.0
BWI	2	50.0	0.0	50.0	3	33.3	66.7	0.0
CLT	**9**	**66.7**	**0.0**	**33.3**	**7**	**85.7**	**14.3**	**0.0**
CVG	9	66.7	11.1	22.2	6	16.7	33.3	50.0
DCA	**9**	**44.4**	**0.0**	**55.6**	**3**	**66.7**	**0.0**	**33.3**
DEN	**9**	**66.7**	**11.1**	**22.2**	**8**	**87.5**	**11.1**	**1.4**
DFW	**9**	**88.9**	**0.0**	**11.1**	**8**	**37.5**	**0.0**	**62.5**
DTW	**11**	**54.5**	**0.0**	**45.5**	**9**	**66.7**	**0.0**	**33.3**
EWR	**9**	**88.9**	**0.0**	**11.1**	**7**	**85.7**	**0.0**	**14.3**
IAD	5	60.0	20.0	20.0	2	0.0	50.0	50.0
IAH	**8**	**62.5**	**12.5**	**25.0**	**8**	**50.0**	**12.5**	**37.5**
JFK	**6**	**50.0**	**0.0**	**50.0**	**4**	**75.0**	**0.0**	**25.0**
LAS	6	20.0	0.0	80.0	5	0.0	20.0	80.0
LAX	4	0.0	0.0	100.0	7	42.9	0.0	57.1
LGA	1	0.0	100.0	0.0	5	60.0	20.0	20.0
MEM	5	20.0	20.0	60.0	5	40.0	0.0	60.0
MIA	3	33.3	0.0	66.7	6	33.3	0.0	66.7
MSP	**11**	**81.8**	**0.0**	**18.2**	**8**	**50.0**	**0.0**	**50.0**
ORD	**11**	**81.8**	**9.1**	**9.1**	**12**	**41.7**	**8.3**	**50.0**
PHL	5	40.0	20.0	40.0	9	33.3	0.0	66.7
PHX	7	28.6	14.3	57.1	9	66.7	11.1	22.2
PIT	**1**	**100.0**	**0.0**	**0.0**	**3**	**100.0**	**0.0**	**0.0**
SEA	10	10.0	10.0	80.0	3	0.0	0.0	100.0
SFO	**6**	**83.3**	**0.0**	**16.7**	**2**	**50.0**	**50.0**	**0.0**
SLC	0	--	--	--	2	50.0	50.0	0.0
STL	**9**	**77.8**	**11.1**	**11.1**	**9**	**77.8**	**11.1**	**11.1**
	182	58.2	7.1	34.6	162	51.6	8.8	39.6

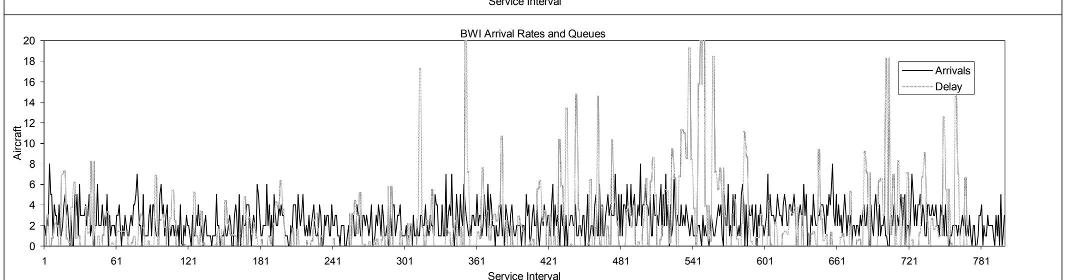
Bold denotes strong candidate for atomistic congestion pricing.

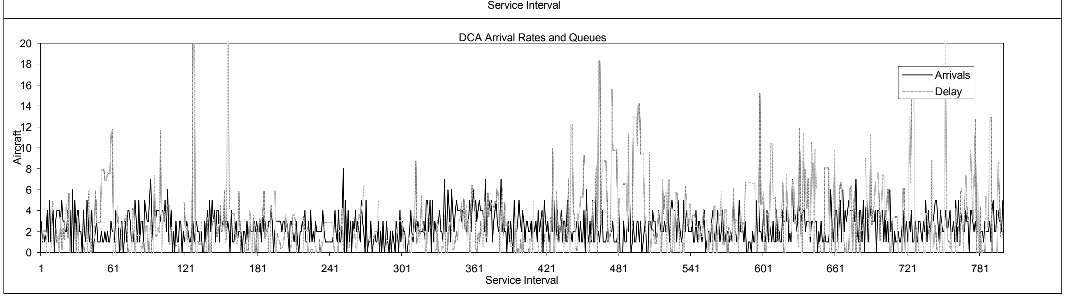

ATL Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

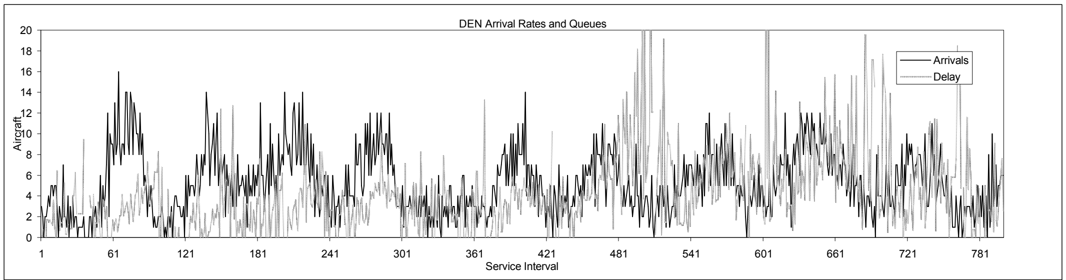

BOS Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

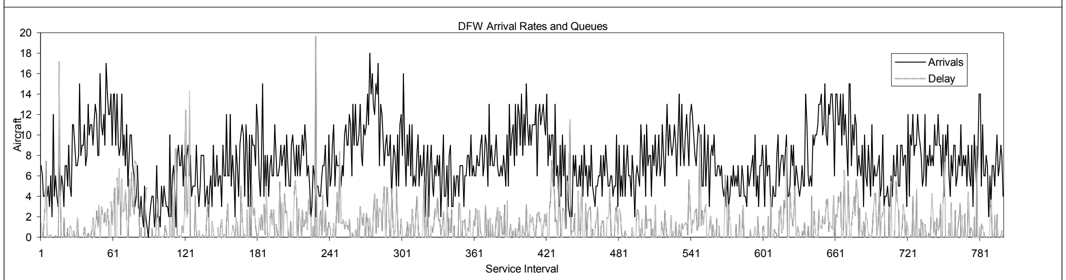

CLT Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

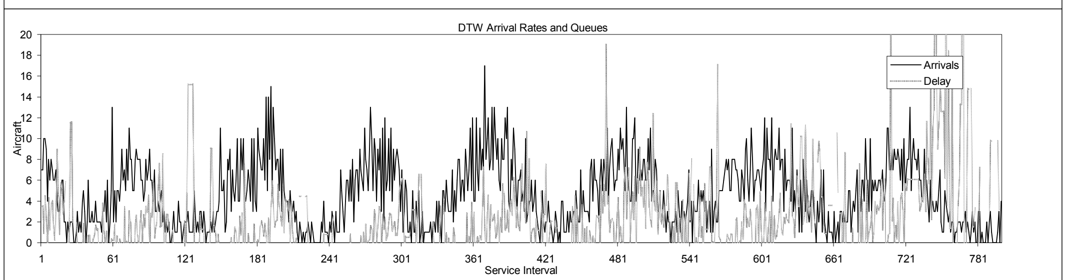

CVG Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

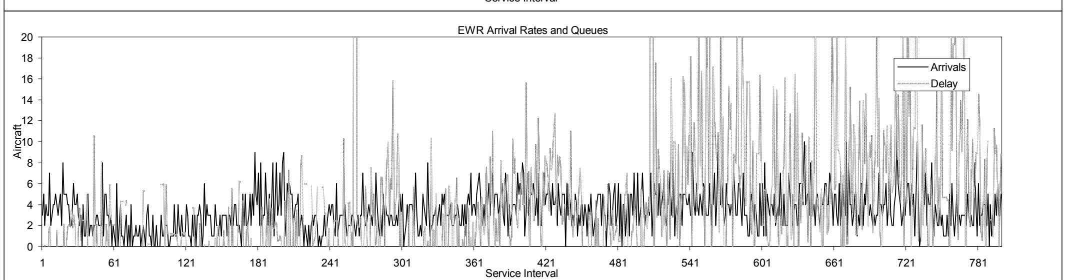

BWI Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

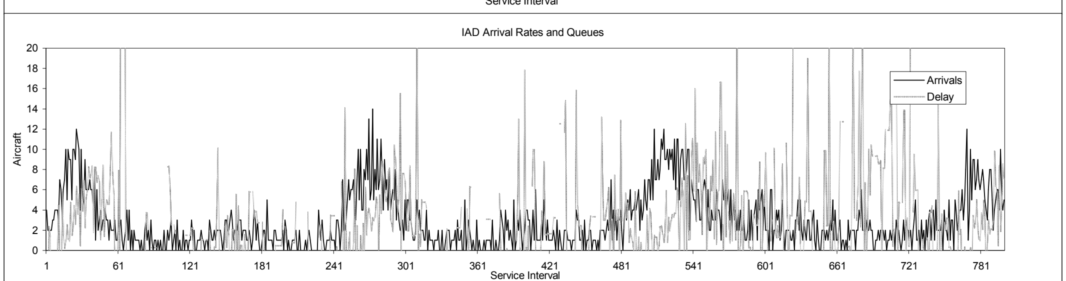

DCA Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

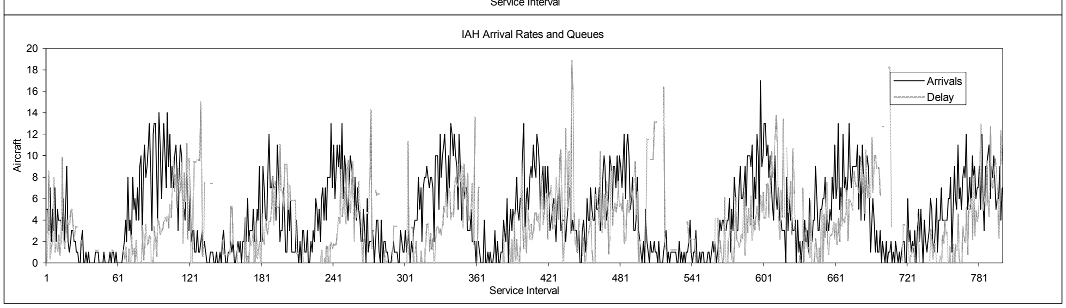

DEN Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

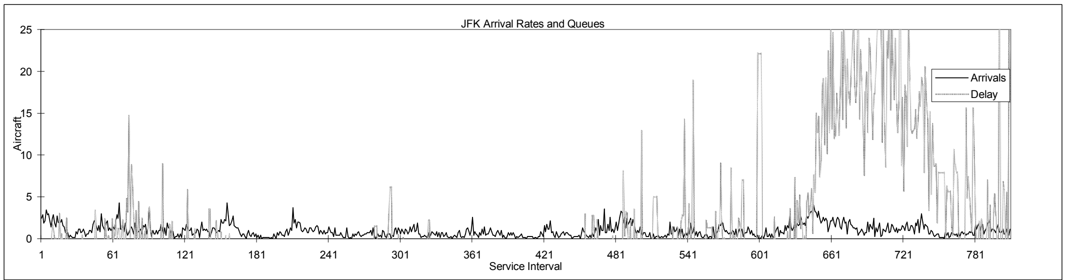

DFW Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

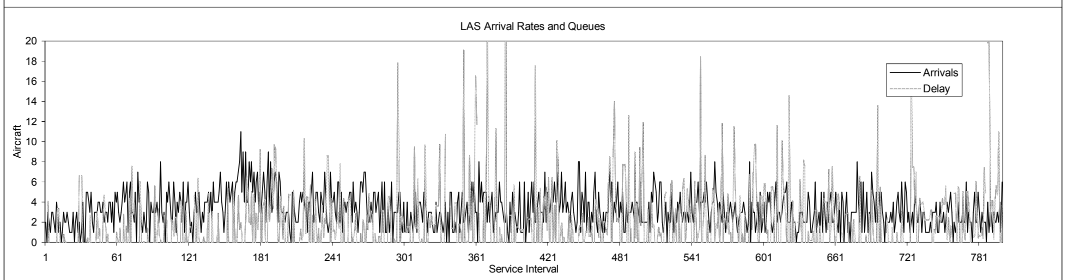

DTW Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

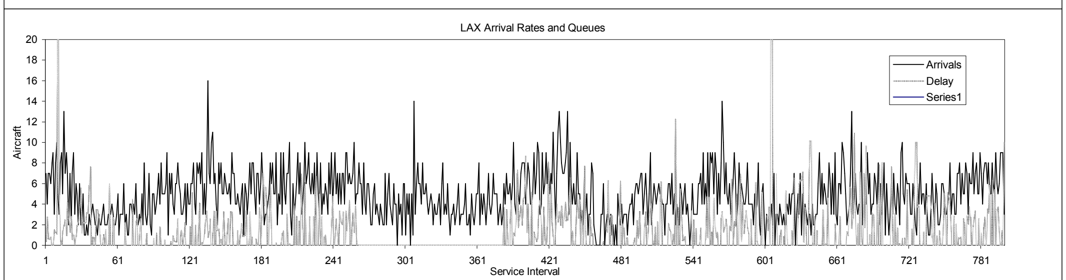

EWR Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

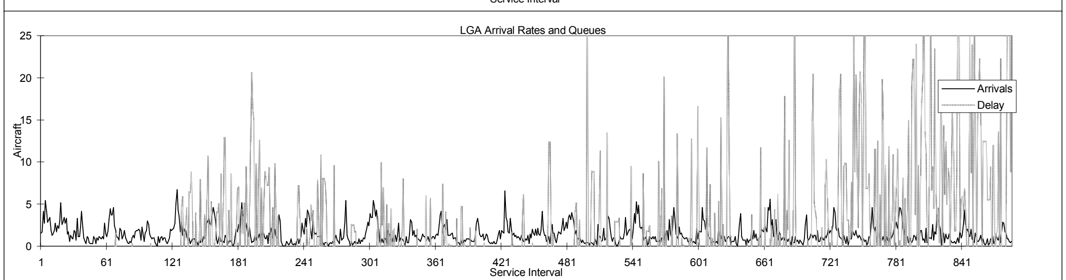

IAD Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

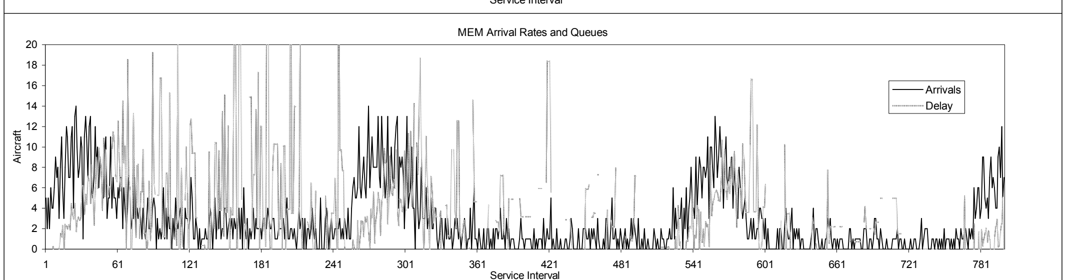

IAH Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

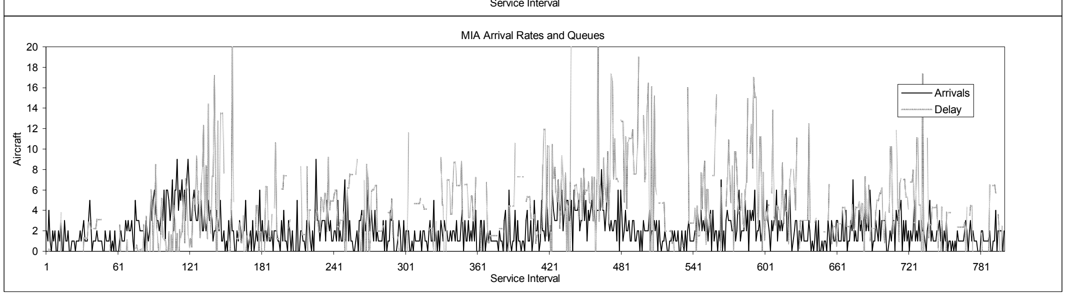

JFK Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

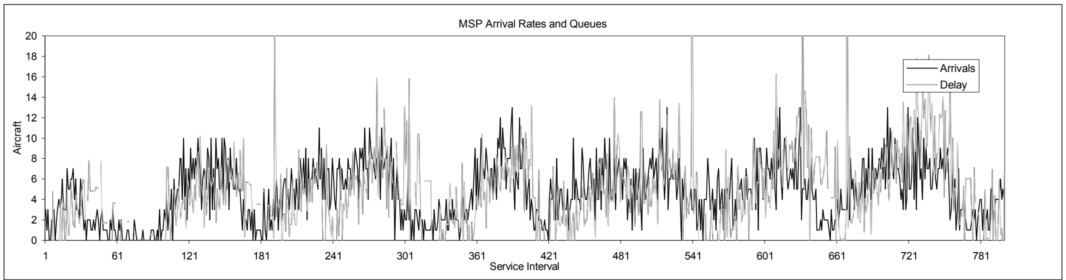

LAS Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

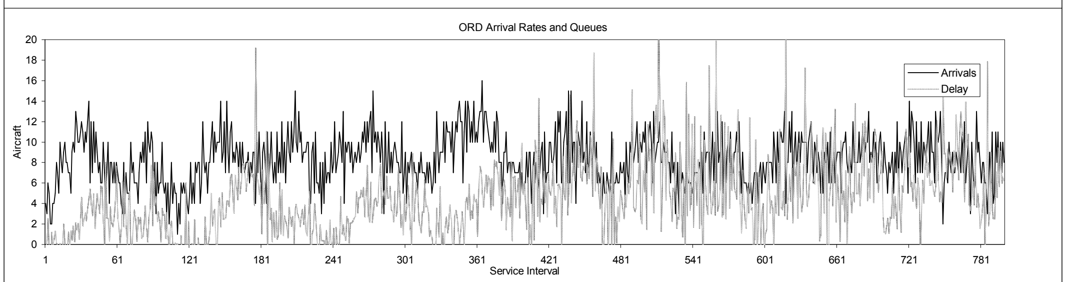

LAX Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
Series1

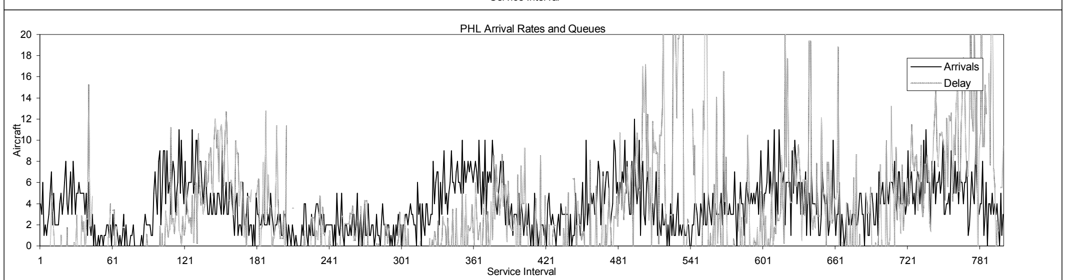

LGA Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

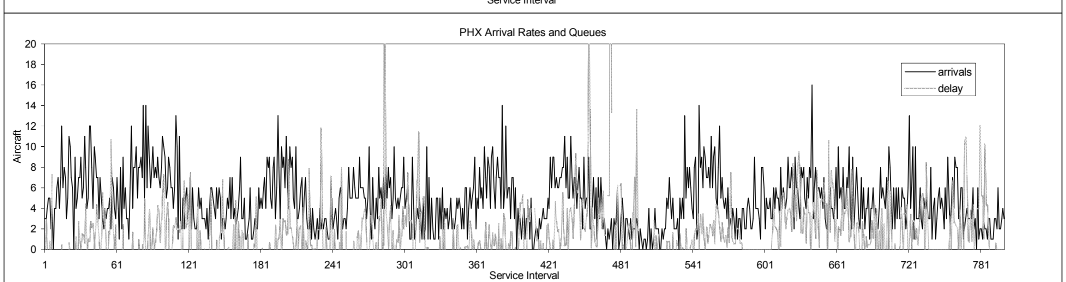

MEM Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

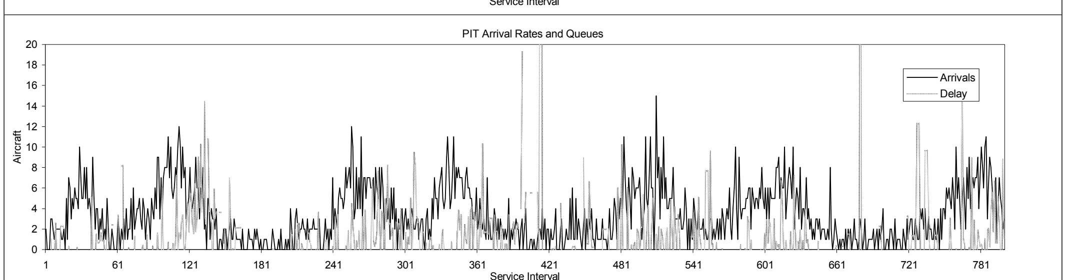

MIA Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

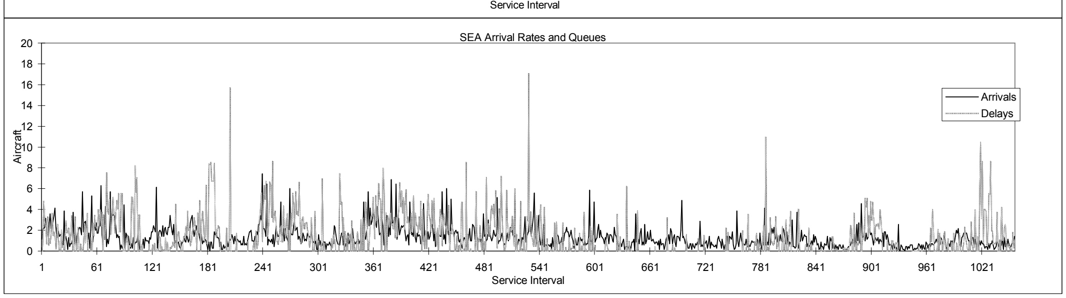

MSP Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

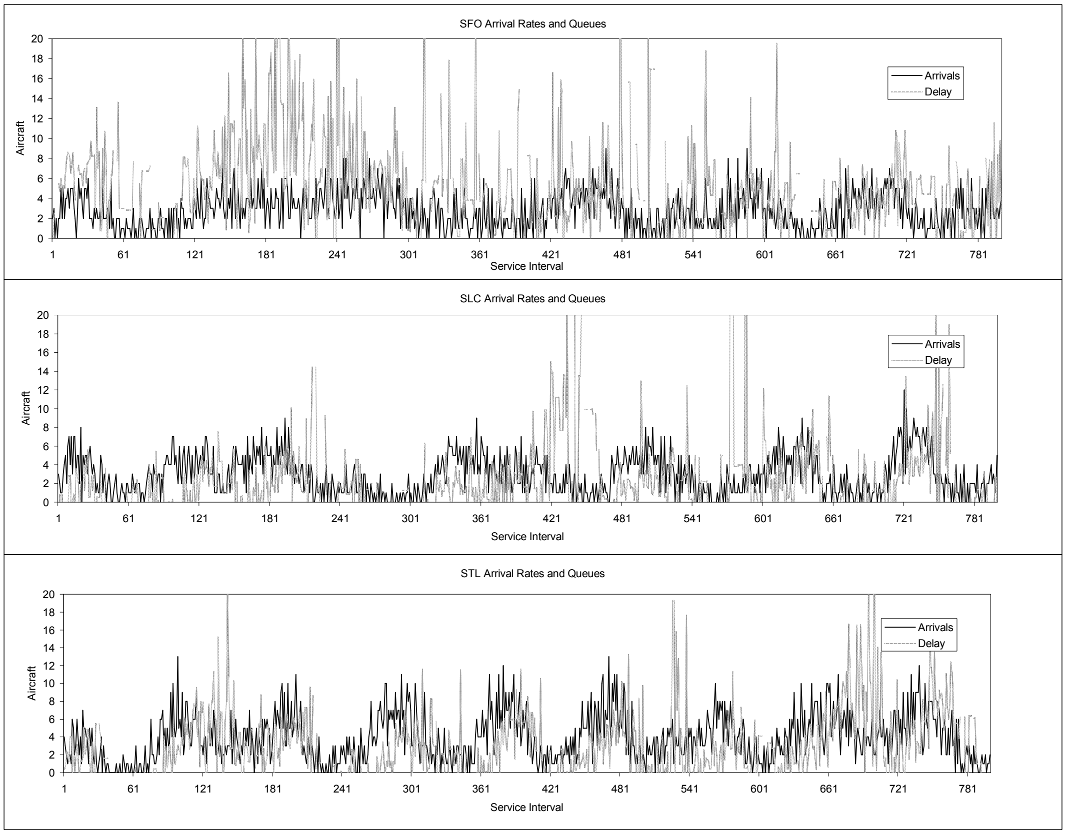

ORD Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

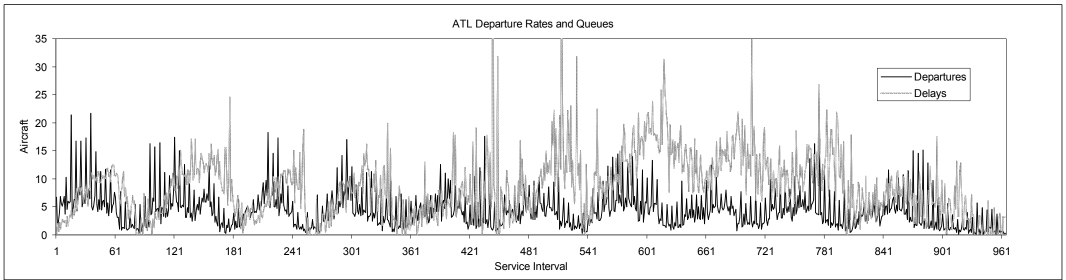

PHL Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

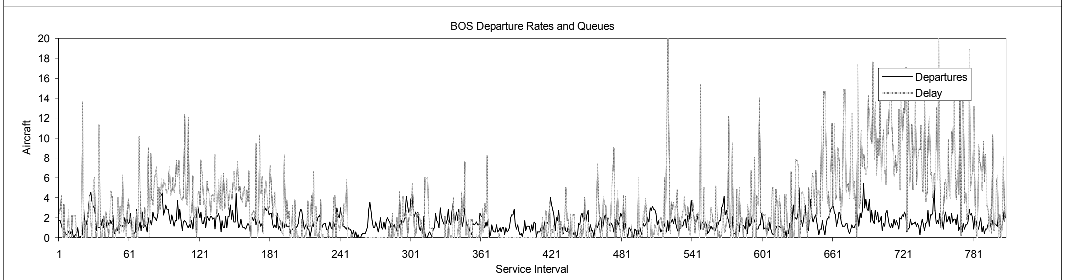

PHX Arrival Rates and Queues
Aircraft
Service Interval
arrivals
delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

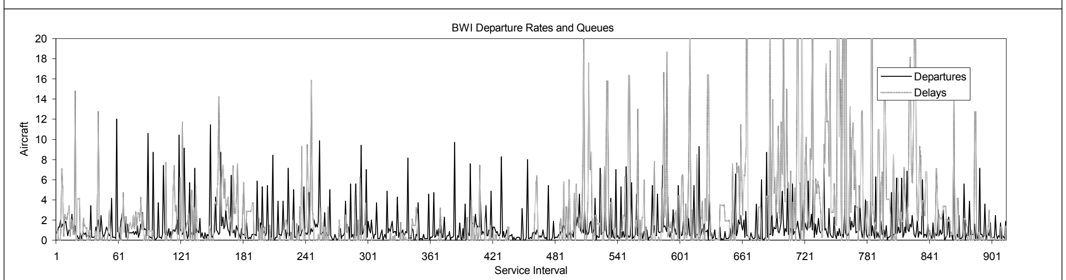

PIT Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781

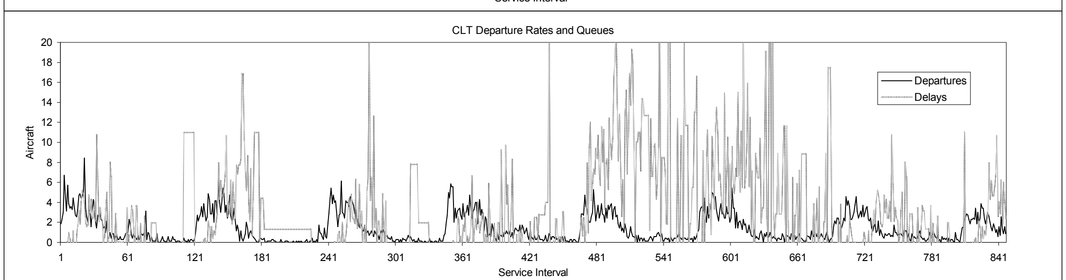

SEA Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delays
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901 961 1021

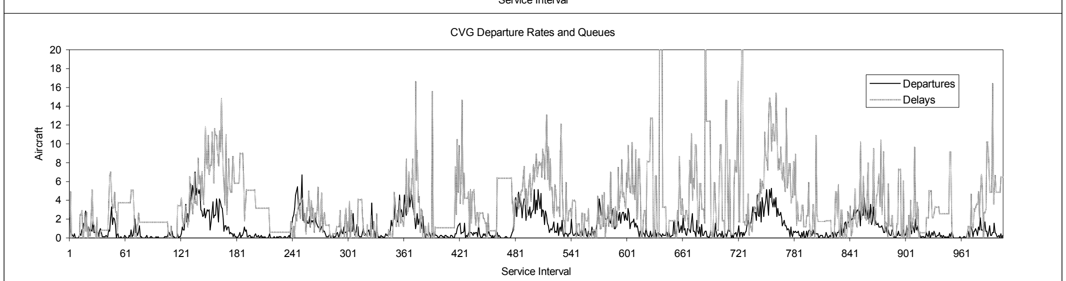

SFO Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
SLC Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay
STL Arrival Rates and Queues
Aircraft
Service Interval
Arrivals
Delay

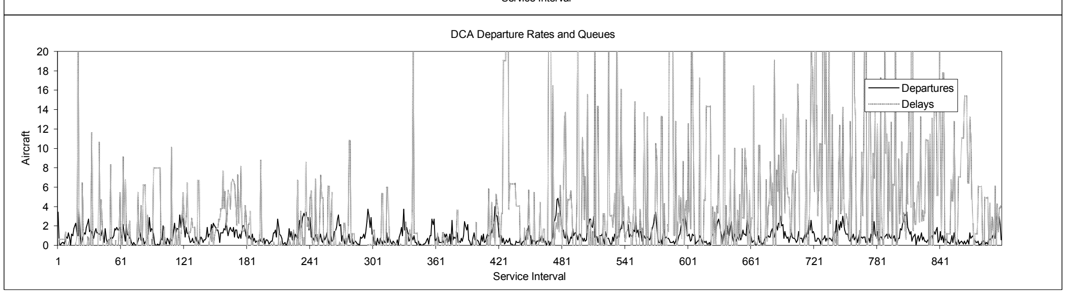

ATL Departure Rates and Queues
Departures
Delays
Aircraft
Service Interval

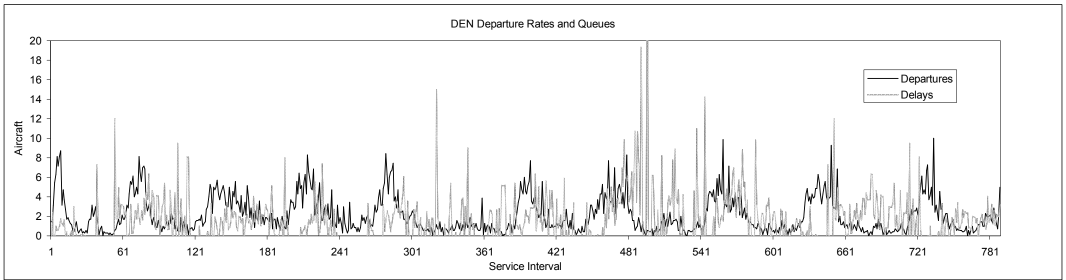

BOS Departure Rates and Queues
Departures
Delay
Aircraft
Service Interval

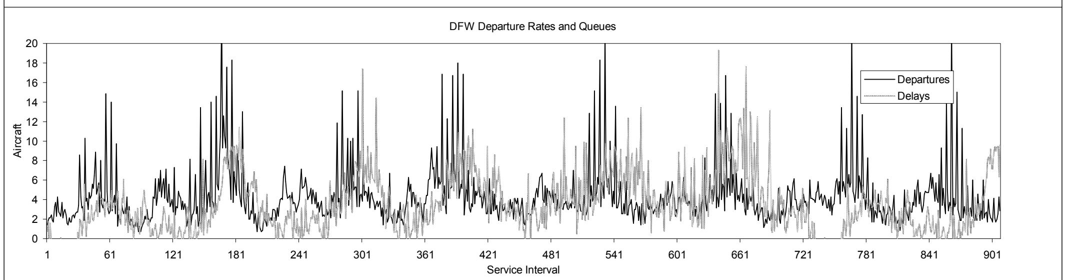

BWI Departure Rates and Queues
Departures
Delays
Aircraft
Service Interval

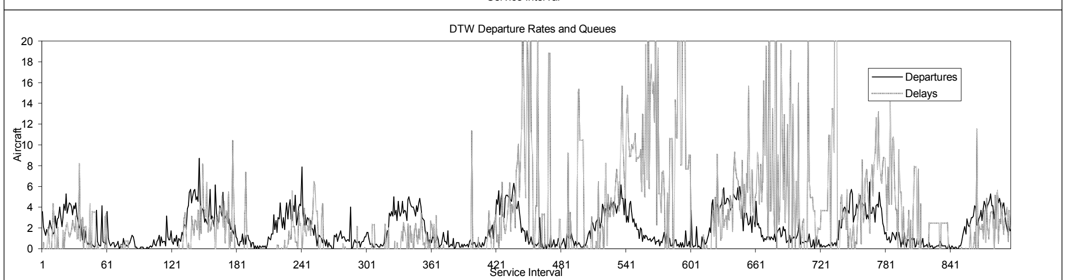

CLT Departure Rates and Queues
Departures
Delays
Aircraft
Service Interval

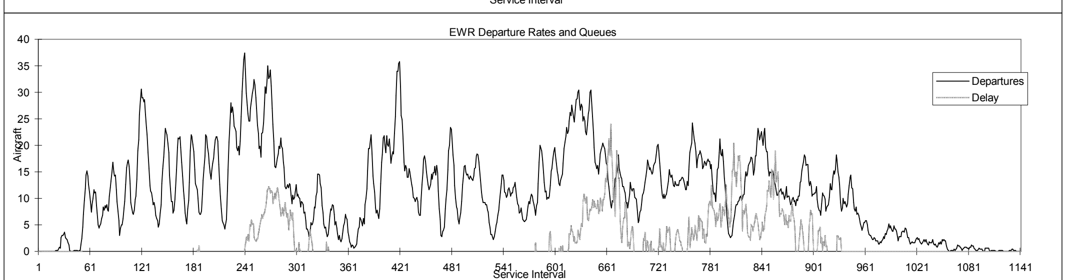

CVG Departure Rates and Queues
Departures
Delays
Aircraft
Service Interval

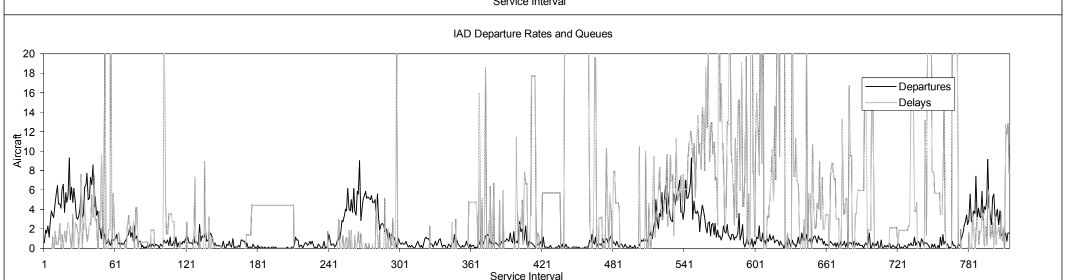

DCA Departure Rates and Queues
Departures
Delay
Aircraft
Service Interval

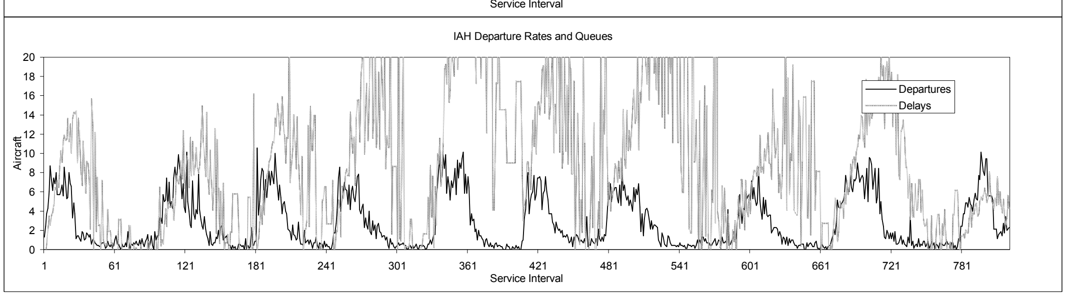

DEN Departure Rates and Queues
Aircraft
Service Interval
Departures
Delays


DFW Departure Rates and Queues
Aircraft
Service Interval
Departures
Delays

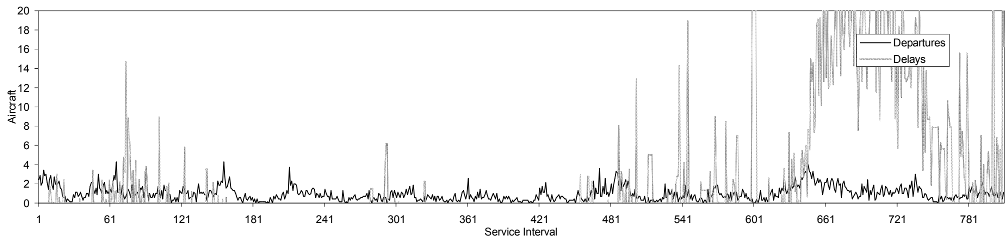

DTW Departure Rates and Queues
Aircraft
Service Interval
Departures
Delays


EWR Departure Rates and Queues
Aircraft
Service Interval
Departures
Delay

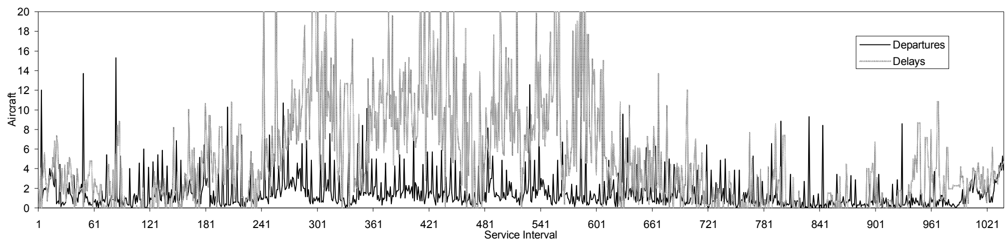

IAD Departure Rates and Queues
Aircraft
Service Interval
Departures
Delays


IAH Departure Rates and Queues
Aircraft
Service Interval
Departures
Delays

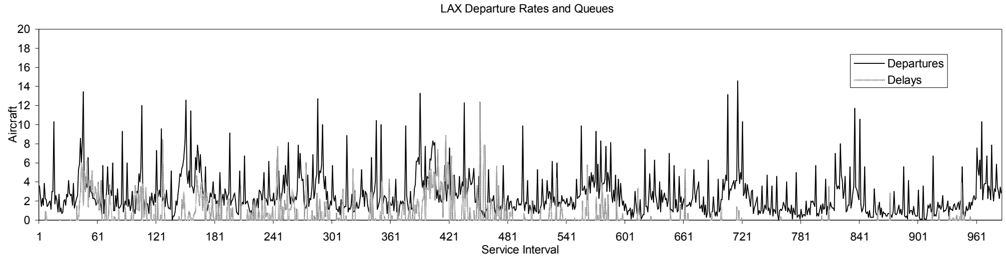
JFK Departure Rates and Queues



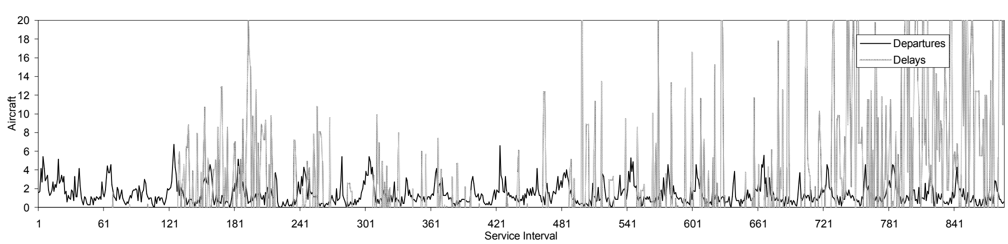
LAS Departure Rates and Queues



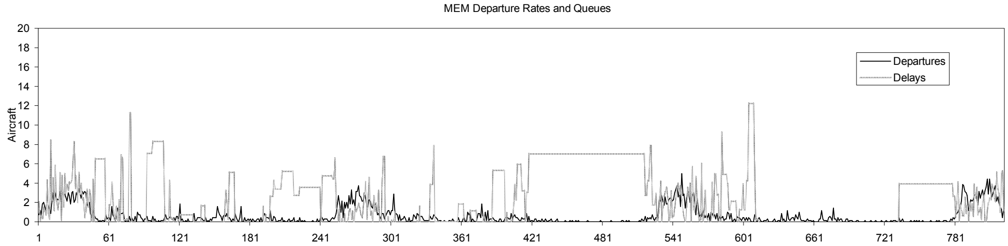
LAX Departure Rates and Queues



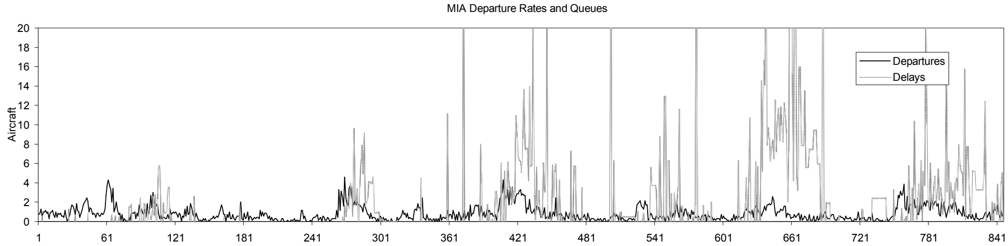
LGA Departure Rates and Queues

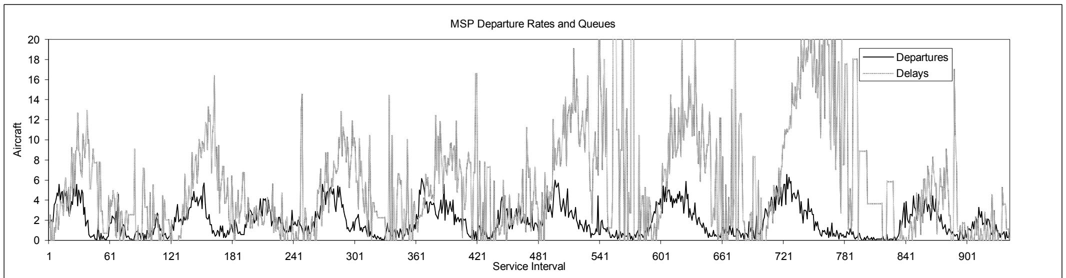


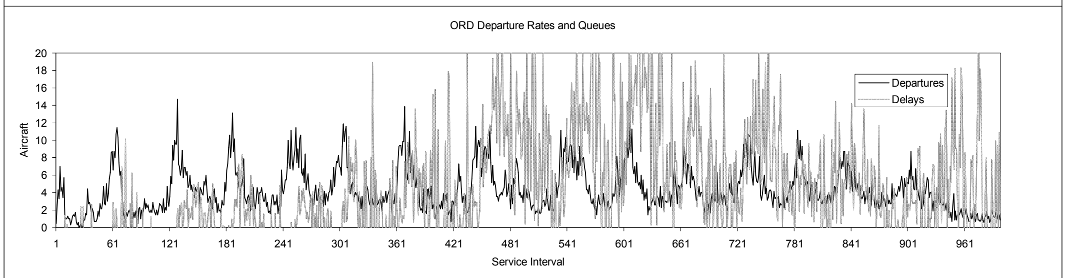
MEM Departure Rates and Queues

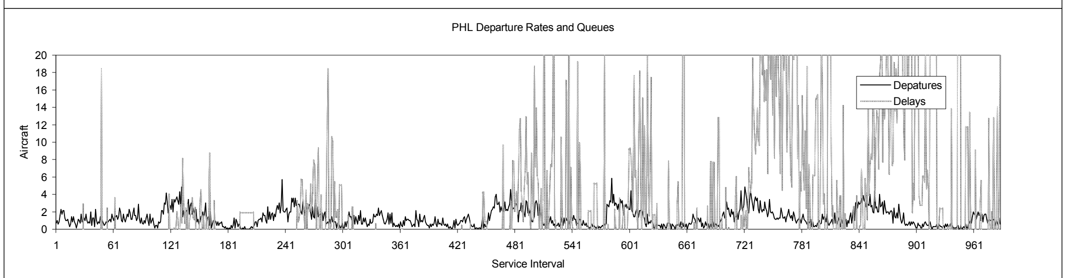


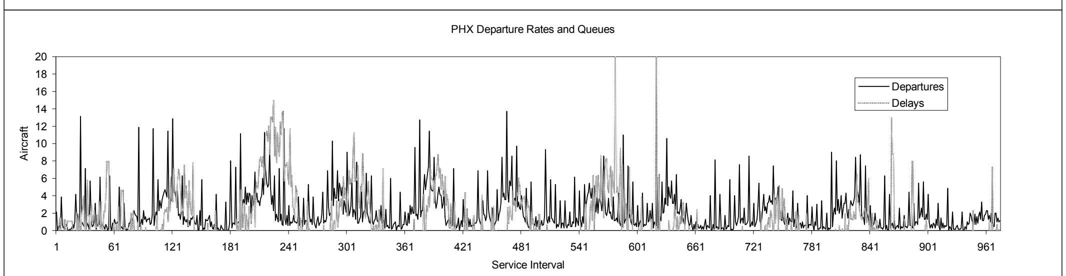
MIA Departure Rates and Queues

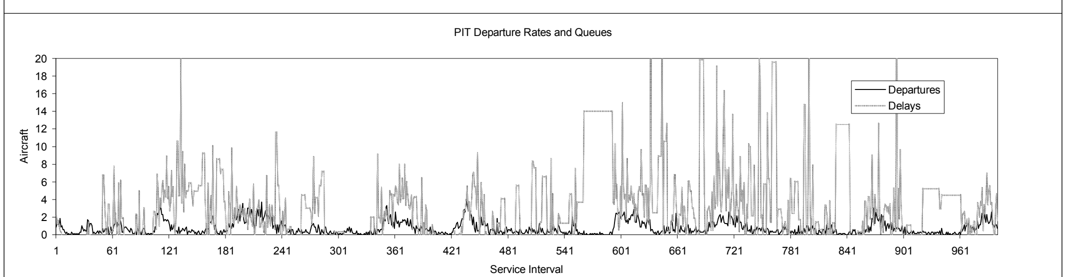


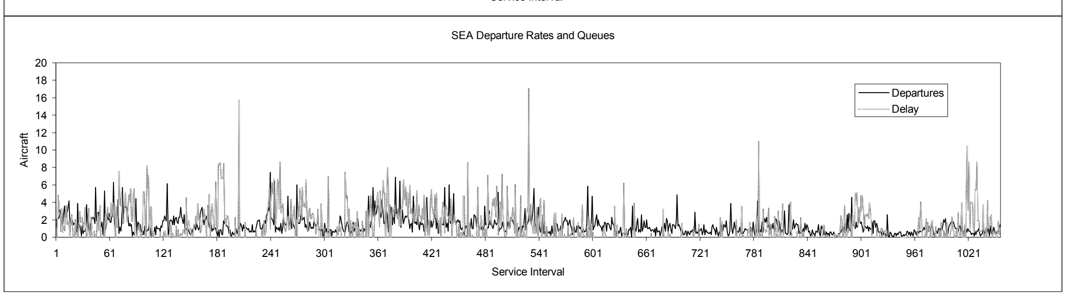

MSP Departure Rates and Queues
Aircraft
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901
Service Interval
Departures
Delays

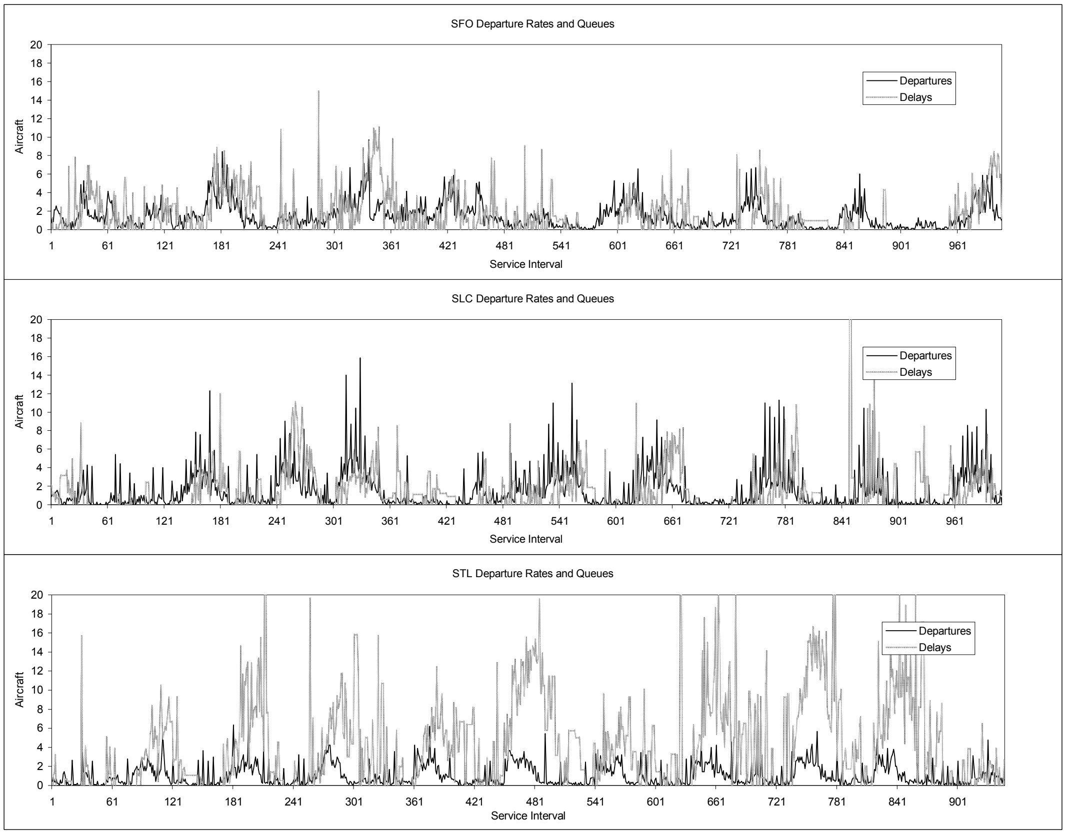

ORD Departure Rates and Queues
Aircraft
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901 961
Service Interval
Departures
Delays


PHL Departure Rates and Queues
Aircraft
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901 961
Service Interval
Depatures
Delays


PHX Departure Rates and Queues
Aircraft
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901 961
Service Interval
Departures
Delays

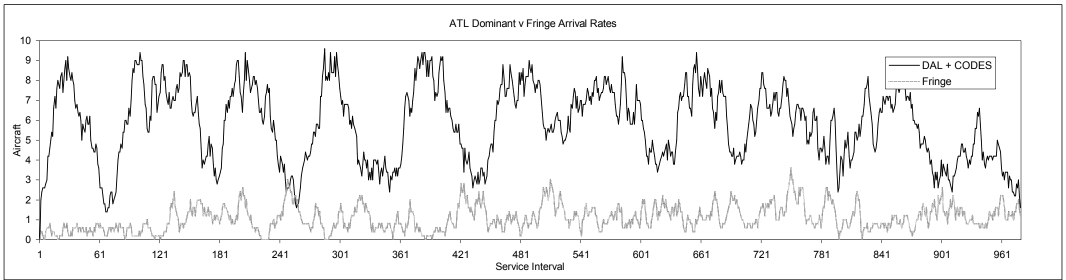

PIT Departure Rates and Queues
Aircraft
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901 961
Service Interval
Departures
Delays

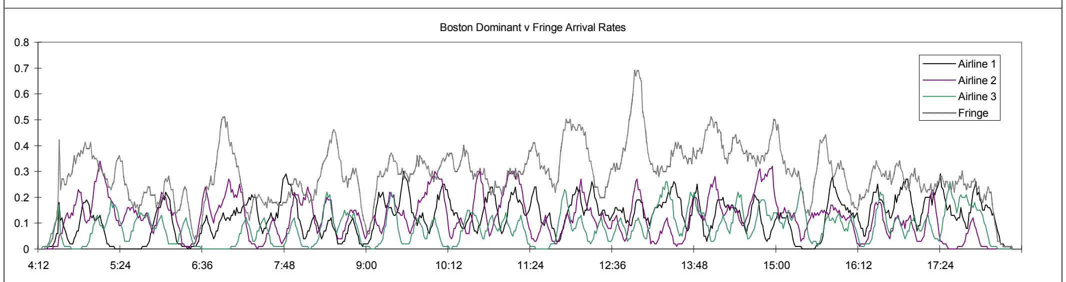

SEA Departure Rates and Queues
Aircraft
0 2 4 6 8 10 12 14 16 18 20
1 61 121 181 241 301 361 421 481 541 601 661 721 781 841 901 961 1021
Service Interval
Departures
Delay

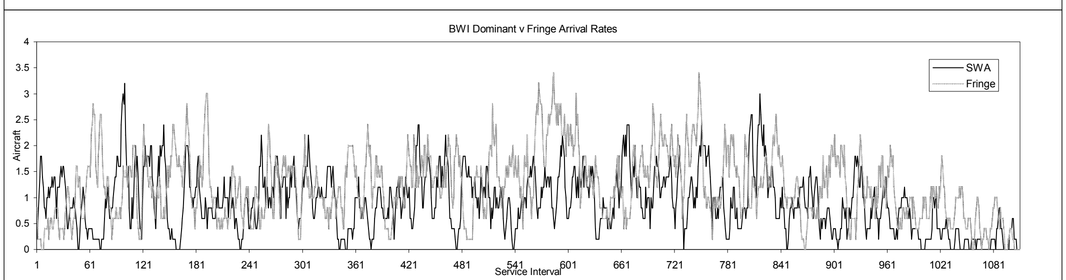


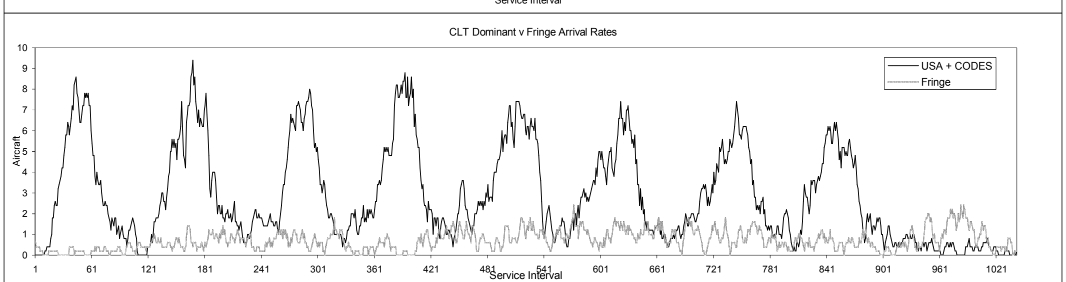
SFO Departure Rates and Queues
SLC Departure Rates and Queues
STL Departure Rates and Queues
Aircraft
Service Interval
Departures
Delays

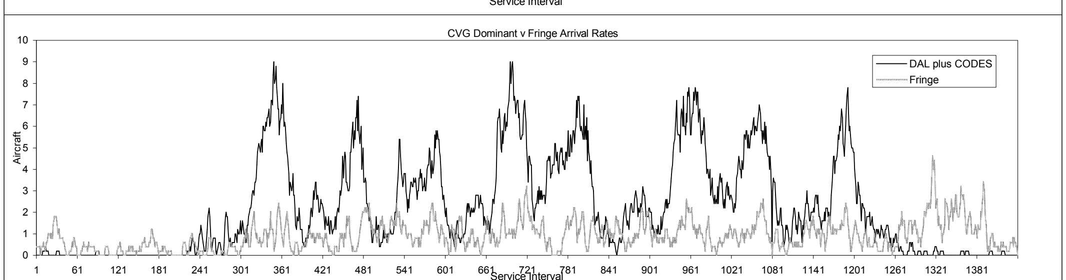
Appendix B--Dominant v Fringe Arrival Rates

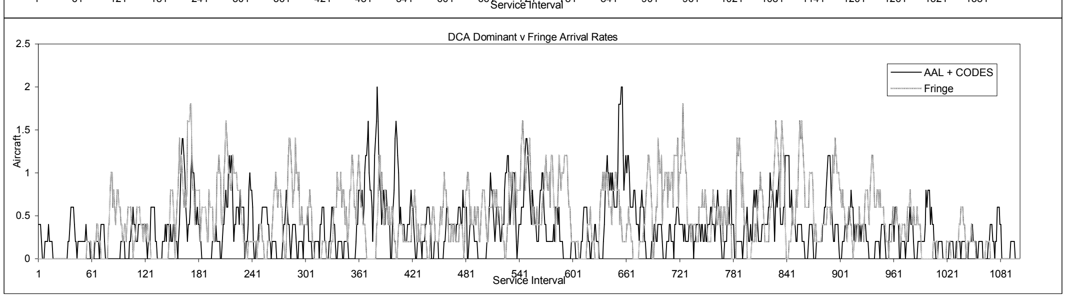


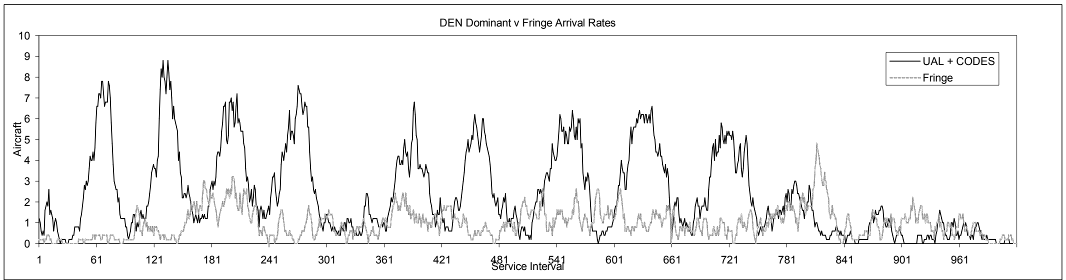


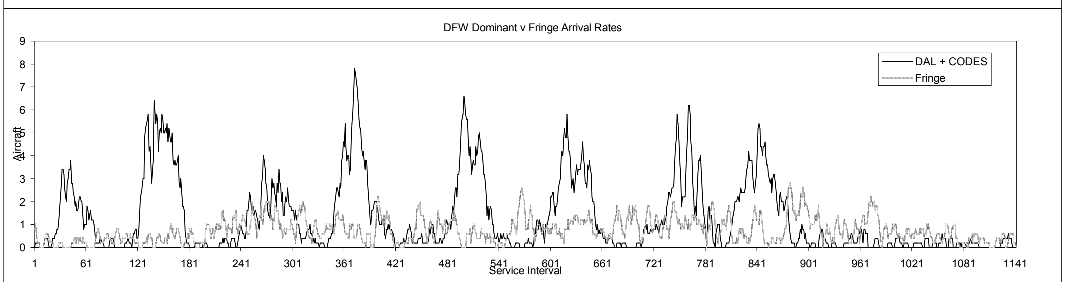


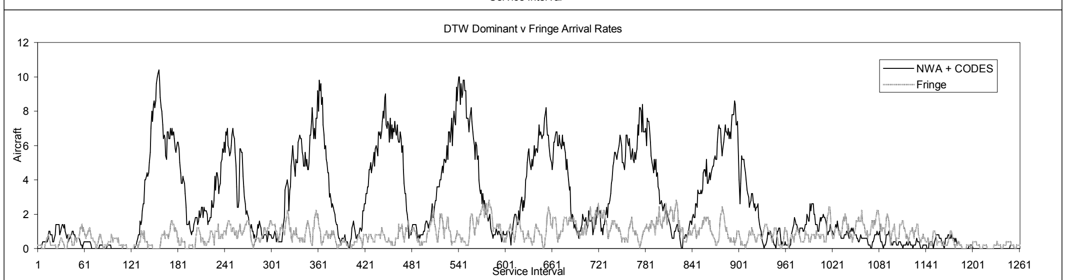


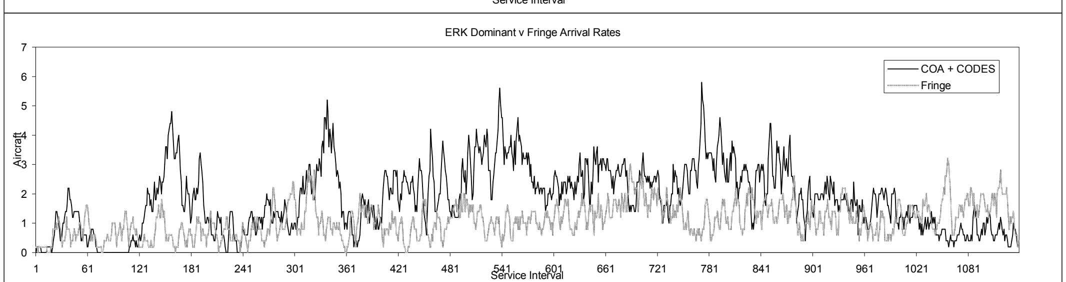


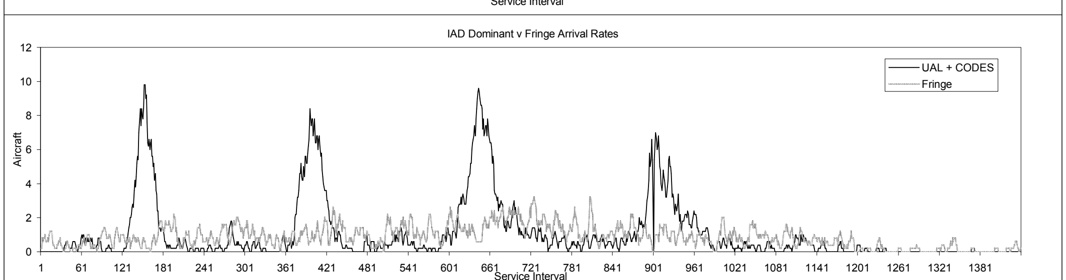


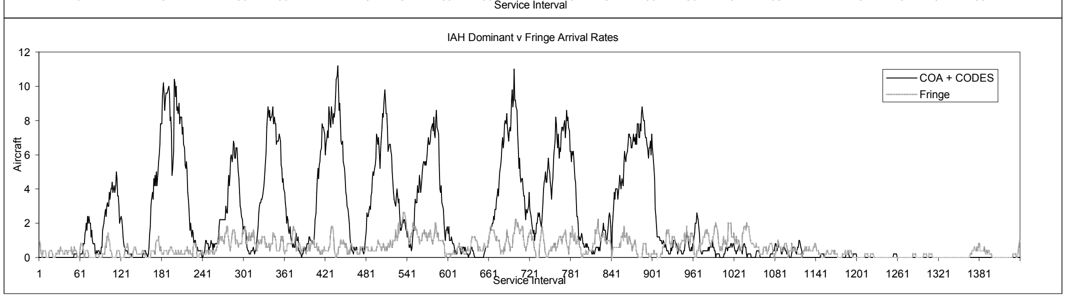

DEN Dominant v Fringe Arrival Rates
UAL + CODES
Fringe
Aircraft
Service Interval

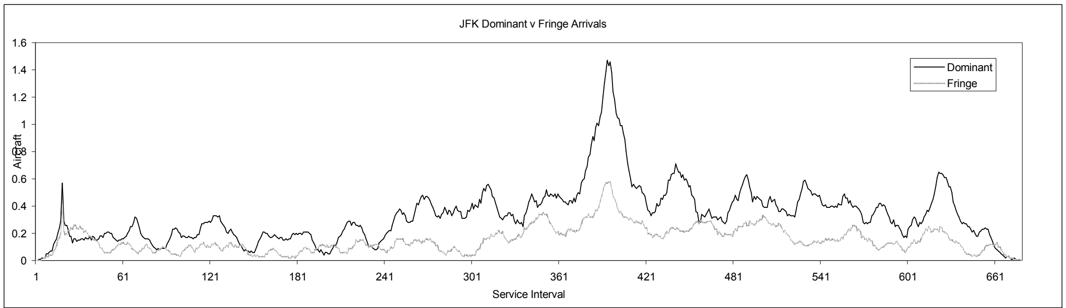

DFW Dominant v Fringe Arrival Rates
DAL + CODES
Fringe
Aircraft
Service Interval

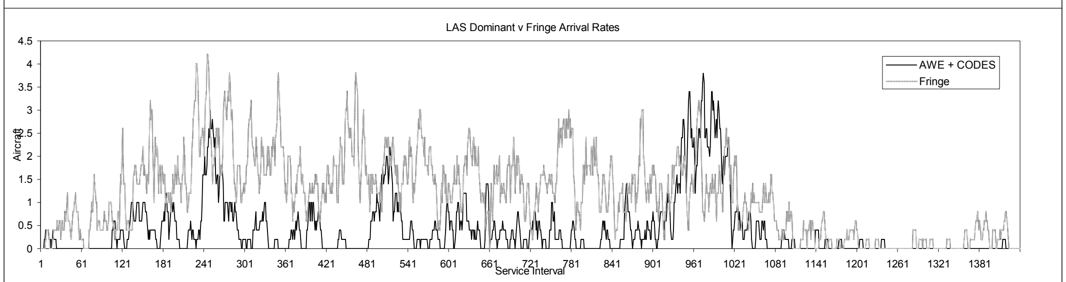

DTW Dominant v Fringe Arrival Rates
NWA + CODES
Fringe
Aircraft
Service Interval

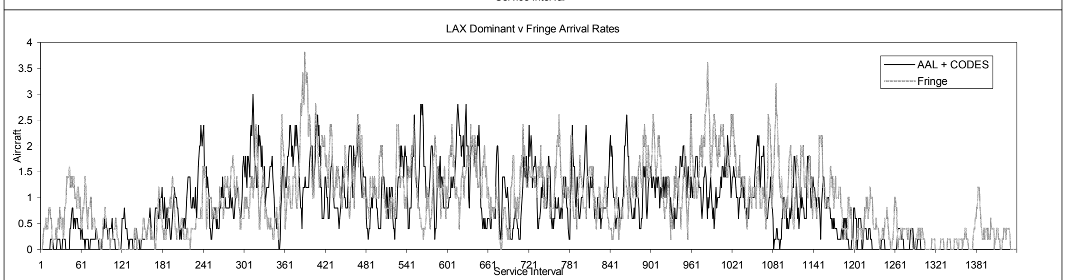

ERK Dominant v Fringe Arrival Rates
COA + CODES
Fringe
Aircraft
Service Interval

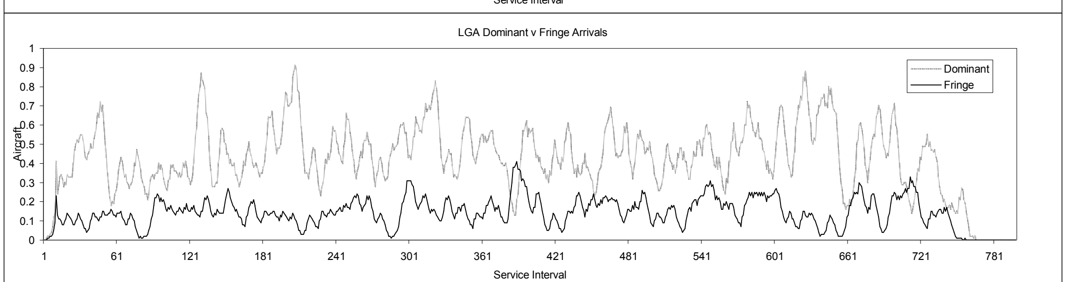

IAD Dominant v Fringe Arrival Rates
UAL + CODES
Fringe
Aircraft
Service Interval

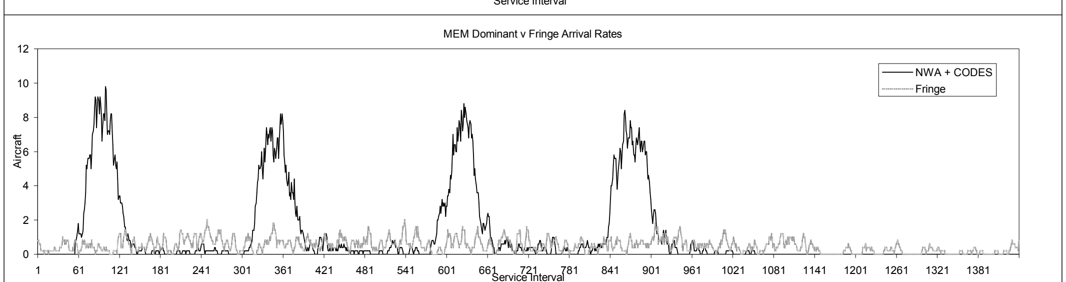

IAH Dominant v Fringe Arrival Rates
COA + CODES
Fringe
Aircraft
Service Interval

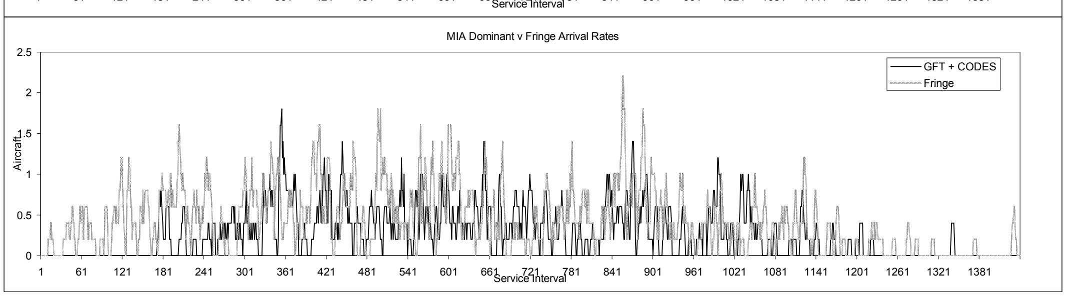

JFK Dominant v Fringe Arrivals
Aircraft
Service Interval
Dominant
Fringe

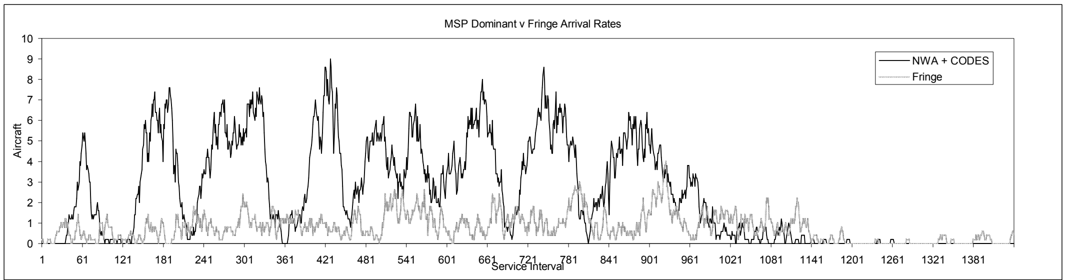

LAS Dominant v Fringe Arrival Rates
Aircraft
Service Interval
AWE + CODES
Fringe

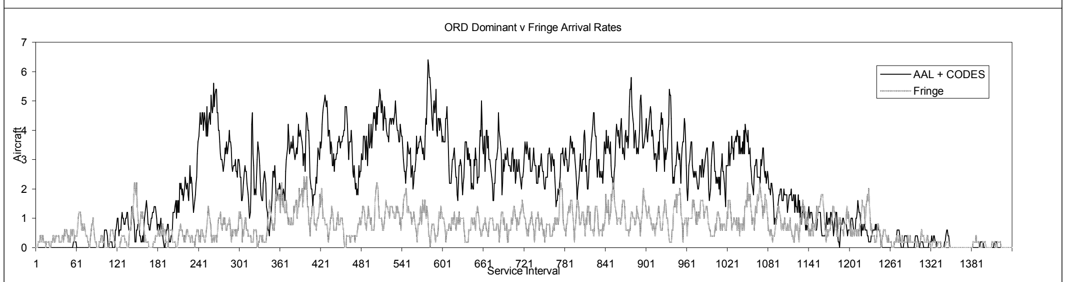

LAX Dominant v Fringe Arrival Rates
Aircraft
Service Interval
AAL + CODES
Fringe

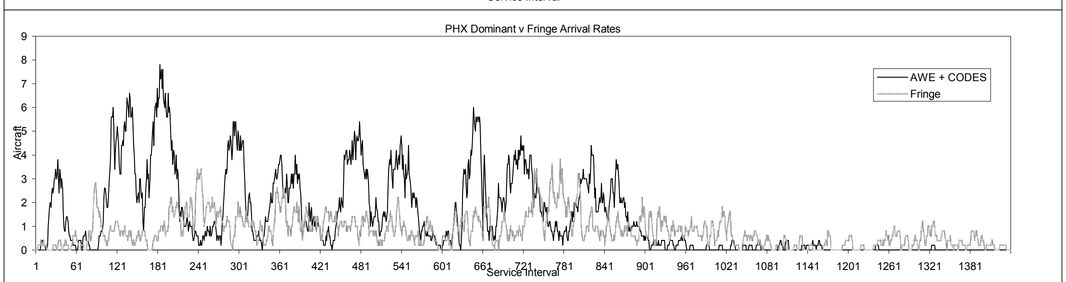

LGA Dominant v Fringe Arrivals
Aircraft
Service Interval
Dominant
Fringe

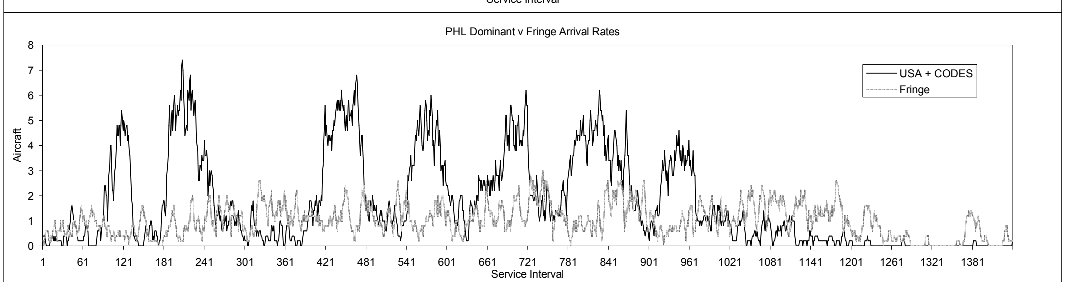

MEM Dominant v Fringe Arrival Rates
Aircraft
Service Interval
NWA + CODES
Fringe

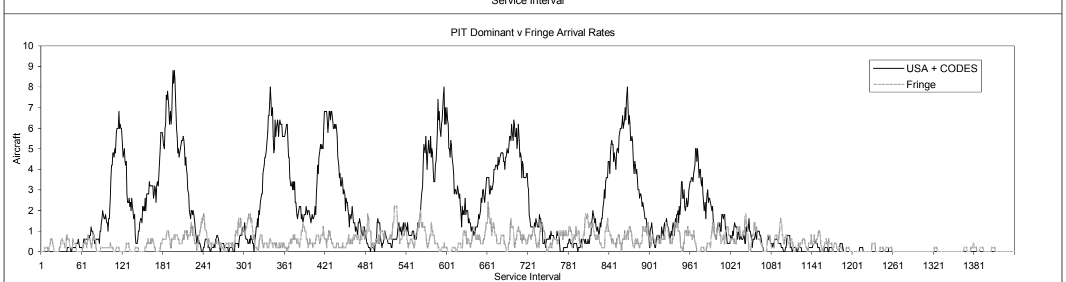

MIA Dominant v Fringe Arrival Rates
Aircraft
Service Interval
GFT + CODES
Fringe

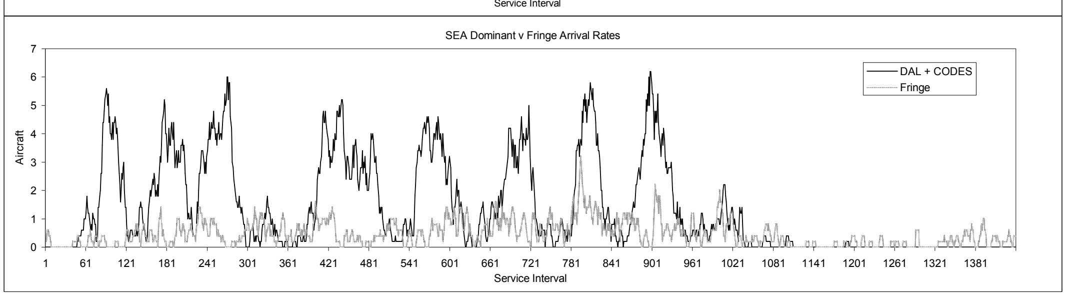

MSP Dominant v Fringe Arrival Rates
NWA + CODES
Fringe
Aircraft
Service Interval

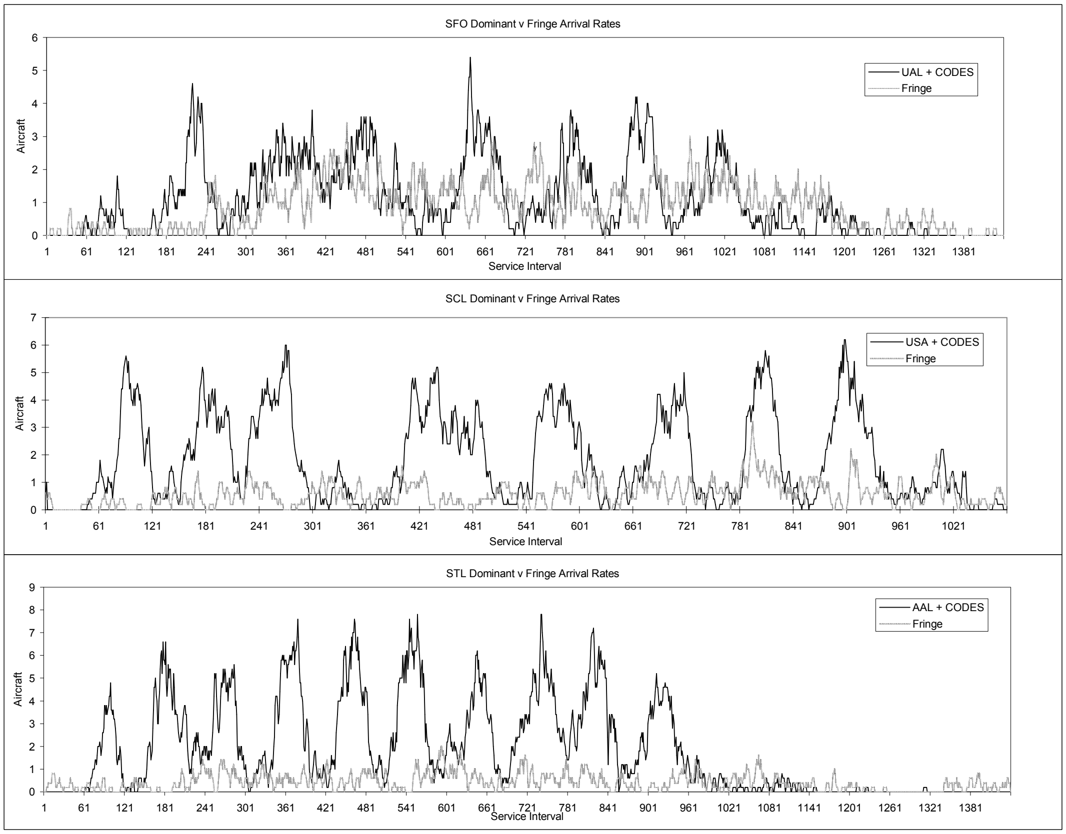

ORD Dominant v Fringe Arrival Rates
AAL + CODES
Fringe
Aircraft
Service Interval


PHX Dominant v Fringe Arrival Rates
AWE + CODES
Fringe
Aircraft
Service Interval

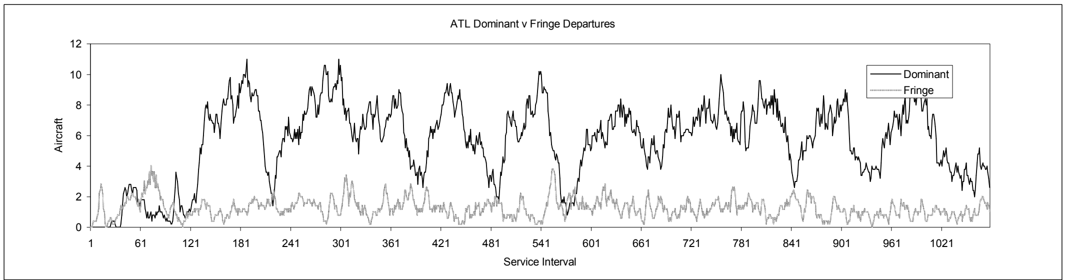

PHL Dominant v Fringe Arrival Rates
USA + CODES
Fringe
Aircraft
Service Interval

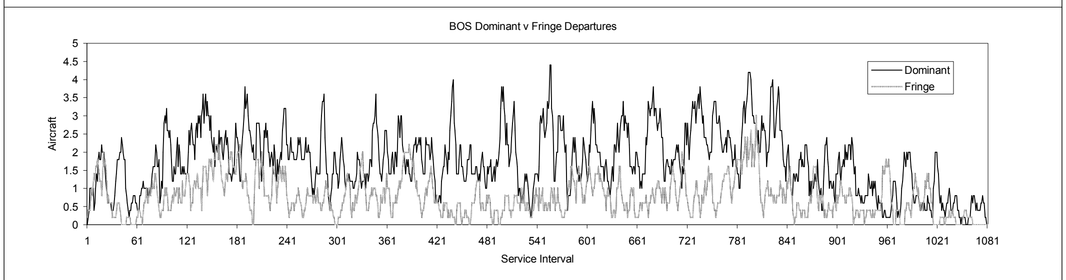

PIT Dominant v Fringe Arrival Rates
USA + CODES
Fringe
Aircraft
Service Interval

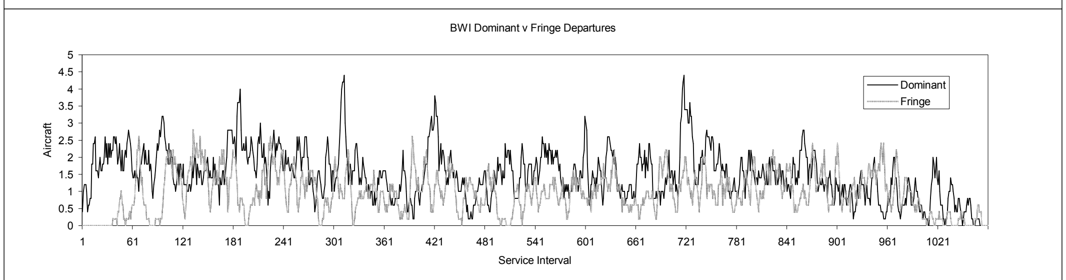

SEA Dominant v Fringe Arrival Rates
DAL + CODES
Fringe
Aircraft
Service Interval

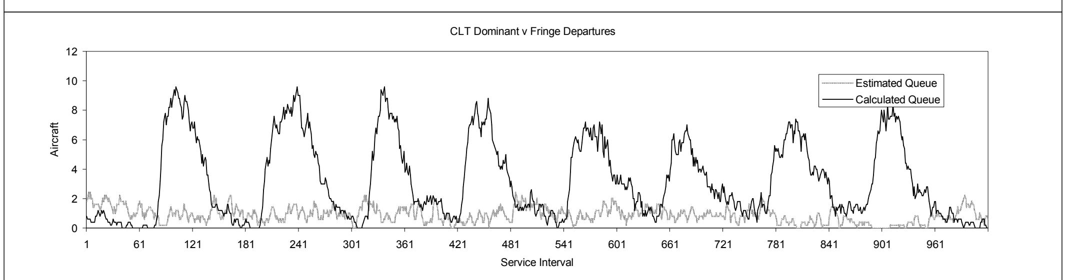

SFO Dominant v Fringe Arrival Rates
Aircraft
Service Interval
UAL + CODES
Fringe
SCL Dominant v Fringe Arrival Rates
Aircraft
Service Interval
USA + CODES
Fringe
STL Dominant v Fringe Arrival Rates
Aircraft
Service Interval
AAL + CODES
Fringe

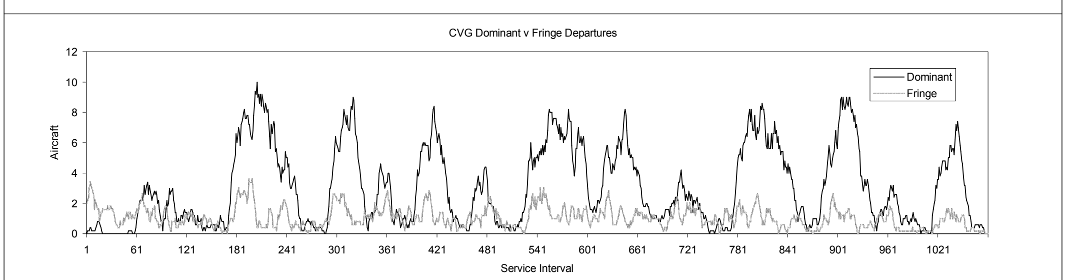
Appendix B--Dominant v Fringe Departure Rates

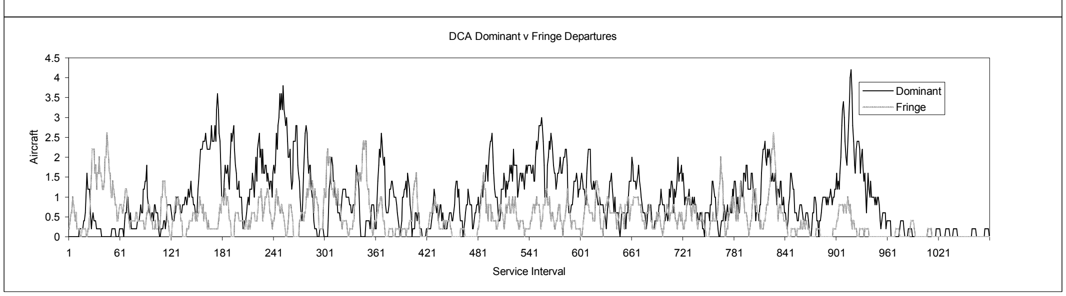


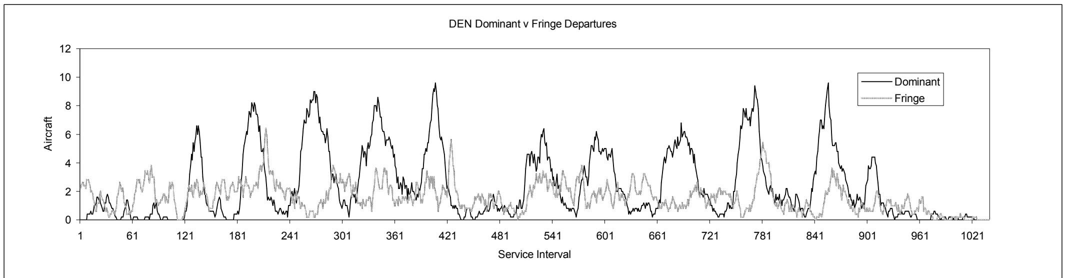


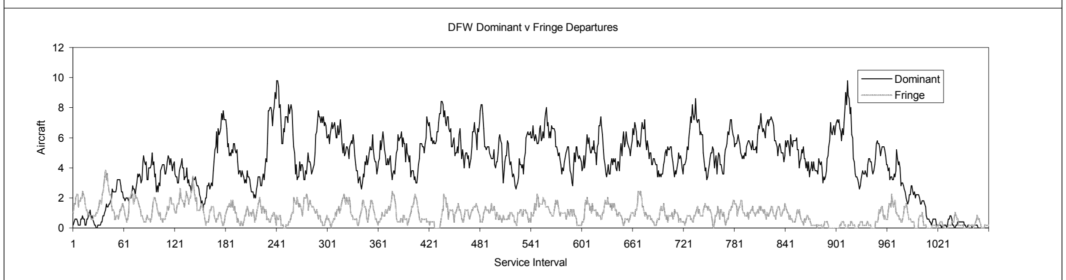


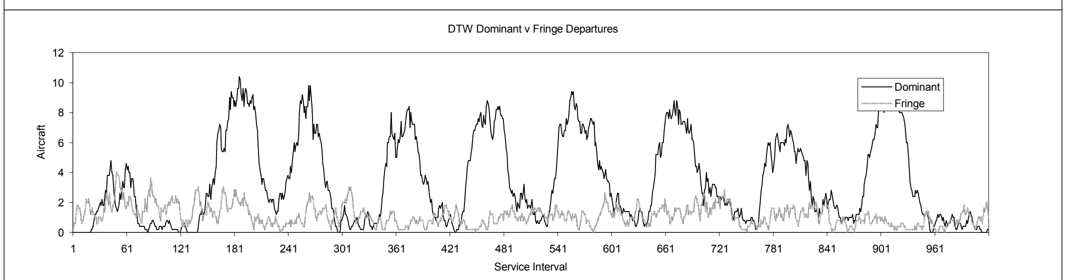


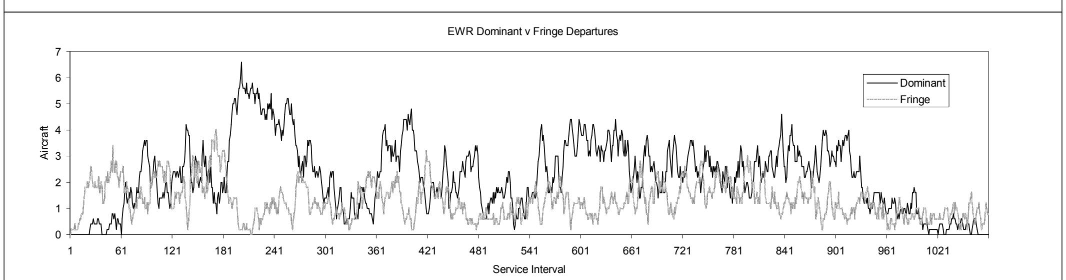


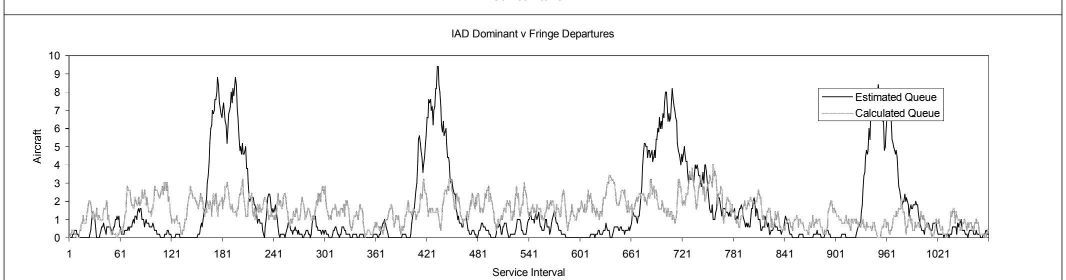


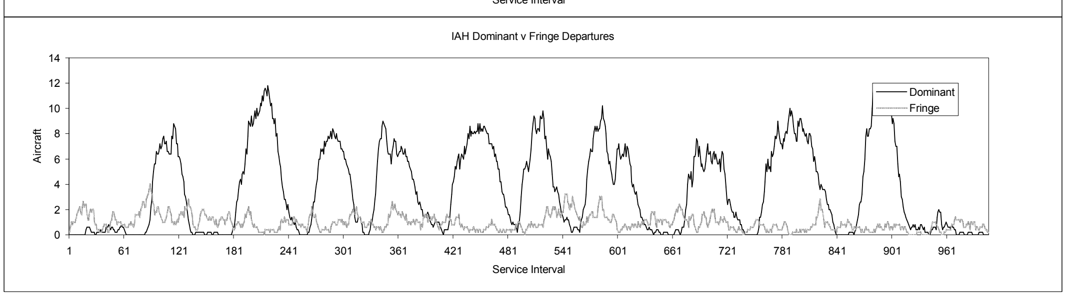

DEN Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

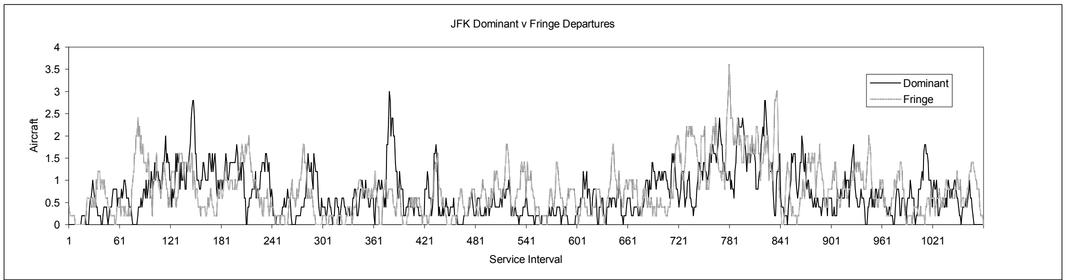

DFW Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

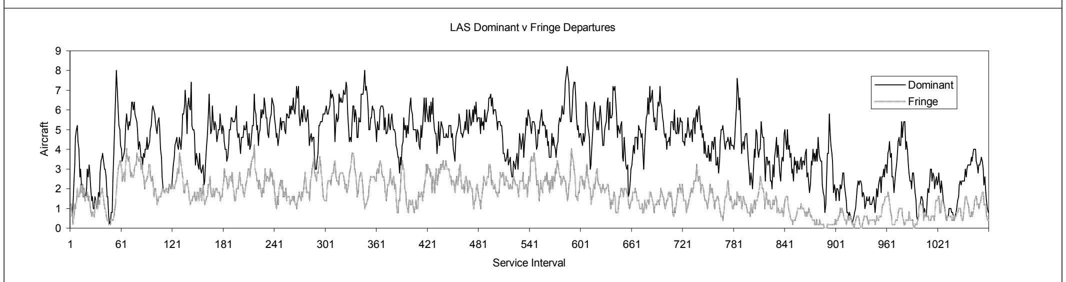

DTW Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

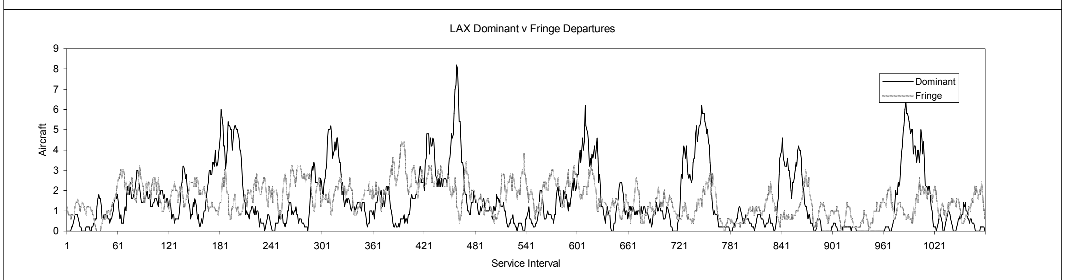

EWR Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

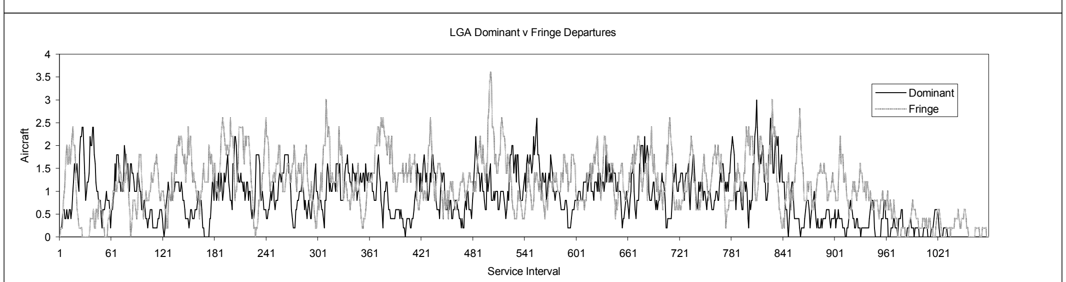

IAD Dominant v Fringe Departures
Aircraft
Service Interval
Estimated Queue
Calculated Queue

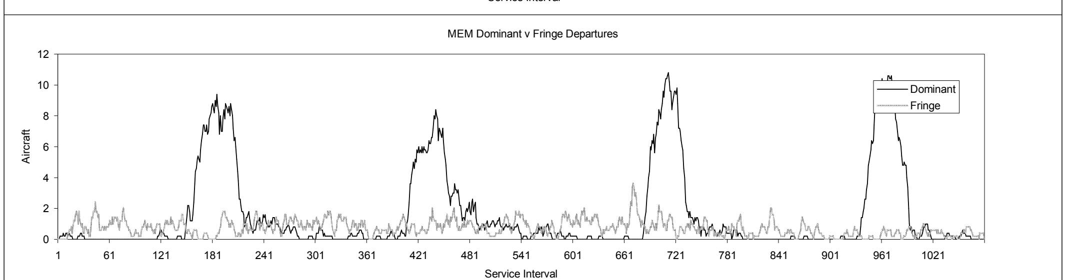

IAH Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

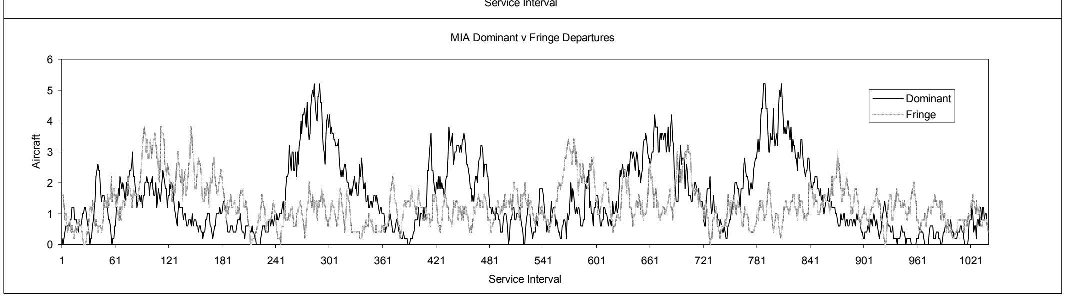

JFK Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

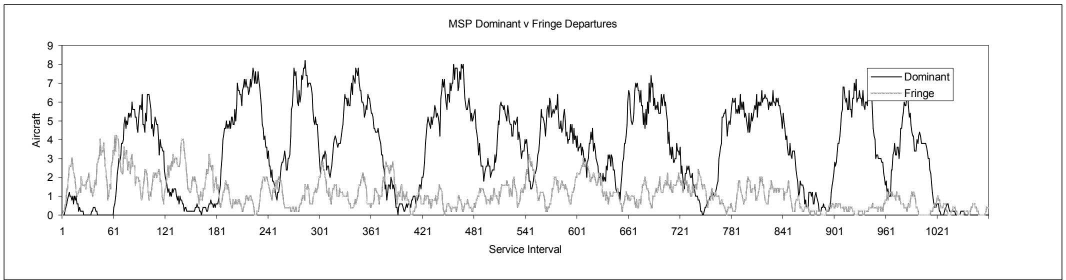

LAS Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

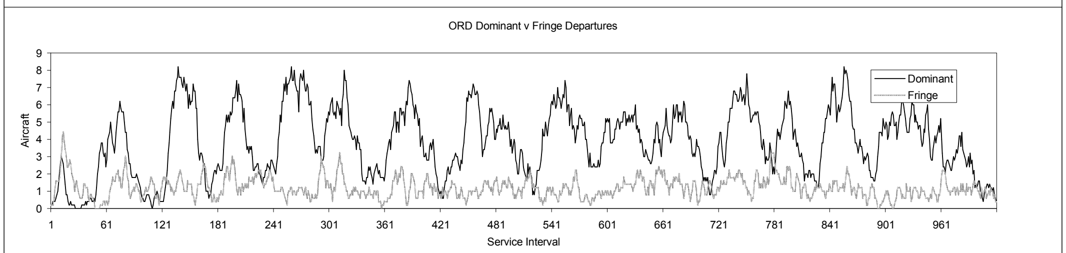

LAX Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

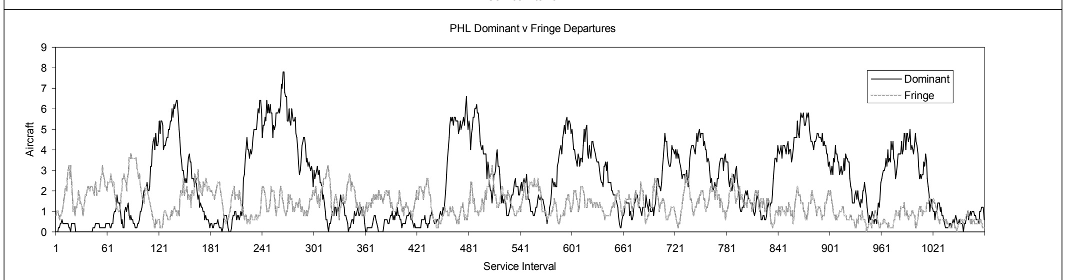

LGA Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

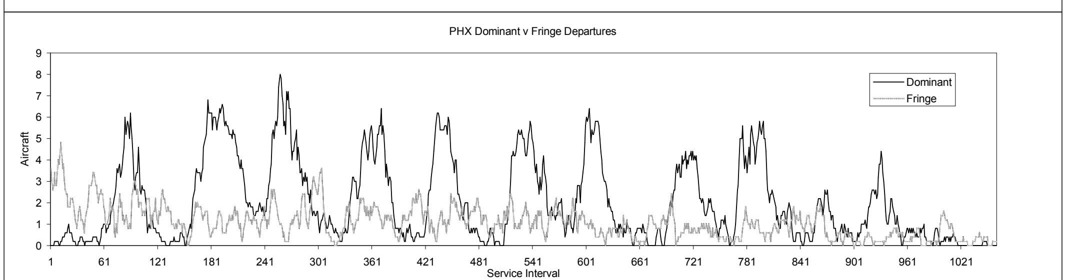

MEM Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

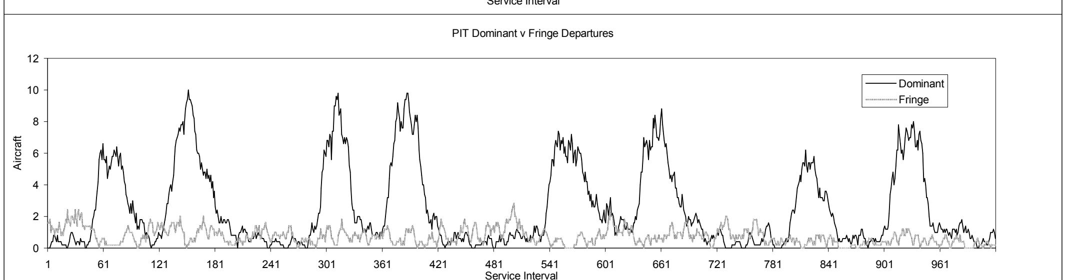

MIA Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

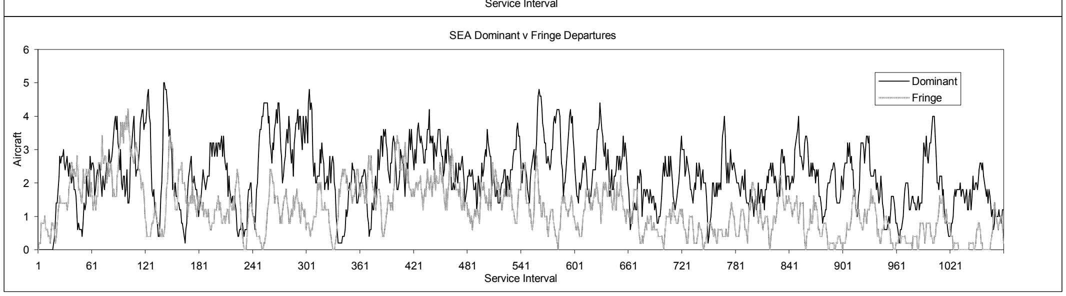

MSP Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe

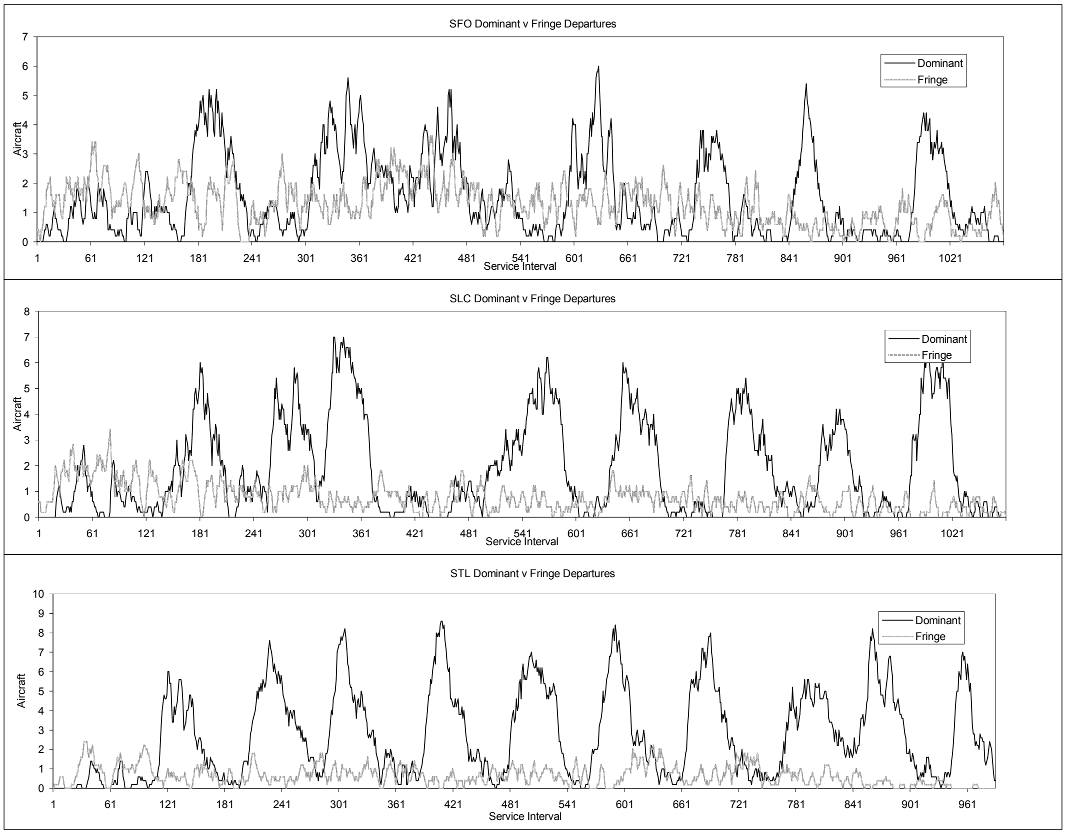

ORD Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe


PHL Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe


PHX Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe


PIT Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe


SEA Dominant v Fringe Departures
Aircraft
Service Interval
Dominant
Fringe


SFO Dominant v Fringe Departures
Dominant
Fringe
Aircraft
Service Interval
SLC Dominant v Fringe Departures
Dominant
Fringe
Aircraft
Service Interval
STL Dominant v Fringe Departures
Dominant
Fringe
Aircraft
Service Interval