Flight Delays and Cancellations

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Abstract

We use a nested logit estimation to determine the causes of flight delays and cancellations both nationally and at New York LaGuardia Airport (LGA). Previous research on delays and cancellations has treated these decisions as separate and independent events. Using a microlevel data set of post-September 11th flights, we present evidence that airports with dominant carriers do not internalize the delay externality since dominant airport carriers have more delays and cancellations. This suggests that congestion pricing may play a larger role than previously indicated in the literature, especially at airports with dominant carriers.

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1 Introduction

One of the critical questions confronting the airline industry in the 21st century is how to handle a growing problem of airport and air traffic congestion. The Federal Aviation Administration (FAA) estimates that commercial aviation delays cost airlines in excess of \$3 billion dollars per year (www.faa.gov), an amount that exceeds the \$2.4 billion of direct financial assistance to the airline industry provided by the federal government under the 2003 Emergency Wartime Supplemental Appropriations Act (GAO, 2004). In addition, longer flight delays also decrease airline ticket prices (Januszewski, 2004). Airport congestion in the future is likely to get worse due to an increase in demand (i.e., low-cost carrier expansion, regional jets, and business aviation) while the supply of airport runway capacity will likely remain constant.[1]

Even before airline deregulation, economists have suggested using congestion-based pricing to allocate landings and takeoffs at the nation's busiest airports (e.g., Levine 1969, Carlin and Park 1970, Borins 1978). More recently, Morrison and Winston (1989) estimate that under optimal congestion pricing total welfare would improve annually by approximately \$4 billion (1988) dollars thanks to a reduction in carrier operating costs and lower passenger delay costs. Daniel (1995) reports that the Minneapolis-St. Paul airport could accommodate 30% more traffic by using congestion pricing due to the de-peaking of departures and arrivals. The FAA is currently considering whether to implement congestion based-pricing for landing and take-off rights in lieu of the existing weight-based landing fee structure at New York LaGuardia Airport (LGA). Congestion-based pricing can efficiently reduce airport congestion if it causes carriers to internalize the delay externality. Before implementing such a fundamental policy shift, it behooves us to learn more about the causes of flight delays and cancellations. The purpose of this paper is two-fold. First, the paper uses a microlevel data set of both national and LGA flights to determine the causes of flight delays and cancellations to see if congestion pricing can effectively reduce airport congestion. Second, the paper explores how congestion pricing may affect the mixture of flights at LGA.

Brueckner (2002) presents a theoretical framework where dominant airport carriers internalize the delay externality, which suggests a limited role for congestion pricing at such airport facilities. Mayer and Sinai (2003a) find smaller congestion externalities at airports with dominant market share. In our paper, however, we find no evidence that dominant carriers internalize the delay externality. In fact, we show that the opposite occurs since airports with dominant carriers have more delays and cancellations post-September 11th. These results suggest that when a carrier has a dominant airport market share, congestion pricing may have a larger impact on flight scheduling than previously indicated in the literature (Brueckner, 2002; Mayer and Sinai, 2003a).

Previous research on delays (Rupp, Owens, and Plumly, 2005; Mayer and Sinai, 2003a & 2003b; and Mazzeo, 2002) and cancellations (Rupp and Holmes, 2004) has treated these flight outcomes as separate and independent events. We find evidence that on-time and cancellation decisions are interdependent, hence this paper uses a nested logit to jointly evaluate flight delays and cancellations. These decision processes are modeled sequentially, where the carrier initially attempts to have an on-time arrival, and in situations where on-time arrivals are not possible (due to a mechanical, weather, airport congestion, or staffing issue) the carrier opts to delay or cancel the flight (see Figure 1). We find significant differences between the logit and nested logit specifications, which underscore the need to properly specify the flight decision process.

Finally, our investigation of flight delays and cancellations both nationally and at LGA serves two additional purposes. First, it will determine which aircraft and flight characteristics are most valuable to the airlines should an auction occur for landing/take-off rights. Second, if a carrier's priorities are reflected by its schedule reliability, then we may be able to provide some insight into the mixture of aircraft that would be used and cities served following an auction of LGA's landing and take-off rights. Next we discuss the history of flight regulations at LGA, followed by our econometric model for flight operations. Section 3 discusses the national and LGA data samples. Section 4 presents the estimation results and section 5 concludes with some comments on how congestion pricing may affect the mixture of LGA flights.

1.1 Flight Regulations at LaGuardia

In 1969 the FAA implemented the High Density Traffic Airports Rule (HDR) to reduce delays at five congested airports: LGA, ORD (Chicago O'Hare), EWR (Newark), JFK (New York), DCA (Washington Reagan). This rule limited the number of flight operations at these airports by requiring that each carrier obtain a "slot" permit[2] for each takeoff or landing during a specified 60 minute period. A few years later in the early 1970's, the HDR was lifted at Newark. In order to increase competition at LGA, on 5 April 2000, President Bill Clinton signed the "Aviation Investment and Reform Act of the 21st Century" (AIR-21) which waived the slot permit requirement (as called slot-exemptions) for new entrants at LGA which serve small hub and non-hub airports[3] with small aircraft (i.e., fewer than 71 seats). This legislation also provided a timeline for eliminating all slot restrictions at both ORD[4] (effective 1 July 2002) and LGA (effective 1 January 2007).

This paper examines the performance of the slot-exempted small aircraft flights to/from small and non-hub airports to determine if small communities' flights received worse service quality at LGA than flights from larger communities using larger aircraft. The response by carriers to this slot-exemption offer was overwhelming as more than 600 exemption requests were filed. Six months later in September 2000 there were 200 new daily scheduled flights added at LGA and by January 2001 there were an additional 300 planned new scheduled daily flights. To put these additional flights into perspective, in April 2000, prior to any AIR-21 exemptions, LGA was operating near capacity at 1,039 daily flight operations with 10% of these flights experiencing delays of 15+ minutes. Six months later, the additional LGA exemption flights boosted the average to 1,163 daily flight operations, 30% of which were delayed (September 2000). In fact, during the fall of 2000 airport congestion got so severe at LGA that this one airport comprised nearly 30 percent of the nation's total flight delays.

Shortly thereafter on 15 November 2000 the FAA implemented a short-term solution to LGA congestion by temporarily capping the AIR-21 slot exemptions at LGA and allocated these slots via a lottery. The FAA also limited LGA to no more than 81 total scheduled operations per hour since this was the maximum airport capacity during good weather between 7 a.m. and 10 p.m. effective 31 January 2001. Even with the current operational cap in place, in April 2004, LGA averaged 1,254 daily scheduled flights on peak weekdays causing LGA to have the third highest delay rates in the country.

On 12 June 2001, the FAA announced[5] that they were seeking a long-term solution to the LGA congestion problem in an effort to bring "airport demand and capacity into equilibrium." The initial phase extended the existing lottery allocation scheme and LGA is to hold an additional lottery for unused allocated slots until 29 October 2005. The second phase is to find a long-term solution using market based solutions (i.e., congested based landing fees which vary during the day and/or auctioning of landing and take-off rights) and administrative options (i.e., encouraging the use of larger aircraft, establishing minimum size, granting larger aircraft scheduling priority, etc.)

There have also been suggestions of maintaining a separate slot pool for service to small communities after the scheduled expiration of the slot allocation rule in 2007. Finally, the terrorist attacks of 11 September 2001 temporarily reduced demand and hence eased LGA congestion. In 2003, however, congestion problems have resurfaced at LGA.

2 Econometric Model

Each day airlines make flight operation decisions in an effort to maximize profits. In addition, carriers must reallocate resources due to equipment failures, crew shortages, severe weather, and periodic security-related airport closures. For each flight the agent managing air traffic for a representative airline chooses between three possible arrival outcomes: cancellation, delay, or on-time.

A choice set consisting of three discrete outcomes suggests the use of a discrete choice econometric model. Suppose that the (net future discounted) profit from flight i with outcome j which incorporates both short-term (e.g., rebooking costs) and long-term (e.g., service quality reputation) effects is represented as

$$\pi_i(j) = \pi_j(X_i) + \varepsilon_{ij} \tag{1}$$

where for outcome j, $\pi_j(X_i)$ is a deterministic function of profits from the vector of observable characteristics X_i of flight i. We assume that $\pi_j(X_i)$ can be approximated by a linear function of X_i; hence the profit function becomes

$$\pi_i(j) = X_i\beta_j + \varepsilon_{ij} \tag{2}$$

where ε_{ij} represents unobserved factors that influence profit. For example, the profit from flight

i being canceled is

$$\pi_i(CANCEL) = X_i\beta_{CANCEL} + \varepsilon_{i,CANCEL} \tag{3}$$

Assume (for the moment) that each ε_{ij} is independent and drawn from an identical Weibull distribution. Then the choice of which outcome j maximizes profit for flight i, as represented in equation (2), is equivalent to the conventional multinomial logit model (Domencich and McFadden, 1975),

$$\Pr(i \text{ chooses outcome } j) = \frac{e^{X_i\beta_j}}{\sum_{k=1\ldots3} e^{X_i\beta_k}} \tag{4}$$

where identification requires $\beta_k \equiv 0$ for one of the three outcomes. It is well-known that the multinomial logit model assumes the independence of irrelevant alternatives (IIA): the ratio of any two outcome choice probabilities is independent of whether the third option is available. For instance, if for a particular flight the probability of each outcome is 1/3, the elimination of one option (e.g., on-time arrival) implies that the probability of each of the other two outcomes (e.g., delay and cancellation) is 1/2, so that the ratio of these probabilities remains equal to one.

An alternative discrete choice specification that does not impose the restrictive IIA assumption is the nested logit model. Moreover, the nested logit model in our setting seems natural given that the decision between these three flight outcomes may likely occur sequentially as two binary choices: first, the carrier decides whether the flight arrives ontime or not ontime, and second, for flights not arriving ontime, the carrier must decide to either delay or cancel the flight.[6] These flight arrival decisions appear as "Decision Process 1" in the Figure 1 schematic.[7]

Next we outline the econometric method involved in estimating the nested logit model. Define the inclusive value I_i as the natural log of the sum of exponentiated (expected) profits from not canceling:

$$I_i = \ln \sum_{k=CANCEL,DELAY} e^{X_i\beta_k} \tag{5}$$

Calculating the probability of choosing each outcome j is now a three-step process which is outlined in Greene (2000):

1. Conditional on not arriving ontime, the probability that a flight is canceled (rather than delayed) is estimated equivalently to a standard (binary choice) logit using only the flights which were not ontime:

   $$\text{Pr}_i(\text{ CANCEL } \mid \text{ ONTIME=0}) = \frac{e^{X_i\beta_{CANCEL}}}{1 + e^{X_i\beta_{CANCEL}}} \tag{6}$$

   The first term in the denominator is simplified by the normalization that $\beta_{DELAYED}$ equals 0.

2. Using the same normalization, the inclusive value is

   $$I_i = \ln\left(1 + e^{X_i\beta_{CANCEL}}\right) \tag{7}$$

3. The probability that the flight is ontime (rather than not ontime) is estimated equivalently to a standard logit model for the decision between ontime and not ontime (either delay or cancel the flight), augmented by an additive inclusive value term in the exponential expressions in both the numerator and denominator:

   $$\text{Pr}_i(\text{ON TIME}) = \frac{e^{X_i\beta_{ONTIME} + \tau I_i}}{1 + e^{X_i\beta_{ONTIME} + \tau I_i}} \tag{8}$$

This is the standard logit model for ontime vs. "other" with the additional inclusive value term.

The unconditional probabilities of cancel and delayed arrivals are straightforward to compute. Because the estimated β and τ parameters are difficult to interpret, we also report marginal effects

$$\text{me}_j(x) \equiv \frac{1}{N} \sum_{i=1\ldots N} \frac{\partial \Pr_i(j)}{\partial x_i}. \tag{9}$$

In sum, we have modeled the flight operation decision process as one in which the carrier first attempts to maximize the number of on-time arrivals. Flights which do not arrive ontime are hence either delayed or canceled.

Due to the substantial differences in size and business models (i.e., low cost vs. full-fare, point-to-point vs. hub spoke, etc.) among the airlines, we use White (1980) robust standard errors in all estimations to address the existence of heteroscedasticity. In addition, all estimations include day of week, month, year, and carrier-specific indicator variables.

3 Data

This paper compares the flight outcomes (on-time arrivals, delayed arrivals, and canceled) nationally with performance at LGA by using U.S. Bureau of Transportation Statistics (BTS) On-Time Performance data for individual domestic flights between 2001 and 2003.[8] All U.S. carriers with revenues from domestic passenger flights of at least one percent of total industry revenues are required to report flight operation decisions for each flight. We obtain every domestic flight between October 2001 and December 2003 for nineteen U.S. carriers.

All variables are constructed from the original data set of 13,047,360 flights from October 2001 to December 2003. Table I indicates a noticeable improvement in airline on-time performance since the September 11th terrorist attacks. Specifically, 2002 marked the lowest yearly cancellation rate (1.2 percent) while 2003 had the highest annual on-time arrival rate (82.7 percent) since the BTS began compiling on-time performance statistics in 1995 (see Figure 2). Due to a reduction in the demand for air travel since September 11th (Ito and Lee, 2004), the number of domestic scheduled flights nationally were reduced by 700,000 in 2002. Scheduled flights rebounded in 2003 to exceed the flight totals from 2001. The return of travellers has caused airport and air travel congestion to resurface in the first ten months of 2004 as both the cancellation rate (1.74 percent) and on-time rate (78.6 percent) are approaching their historical averages (see Table I).

Due to the computational constraints presented by the nested logit estimation, for the national sample we randomly select a 1 percent subsample, resulting in 130,482 flights. Incomplete data reporting (most notably weather-related) in addition to missing/incorrect aircraft tail numbers reduces the sample by 9,939 flights or 7.6 percent. We also omit a handful of on-time performance observations that may have been coded incorrectly (i.e., flights that arrive more than an hour early or 17+ hours late). Our second sample includes every scheduled LGA arrival between October 2001 and December 2003, resulting in 211,632 flights. Table II provides summary statistics for U.S. domestic flights for both the national sample and LGA arrivals over the twenty-seven month sample period.

For each scheduled flight arrival, exactly one of these indicators (canceled, delayed, or ontime) equals one, while the other two equal zero.[9] In most estimations the paper adopts the Department of Transportation's (DOT) convention that a flight is considered ontime if it arrives (departs) less than 15 minutes after its scheduled arrival (departure). The DOT ontime definition is the industry standard measure for on-time performance. During our twenty-seven month sample period, Figures 3 & 4 indicate that LGA consistently experiences more cancellations and flight delays (especially since April 2002) compared to national averages. A chi-square test overwhelmingly rejects that the national and LGA samples have equivalent proportions of cancellations, delays, and on-time arrivals.[10]

Descriptive statistics from Table II show a higher national on-time arrival rate (82 percent) compared to LGA (79 percent). The LGA cancellation rate (3.1 percent) is twice the national average (1.4 percent). If we adopt a more forgiving definition of on-time arrival, (i.e., arriving at the gate within 30 minutes of the scheduled arrival), then 90 percent of national flights and 86 percent of LGA flights are ontime. Finally, the average arrival delay os slightly longer at LGA (4.2 minutes) than nationally (3.5 minutes). Assuming that arrival delays are normally distributed, we can reject the hypothesis that the national and LGA samples have equivalent lengths of arrival delays.[11]

One caveat of using on-time arrival data is that arrival times are subject to schedule padding. This study, however, focuses on arrival delays instead of departure delays since passengers are more likely concerned with getting to their destination on-time, rather than pushing back from the gate on-time. Given that we find similar results for the on-time departure/cancellation nested logits and minutes of departure delay estimations (see Appendix I) compared to their on-time arrival counterparts, this study focuses on flight arrivals.

Most variables are constructed from the BTS TranStats data base, while some come from other sources. Aircraft tail numbers provided by the BTS are matched to the FAA Aircraft Registry database to determine aircraft *seating capacity*.[12] LGA aircraft are slightly larger (152 passenger seats) than the national average (143 seats).

We match individual flights to quarterly passenger fare data from the U.S. Office of Airline

Information's *Airline Origin and Destination (O&D) Survey.* This survey is a 10% sample of domestic airline tickets from reporting carriers. These fare data enable us to estimate flight revenue since actual flight revenue is unobservable. In the national sample average nonstop one-way *air fare* for carrier j on route r is \$155.83.[13] Average ticket prices are about \$15 higher at LGA (\$170.14). *Yield* (also known as average revenue passenger mile) is average nonstop one-way *air fare* (local air fare) divided by nonstop flight *distance* (miles between airports). The proportion of *local passengers* on a route is found by dividing the number of quarterly nonstop tickets sold (from the O&D Survey 10% ticket sample data) by the total number of occupied seats (from T-100 domestic market data at the TranStats database) during the quarter for carrier j on route r. Finally, we multiply *local passengers* by 10 to get the correct proportion given that the ticket data is a 10% sample. Nationally, the average proportion of *local passengers* is 39.4%, whereas LGA has a much higher proportion (67.5%) of *local passengers.*

We multiply average one-way *air fare* by *seating capacity* to obtain *potential revenue* per flight. In the national sample average *potential revenue* is \$22,880 (\$25,750 for LGA) per flight. *Potential revenue* provides an upper bound of flight revenue since most flights do not have 100% occupancy rates. *Average revenue* per flight provides a more realistic portrayal of flight revenue since it is the average one-way *air fare* multiplied by the monthly average number of occupied seats (*seating capacity* multiplied by average *load factor*) for carrier j on route r. *Load factor* represents the proportion of total seats that are occupied by passengers and is obtained from the T-100 domestic market data. In this sample the national average *load factor* is 67.1 percent (63.3 percent at LGA) and mean *average revenue* is \$15,610 (\$16,672 at LGA) per flight. In sum, we find that LGA flights have slightly higher fares (\$15), larger planes (9 more seats), higher average revenue (by \$1,000), and lower load factors (by 4 percent). LGA routes are more likely to be served by multiple carriers and LGA bound flights are more likely to originate from a carriers' hub.

To measure the effect of airline hubbing on schedule reliability we include indicator variables for both *airline hub origination* and *airline hub destination* flights. Performance by hub carriers is critical to maintaining its network of flights and may also have revenue implications since consumer demand is higher for airlines with large operations from an origin city (Morrison and Winston, 1989). Moreover a majority of passengers at a typical hub are making connections (Morrison and Winston, 1995). Perhaps more importantly, some of these passengers may be making international connections. A flight delay or cancellation for a *hub destination* flight can cause considerable passenger inconvenience, especially for connecting passengers. Our proxy of connecting passengers is the interaction variable (*seating capacity*hub destination*) which multiplies aircraft *seating capacity* by one for *hub destination* flights, and zero otherwise.

We also analyze the performance of various-sized hubs since larger airline hubs have larger banks of flights and hence more congestion. Using the convention of Mayer and Sinai (2003a), we also define airline hub size using the number of connecting flights at the origination airport. Airlines that offer 71+ connections are called *large airline hub origination*, those that offer between 46 and 70 connections are called *medium airline hub origination*, and those that offer between 26 and 45 connections are called *small airline hub origination* having. Similar size categories are used for *hub destination* flights. *Airport concentration origination (destination)* is the sum of the squared carrier shares as a percentage of all daily flights at the origination (destination) airport.

We also examine the effect of route competition on schedule reliability. *Monopoly* routes comprise slightly more than half (52.4 percent) of the sample. We use airport pairs instead of city pairs as our "market" definition since airport congestion varies substantially between airports in the same city (i.e., Chicago O'Hare and Chicago Midway). Nationally, one-third of the sample involves routes served by two carriers, with the *large duopoly carrier* having a larger route market share than its counterpart, the *small duopoly carrier*.[14] LGA routes are more competitive with only one-third being served by a single carrier and about one-half of LGA routes having two carriers.

We include a variety of scheduling and logistical variables such as the number of *hours until next flight* by carrier j on route r. The median wait between flights is 3 hours and 15 minutes. LGA flights per route are much more frequent with the median wait being just 1 hour and 46 minutes between flights about half the national average. To control for the possibility of cascading delays (Mazzeo, 2003) during the day, *time01* is the renormalized scheduled departure time between 0 (midnight) and 1 (11:59 p.m.).

We include the *daily total number of carrier flights* on route r by carrier j to examine schedule reliability of routes with frequent daily service. For example, passengers on a sparsely occupied plane on a route with frequent daily service might be subject to more flight cancellations. The average daily flight frequency is considerably higher at LGA (9.4 flights per carrier per route) than nationally (6.1 flights). Finally, the total number of daily airport operations proxies airport congestion. We control for poor weather conditions by including daily weather data at origination and destination airports[15] from the U.S. National Oceanic & Atmospheric Administration (NOAA).[16] *Rain origination (destination)* is the amount of daily precipitation at the origination (destination) airport measured in inches. *Minimum temperature origination (destination)* is the daily coldest temperature reading in Fahrenheit at the origination (destination) airport. Finally, *frozen precipitation origination (destination)* is an interaction term multiplying *rain origination (destination)* by one if daily *minimum temperature origination (destination)* < 33, otherwise zero.

4 Results

4.1 Nationally

Since previous airline studies have used discrete choice models to estimate late arrivals (Mazzeo, 2003), on-time arrivals (Mayer and Sinai, 2003b), and flight cancellations (Rupp and Holmes, 2004), Table III presents logit estimations for on-time arrivals (Model 1) and flight cancellations (Model 2) for the national sample of U.S. domestic flights between October 2001 and December 2003. Using the same explanatory variables and data, Table IV (Model 3) shows nested logit estimations for flight arrivals where the carrier first decides whether the flight arrives on-time, and then for flights which fail to arrive on-time, the carrier makes a second decision to delay or cancel. To determine whether the simpler conditional logit model or more complicated nested logit model is appropriate, we use a Hausman (1978) specification test[17] to check the independence of irrelevant alternatives (IIA) assumption. The corresponding p-value < 0.01 overwhelmingly rejects the IIA assumption and hence suggests that the nested logit model should be employed.

A comparison of the logit and nested logit results reveals several notable differences. For example, the logit estimation (model 1) suggests that carriers with frequent daily service on a route have significantly fewer on-time arrivals; whereas the nested logit specification (model 3) reports no statistically significant link between on-time performance and flight frequency. We attribute this change to the fact that routes with frequent daily service routes have significantly higher cancellation rates. In the cancellation estimations we also find differences between logit and nested logit estimates. For example, aircraft with seating capacity of fewer than 71 passengers are subject to significantly more cancellations in the logit specification (model 2), yet the nested logit estimation (model 3) shows that carriers are more likely to delay, not cancel, smaller aircraft flights. The richer nested specification can account for the fact that small aircraft have more flight delays, while the logit estimation of flight cancellations cannot. Similarly, relying on the logit estimates we would conclude that busier destination airports have significantly higher cancellation rates. The nested logit estimates from model (3), however, indicate that airport destination with more flights are more likely to have arrival delays, not cancellations. In sum, these discrepancies indicate the value of using the nested logit specification. Since the Hausman test suggests that delays, cancellations, and ontime arrivals are interdependent, the remainder of the paper uses nested logits to analyze flight arrivals.

4.1.1 Economics of Delays and Cancellations

If cancellations are just considered as a really long flight delay, then the same factors which cause a delayed flight should also generate more cancellations. For example, an equipment failure that causes an extended delay may eventually result in a flight cancellation due to existing flight-time crew limits. From the passenger's viewpoint, a flight cancellation causes the traveller to be delayed until the next departing flight with an available seat. Hence factors that contribute to both delays and cancellations are likely generated by external factors (such as weather or airport congestion) that are beyond the control of the carrier. On the other hand, situations were delays and cancellations move in opposite directions suggest that the carrier is trading-off fewer (more) flight cancellations for more (fewer) flight delays.

We discuss the model (3) results extensively since these results are representative of our empirical findings across all models. We also use model (3) as the baseline for making comparisons later in the paper when conducting robustness checks. A common finding is that external factors contribute to both delays and cancellations. For example, poor airport weather conditions such as rain and especially frozen precipitation contribute to fewer on-time arrivals and more cancellations. Likewise fewer on-time arrivals and more cancellations are also linked to origination airport congestion. Congestion at the destination airport, however, only impacts the on-time arrival rate and not cancellations.

Airport congestion is especially prevalent at the nation's four slot-restricted airports LGA, JFK, DCA and ORD (prior to 1 July 2002). Hence it is not surprising that fewer on-time arrivals and more cancellations occur for flights taking-off and/or landing at slot controlled airports. We should also find some evidence that suggests a trade-off between cancellations and length of flight delays at *slot origination* airports. Model (4) in Table IV shows that arrival delays are nearly 1 minute shorter at *slot origination* airports. Since carriers have just 60 minutes to use a slot or lose it,[18] extended delays are typically an option at slot airports. As a result, both cancellations and shorter arrival delays are more common at slot airports.

4.1.2 Economic Variables

Bratu and Barnhart (2004) argue that flight-based on-time performance measures (such as the DOT 15 minute on-time definition) understate the true level of passenger inconvenience because flight measures fail to consider the additional passenger delays due to flight cancellations and missed connections. Concern about the welfare of connecting passengers may partly explain why carriers provide better service for connecting passengers than *local passengers*. In addition, there may be cost reasons for providing better service to connecting passengers since carriers want to avoid having to rebook passengers, especially those with multiple trip legs.[19] For example, American Airlines typically charges a $100 fee to passengers who make changes to existing reservations. Table IV shows significantly lower on-time arrival rates, more frequent cancellations, and longer arrival delays on routes with more *local passengers*. Arrival delays have a larger impact on connecting passengers. A thirty minute arrival delay may be no big deal to a local passenger, however, this same flight delay may cause a four hour passenger delay for a connecting passenger who misses her flight connection.

We considered three different measures of flight revenue: *average revenue* (model 3), *potential revenue*, and *yield*. Overall, similar results are found for these three revenue measures, hence we opt to report only the *average revenue* findings since they are representative of our revenue findings. Given that Rupp, Holmes, and DeSimone (2005) report fewer delays and more on-time departures for higher potential revenue flights following a security-related airport closure, we expected to find better service quality on higher revenue routes. Moreover economic variables likely play an important role in the flight decision process given that airline operation software currently enables airlines to solve complicated flight operation algorithms while protecting revenues.[20] Our empirical evidence, however, suggests otherwise as revenue is either insignificant or inversely associated with service quality.

Specifically, models (3) and (4) indicate that higher *average revenue* is associated with fewer on-time arrivals, more cancellations, and longer arrival delays. Given that carriers are likely very concerned with protecting revenue streams, we think it is highly unlikely that carriers are more likely to cancel higher revenue/more profitable routes. Caution should also be taken before inferring too much from these revenue results since we do not observe actual passenger fare data for a given day and flight. Instead, the lowest level of aggregation for publicly available data is quarterly fare averages for a specific route and carrier. Since actual flight revenue varies considerably within a day (e.g., suppose the early flights are full and the afternoon flights are empty), *average revenue* may be a poor proxy for actual revenue, hence the poor explanatory power. Nonetheless, we believe that revenue should matter, hence *average revenue* is included in all estimations.

Turning to other economic variables we find that full planes (*route load factor)* have significantly fewer on-time arrivals and flight cancellations. We interpret the marginal effects estimates for on-time arrival (-0.0657) and cancellation (-0.0278) in model (3) as follows, a one-standard deviation increase in mean *route load factor* (i.e., 80% of seats occupied instead of 67%) reduces the likelihood of an on-time arrival by 0.85 percentage points and lowers the cancellation rate by 0.25 percentage points.[21] On first glance this cancellation effect seems small. Recall, however, that the average flight cancellation rate in the sample is just 1.4 percent. Hence this change represents a 26% reduction in flight cancellations for routes with fuller flights. Model (4) also shows that a one-standard deviation increase in *route load factor* lengthens the arrival delay by approximately 1 minute. These results suggest that carriers are minimizing passenger service disruptions by not canceling full flights. These fuller flights, however, take longer to load, resulting in fewer on-time arrivals and slightly longer arrival delays.

Our examination of aircraft size indicates that larger aircraft typically deliver better service quality. Carriers may be minimizing passenger inconvenience by proving better service on larger planes. We cannot, however, rule out the alternative hypothesis that larger planes provide better service because these aircraft typically fly long-haul routes and thus accumulate less wear and tear. Larger planes have significantly higher ontime arrival rates and lower cancellation rates. Specifically, model (3) indicates that a one-standard deviation *seating capacity* increase (60 additional seats) reduces the cancellation rate by 0.38 percentage points (or 27 percent) and increases the on-time arrival rate by 0.77 percentage points. Small aircraft (fewer than 71 seats) experience significantly lower on-time arrival rates (5 percentage points lower) and longer arrival delays (2.6 minutes). These small aircraft, however, are neither more likely nor less likely to be cancelled. Finally, the *seating capacity*hub destination* interaction term has little effect on flight cancellations and on-time arrivals.

4.1.3 Airport Concentration and Hub Airlines

Our proxy for airport competition is *airport concentration at origination* and *destination.* We find no evidence to support the theoretical model proposed by Brueckner (2002) that concentrated airports have fewer flight delays due to dominant carriers internalizing the airport congestion costs. In fact, our empirical results indicate that the opposite is occurring since service quality suffers at highly concentrated origination airports. Specifically, flights that originate from more concentrated airports are significantly less likely to arrive ontime, have higher cancellation rates, and experience longer arrival delays. The model (3) marginal effects suggest that a one-standard deviation increase in *airport concentration at origination* (0.21 points) reduces the on-time arrival rate by 0.44 percentage points (or less than 1 percent) and increases cancellations by 0.12 percentage points (approximately an 8 percent increase). Or stated alternatively, the increase in flight delays from a one-standard deviation increase in *airport concentration at origination* is equivalent to the congestion induced delays associated with an origination airport scheduling an additional 169 daily flights.

These delay results also contradict the empirical results presented by Mayer and Sinai (2003a) which shows an inverse relationship between airport concentration and flight delays. There are several differences between this paper and prior work. Foremost, the paper estimates delays and cancellations jointly rather than separately. Second, this paper uses the DOT delay definition rather than travel time in excess of the minimum (Mayer and Sinai, 2003a). Third, this paper includes many microlevel variables allowing us to control for weather, aircraft, flight and route characteristics. Finally, the sample period includes only flights after September 11th, 2001. Our findings are more in line with a recent paper by Zhang and Yuen (2004), who modify the Brueckner (2002) model by using variable passenger time costs and find an increase in airport congestion across every market structure in comparison to Brueckner. In sum, our empirical results suggest that in situations where a carrier has a dominant market share, congestion based pricing may play a larger role than previously indicated in the literature (Brueckner, 2002; Mayer and Sinai, 2003a).

The *airline hub origination* results suggest a trade-off between cancellations and delays. Specifically, flights originating from an airline hub are subject to fewer cancellations and fewer ontime arrivals. Several factors may explain why hub origination flights have 0.34 percentage points (or 24%) lower cancellation rates. Hub airlines have better access to spare aircraft, on-site maintenance facilities, and/or replacement flight crews. With regard to flight delays, because hub airlines typically group their flight departures[22] (also known as a flight bank) in an effort to minimize passenger connection times, the result is short intervals of airport congestion during the day and hence frequent and marginally longer arrival delays for hub airlines. Non-hub airlines offer flight schedules that avoid peak congestion periods at the hub airport. Consistent with Mayer and Sinai (2003a), we also find that the presence of a hub airline or "hubbing effect" dominates the *airport concentration* or "congestion externality effect." Our estimations indicate that the hubbing effect on flight delays is more than three times as large as a one-standard deviation increase in *airport concentration at origination.*

Hub airlines realize that their flight bank schedules cause congestion, this may explain why hub carriers schedule longer periods at the gate or "turnaround" between aircraft arrival and next scheduled departure than non-hub airlines. For example, for every U.S. domestic flight in April 2003, the average turnaround time for non-hub carriers is 53 minutes (excluding aircraft parked overnight). In comparison hub carriers scheduled an average of 77 minutes to turnaround an aircraft, with larger hubs scheduling larger buffers.[23] Even with longer scheduled aircraft lay-overs, hub airlines still have difficulty in pushing back from the gate ontime as they have significantly more frequent and longer departure delays (see Appendix I). These findings may explain why several carriers recently began rescheduling traffic at their hubs in order to avoid peak-time congestion. For example, Continental credits its improved flight operations to de-peaking its Newark hub in the summer of 2000, while American began experimenting with evening out flights at Chicago O'Hare in October, 2000 (McCartney, 2000). Due to its successful experiment in Chicago, American decided to reschedule operations at its largest hub, Dallas-Fort Worth, starting in November, 2002 (McCartney, 2002). Finally, we should mention that part of U.S. Airways turnaround plans include revamping its flight schedules at Philadelphia and Charlotte by reducing the time its planes sit on the ground and smoothing out the flow of flights to avoid peak congestion periods (Carey, 2004). A Delta Airlines press release announced "revolutionary schedule change" effective 31 January 2005 to mark the depeaking of its Atlanta hub in an effort to improve on-time performance (news.delta.com).

Airline hub destination flights experience a noticeable improvement in on-time performance compared to *airline hub origination* flights. This result is attributed to the more even distribution of flight arrival times during the day by hub airlines compared to the spiking of flight departures by hub airlines at peak travel times. A secondary reason for this result is that in order to maintain a hub-spoke network carriers need on-time arrivals at the hub. We find that *airline hub destination* flights are marginally more likely to arrive ontime and arrival delays are neither longer, nor shorter than for non-hub destined flights. Finally, we find no evidence in the national sample (Model 3) that route competition (*monopoly, large duopoly carrier* or *small duopoly carrier*) influences on-time arrivals or cancellations in a predictable manner.[24]

4.1.4 Logistical Issues and Weather

The logistical variable with the most explanatory power is the *renormalized schedule departure time*. Figures 5 (cancellations) and 6 (arrival delays) show the average cancellation and delay rates for 15 minute intervals throughout the day.[25] These figures show that cancellations and especially delays build through out the day, reaching a peak nationally for scheduled departures at 4:30 p.m. (cancellations) and 7 p.m. (arrival delays). Empirically, the nested logit estimates indicate reveal significantly fewer on-time arrivals and more cancellations for scheduled departures later in the day. The magnitude is non-trivial. Specifically, the marginal effects from model (3) suggest that scheduled departures at 6:30 p.m. versus 2 p.m. (i.e., a one standard deviation increase in *renormalized schedule departure time*) have 4 percentage points (or 5%) lower on-time arrival rates and 0.07 percentage points (or 5%) higher flight cancellation rates. In addition, the 6:30 p.m. departures (instead of 2 p.m.) have 3 minutes longer arrival delays.

Even for this post-September 11th sample, we find airport congestion remains a significant flight delay factor between 2001 and 2003. Busier airports are subject to significantly more delays and cancellations. Since the airport capacity is unique to each facility, the marginal effect of adding more flight operations would impact every airport differently. Hence we will not attempt to interpret the airport congestion marginal effects. Airport congestion at the destination provides a larger impact on flight delays than origination airport congestion since we find that *daily total destination airport flights* (-0.0035) has larger marginal effects than *daily total origination airport flights* (-0.0026). This finding is consistent with the FAA's 2001 Airport Capacity Benchmark report, which found that airborne flights and departures are more likely to be delayed due to lack of arrival capacity, not departure capacity.

In terms of flight frequency (*daily total carrier flights on route*), we find that frequently served routes are neither more, nor less likely to arrive ontime. We do, however, find that flight cancellations are more common for carriers with frequent daily service on a route. This suggests that carriers consolidate flights on frequently served routes. We estimate that an additional daily flight on a route, increases the cancellation rate by 0.08 percentage points (or about 6%).

Flights of greater *distances* (miles between airport pairs) are less likely to be cancelled and have shorter arrival delays than shorter flights. Longer flights provide pilots with a greater opportunity to "make-up" time while airborne, which may explain the shorter arrival delays. Since passengers have fewer substitutes for long-haul flights, carriers may try to avoid canceling these flights. Whereas for short-haul flights, carriers (especially commuter airlines) are notorious for providing buses, rental cars, and taxis to passengers displaced by a flight cancellation. Hence canceling a short-haul flight may be less costly and less inconvenient for passengers than canceling a coast-to-coast flight.

We do not find any link between the length of the wait between flights on a route and flight cancellations. As expected, severe weather adversely impacts flight schedules. Precipitation, especially in the frozen form, at both origination and destination airports contributes to more cancellations and fewer on-time arrivals. The next section examines flight operations at New York's LaGuardia Airport.

4.2 New York LaGuardia Airport (LGA)

There are more similarities than differences between flight operations at LGA and the national sample. The same factors that influence schedule reliability nationally, such as severe weather, congestion, deteriorating service quality during the day also appear at LGA. We are unable to compare the performance of hub and non-hub airlines at LGA since there are no hub airlines at this airport. In addition, due to lack of variation in LGA airport concentration during the 27 month sample period, LGA airport concentration is not identified and hence is excluded from the estimations. All other explanatory variables from the national sample are included in the LGA estimations. We begin by discussing the similarities between the two samples.

Table V shows that routes with fuller planes (*route load factors)* have lower on-time arrival rates, longer arrival delays, and fewer cancellations. These results suggest that full planes arriving at LGA experience a trade-off of being delayed but not canceled. The *route load factor* marginal effects (model 5) and minutes of arrival delay (model 6) for LGA are approximately twice as large as the national sample. Full planes require more loading time, resulting in departure delays (see Appendix I). For LGA bound flights, the arrival delay for fuller planes is longer due to airport congestion since the carrier can no longer use its pre-assigned landing time and hence is pushed to the back of the queue of arriving flights. Consistent with the national sample, long-haul flights bound for LGA also have significantly lower cancellation rates and shorter arrival delays. Next we look at scheduled departure time.

Figures 5 & 6 show that LGA arrivals have substantially higher cancellation and delay rates compared to the national averages for each 15 minute scheduled departure interval between 6 a.m. and 9 p.m.. The performance of LGA arrivals reflects the national trend of deteriorating flight schedules throughout the day. The 15 minute interval with the highest cancellation rate (5%) is scheduled departures between 4:15-4:30 p.m bound for LGA. Shortly thereafter, arrival delays reach their peak (36%) for scheduled departures between 5-5:15 p.m. and destined for LGA. Service quality for LGA arrivals begins to approach the national averages for scheduled departures after 9:15 p.m. (for flight delays) and after 9:30 p.m. (for flight cancellations). This corresponds to the lifting of slot restrictions after 10 p.m. at LGA. Given the data patterns depicted by Figures 5 & 6, it is not surprising that Table V reveals less reliable schedules for LGA arrivals with *scheduled departure times* later in the day.

Table V also illustrates that LGA is currently operating at or near capacity. For example, the marginal effects for *daily total origination airport flights* indicate that an additional 100 flights at an origination airport (not LGA) would reduce on-time arrivals by 0.62 percentage points. Whereas if LGA schedules an additional 100 flights ontime arrivals would fall by 8.1 percentage points, which is an effect 13 times larger than experienced by non-LGA airports. Finally, severe weather at LGA wreaks havoc with flight schedules. For example, an equivalent amount of rain or frozen rain causes twice as many flight cancellations at LGA compared to the national averages. Next, we highlight some operational differences at LGA.

We begin by examining the performance of LGA slot-exempted flights: small aircraft from non-hub/small hub airports. Comparing Tables IV & V shows that small aircraft (*aircraft seating capacity* $<$ *71 passengers*) have significantly lower on-time arrival rates both at LGA (6.5 percentage points lower) and nationally (5 percentage points lower). Small aircraft also experience longer arrival delays both at LGA (3.7 minutes) and nationwide (2.6 minutes). Differences appear for flight cancellations, as small aircraft bound for LGA have significantly higher cancellation rates (0.2 percentage points higher) whereas nationally, there is no link between cancellations and small aircraft. The continuous measure *seating capacity of aircraft* indicates that larger aircraft have significantly fewer cancellations both at LGA and nationally. We find worse service quality (fewer ontime arrivals and longer delays) for flights originating from *1997 non-hub/small airports* and bound for LGA. In comparison, flights from these same *1997 non-hub/small hub airports* in the national sample did not have lower on-time arrival rates, nor did they have longer arrival delays.

In sum, the Aviation Investment and Reform Act of the 21st Century (AIR-21) granted certain flights (small aircraft serving small hub and non-hub airports) slot exemptions to promote competition at LGA. We find some evidence that suggests these slot exempted flights are more likely to be canceled (small aircraft), have lower on-time arrival rates (small aircraft and non-hub/small hub airports), and experience longer flight delays (small aircraft and non-hub/small hub airports) at LGA. This begs the question of whether the air traffic control at LGA should be criticized for granting larger aircraft priority in the landing queue? Moreover should carriers be criticized for favoring larger aircraft over smaller aircraft when deciding which flights to cancel? We believe that both of these parties (air traffic control and carriers) are making rational decisions that are in the best interests of the majority of passengers. Combining the finding of Morrison and Winston (1989) that optimal congestion pricing fees will also have a larger impact on commuters and general aviation than commercial carriers with our finding of worse service quality for small aircraft serving smaller airports suggests that congestion-based pricing at LGA will likely reduce the number of scheduled flights to smaller airports.

Nationally, if a monopolist carrier charges high prices or provides poor service quality on a route then such behavior would likely attract entry. Since the slot permit requirement at LGA creates a barrier to entry, LGA carriers have little incentive to provide high service quality on routes with limited competition. Table V shows that LGA *monopoly* routes have lower on-time arrival rates (3.75 percentage points), marginally higher cancellation rates (1 percentage point), and longer arrival delays (2.5 minutes). In comparison, the national sample (see Table IV) had no significant differences in the service quality by *monopoly* carriers. The *large duopoly carrier* at LGA also has significantly higher cancellation rates (1.3 percentage points) and longer arrival delays (1.2 minutes). Finally, the *small duopoly carrier* at LGA has slightly longer arrival delays (about 1 minute).

We conclude with some remarks about two logistical variables. First, we find a trade-off between more cancellations and fewer/shorter delays for LGA routes with frequent service (*daily total carrier flights on route).* In comparison, the national sample linked cancellations with flight frequency, however there was no relationship between on-time arrivals and frequency of service. Routes with hourly scheduled departures (between 6 a.m. and 9 p.m.) are not uncommon at LGA (i.e., Delta LGA-ATL, American LGA-ORD, US Airways LGA-BOS). Our findings suggest that should a mechanical issue arise on one of these frequent service routes, carriers would likely cancel rather than delay the flight. Moreover, extended delays are not possible at LGA since a carrier forfeits any unused slots after 60 minutes. Finally, we find fewer cancellations on routes that have longer time gaps between flights (*hours until next flight)* by the same carrier on a route.

4.3 30 and 45 Minute "On-time" Arrivals

We examine two additional on-time arrival definitions to verify the robustness of our results. Overall, the results are comparable in the national sample whether we define on-time arrivals as flights which arrive at the gate within 15, 30, or 45 minutes of their scheduled arrival time. For example, across all models we find higher on-time arrival rates during good weather for larger aircraft, earlier in the day departures and airports with less traffic. There are only a handful of differences between these on-time measures, to which we now turn.

Models (7) and (8) define on-time arrivals as flights reaching the gate within 30 and 45 minutes, respectively. *Route load factor* no longer adversely impacts on-time arrivals when using these more forgiving on-time measures. The disappearing *route load factor* result suggests that fuller planes take more than 15 minutes (but less than 30 minutes) longer to load. One other notable change is significantly fewer ontime arrivals (30+ minutes) occur for *non-hub/small hub airport origination flights* (see model 7). Frequent extended flight delays may not be uncommon at smaller airports because such facilities may have less access to mechanics, equipment, spare parts, and labor personnel. We are cautious about inferring too much from this small airport result since the 45 minute on-time definition (model 8) shows no link between on-time performance and small airports. The final section explores the relationship between hub size and service quality.

4.4 Airline hub size

Model (9) investigates how the size of an airline's hub effects schedule reliability using the national sample. Previously we found fewer ontime arrivals and fewer flight cancellations for *airline hub origination* flights. We find that regardless of hub size: *small*, *medium*, and *large airline hub origination* flights all have significantly worse on-time arrival rates compared to non-hub airlines. Large hub airlines register the worst on-time performance. Specifically, the model (9) marginal effects for small, medium, and large airline hubs indicate -1.25, -1.98, and -3.31 percentage points lower on-time arrival rates, respectively. These results reflect the fact that large hub airlines have larger flight banks and hence more congestion which make on-time arrivals more difficult. Moreover these findings also indicate that hub airlines (especially large hubs) have the largest opportunity to improve ontime performance by smoothing or depeaking flight schedules. The trade-off from smoothing hub operations is longer passenger layovers. In terms of flight cancellations, originations from larger airline hubs have significantly fewer flight cancellations. The marginal effects for small, medium, and large airline hubs are -0.20, -0.34, and -0.32 respectively.

Previously we found that flights destined for an airline's hub had marginally better on-time arrival rates. Now we can be more specific since on-time arrival rates are significantly better for small airline hub destined flights. Whereas, flights destined for medium and large airline hubs have neither better, nor worse, on-time arrival rates. The better performance by small hub airlines is attributed to smaller flight banks which do not exceed the airport flight capacity. The final section provides some concluding remarks.

5 Conclusion

We use a nested logit estimation to determine the causes of flight delays and cancellations both nationally and at New York LaGuardia Airport (LGA). We focus on LGA flight operations since the FAA is currently considering congestion-based pricing of landing and take-off rights at this airport. Recent theoretical (Brueckner, 2002) and empirical work (Mayer and Sinai, 2003a) suggest that carriers with a dominant airport market share internalize the delay externality. Hence indicating a limited role for congestion pricing at facilities with dominant airport carriers. Using a microlevel data set of post-September 11th flights, we present evidence that airports with dominant carriers do not internalize the delay externality because these airports have higher delay and cancellation rates. This suggests that congestion pricing may play a larger role than previously indicated in the literature, especially at airports with a dominant carrier.

The presence of a hub airline provides more than three times the impact on flight delays as the effect of a one-standard deviation increase in *airport concentration at origination.* Clearly the "the hubbing effect" dominates the "congestion externality effect," a result consistent with Mayer and Sinai (2003a). Frequent flight delays for hub airlines is likely the product of airport congested created by the clustering of flight departures by the hub airline to minimize passenger connection times. Hub airlines appear to be trade-offing off more delays for fewer flight cancellations. The lower cancellation rates for hub airlines are attributed to better access to replacement crews, spare parts, ground maintenance staff, and substitute aircraft.

Larger airline hubs have worse on-time performance. Larger hubs are also less efficient because hub carriers schedule longer periods at the gate (averaging 77 minutes between aircraft arrival and next scheduled departure) compared to non-hub airlines (53 minutes). The larger the hub, the longer the scheduled period at the gate. Even with longer scheduled aircraft lay-overs, hub airlines are still significantly less likely to push-back from the gate ontime. These findings suggest that hub carriers can increase on-time arrival rates and shorten aircraft idle periods by smoothing flight schedules, especially at large and medium size hub airports. This may explain why Delta Air Lines recently depeaked Atlanta (31 January 2005). Moreover US Airways made smoothing the flow of flights at both Philadelphia and Charlotte beginning in February 2005 part of its bankruptcy turnaround plan.

Carriers serving LGA have little incentive to improve schedule reliability on routes with limited competition since entry by another carrier is highly unlikely. In an effort to make LGA more competitive, the Aviation Investment and Reform Act of the 21st Century granted slot exemptions to new entrants serving small airports with small aircraft. We find less reliable schedules for slot exempted LGA flights. Specifically, small aircraft (fewer than 71 seats) have higher cancellation rates and lower on-time arrival rates. Both small aircraft and non-hub/small hub airports have longer arrival delays.

We now address how congestion pricing may affect the mixture of flights at LGA. First, we observe less reliable schedules for smaller communities served by small aircraft which suggests that small community flights may be a lower priority for LGA carriers. Morrison and Winston (1989) report that optimal congestion pricing will have a larger impact on commuters and general aviation than commercial carriers. These two findings suggests that smaller communities may experience a drastic reduction in service should the FAA opt to auction landing and take-off rights at LGA. If providing LGA flights to small airports is an FAA priority, then a separate congestion-pricing pool reserved for flights to small hub and non-hub airports may be necessary to prevent these communities from losing service. Second, larger aircraft may become more prevalent at LGA following an auction given the lower cancellation rates for larger arriving aircraft at LGA. Moreover larger aircraft have lower average landing costs per person due to more passengers sharing the congestion pricing burden. Third, assuming that the number of flight operations is held constant at LGA, then carriers may place a higher value on earlier in the day departure and arrival slots at LGA given that these flights are more reliable than later in the day departures. Fourth, since long-distance LGA flights are subject to fewer cancellations, LGA may experience an increase in long-haul flights following an auction.[26]

In sum, since LGA operates at maximum airport capacity between 7 a.m. and 10 p.m. there are no off-peak operating periods to reschedule flights. Hence congestion pricing at LGA is not likely to solve its congestion woes, rather this policy change will likely have a larger impact on the mixture of LGA flights with larger aircraft, flights to larger hub airports, and long-haul routes becoming more prevalent.

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Notes

[1] One exception is the construction of an additional runway at Boston Logan Airport scheduled completion 2006.

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

[3] *Small hub* and *non-hub* airports with less than 0.25 percent of the total annual boardings in the United States in 1997 were exempt from slot restrictions (49 U.S.C. 41714, H-7, H-8, 5 April 2000).

[4] While Chicago O'Hare is no longer considered a "slot-controlled" airport, the FAA reached an agreement with the domestic airlines in 2004 to "voluntarily" limit the number of scheduled flights (88 per hour between 7 a.m. and 8 p.m.) at O'Hare to improve on-time performance (18 August 2004, DOT press release #138-04).

[5] The 12 June 2001 Federal Register (Vol. 66, No. 113) welcomed public comments on how to optimally reduce airport congestion at LGA. The FAA is currently considering market solutions (such as auctions) and administrative options (e.g., minimum aircraft size) to allocate scarce runway space.

[6] The nested logit model does not require a sequential decision process: an econometrically equivalent interpretation is that the decision between the three outcomes occurs at one time, but the errors are heteroskedastic. The sequential decision interpretation, however, is natural in this context.

[7] An alternative ordering (see Decision Process 2 in Figure 1) is that carriers first choose to cancel or not cancel a flight with the second decision being whether the flight arrives on time or is delayed. Given the similar results for "Decision Process 2" (see Appendix II), this paper uses the more intutively appealing, first decision process.

[8] http://www.transtats.bts.gov.

[9] The other possible outcome is a diverted flight. Given that flight diversions are relatively rare events, on average just 28 of 10,000 scheduled flights are diverted, we exclude flight diversions from our sample.

[10] A $\chi^2_2 = 1393.9$ easily exceeds the 9.21 critical value at the 1% significance level.

[11] Testing the hypothesis that national minutes of arrival delay = 4.23 reveals t = -8.09.

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

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

[14] Wholly-owned subsidiaries (i.e., American Eagle and American Airlines) are considered a single carrier.

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

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

[17] Specifically, we first estimate the model using the full set of available choices for the second decision (cancel or delay). Then we re-estimate the model after removing the delay option. We then use Stata's "hausman" command.

[18] Exceptions are granted to this 60 minute slot window during poor weather.

[19] Anecodotal evidence is provided by the common gate agent announcement: "we are seeking passengers with flexible travel plans who are not making connections to give up their seat(s) in exchange for a travel voucher."

[20] Once such software is OpsSolver by Caleb Technologies Corp. which allows carriers to find the best solution to a service disruption by "using a combination of delays, cancellations, ferries, equipment swaps, and spare aircraft...while simultaneously considering the impact on passengers, maintenance, revenue, and operating costs" (www.calebtech.com/solutions/ accessed 5 July 2004).

[21] The marginal effects for ontime arrival, cancellation and delay sum to 0. For example, the delay marginal effects for *route load factor* in Model 3 is calculated: -0.0657 (ontime) + -0.0278 (cancel) + (delay) = 0. The delay marginal effect = 0.0935, which suggests that fuller flights have more arrival delays.

[22] For a discussion of flight schedule departure times see Borenstein and Netz (1999).

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

[24] The one exception is significantly more flight cancellations are found for *small duopoly carriers* in model (3).

[25] Figures 5 and 6 plot cancellation and delay averages for 15 minute intervals with 200+ scheduled flights.

[26] A perimeter rule at LGA currently prohibits incoming and outgoing flights from exceeding 1,500 miles.

Figure 1: Schematic of Flight Arrival Decisions

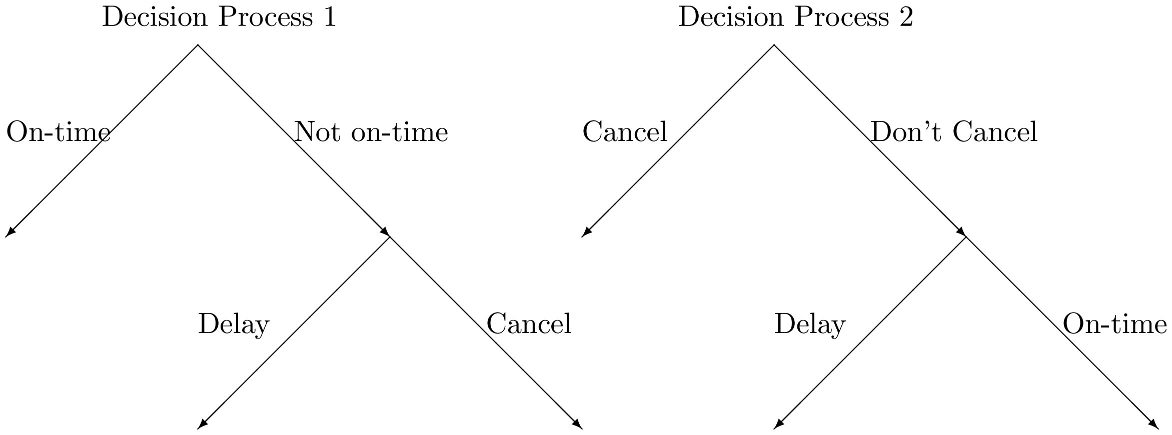
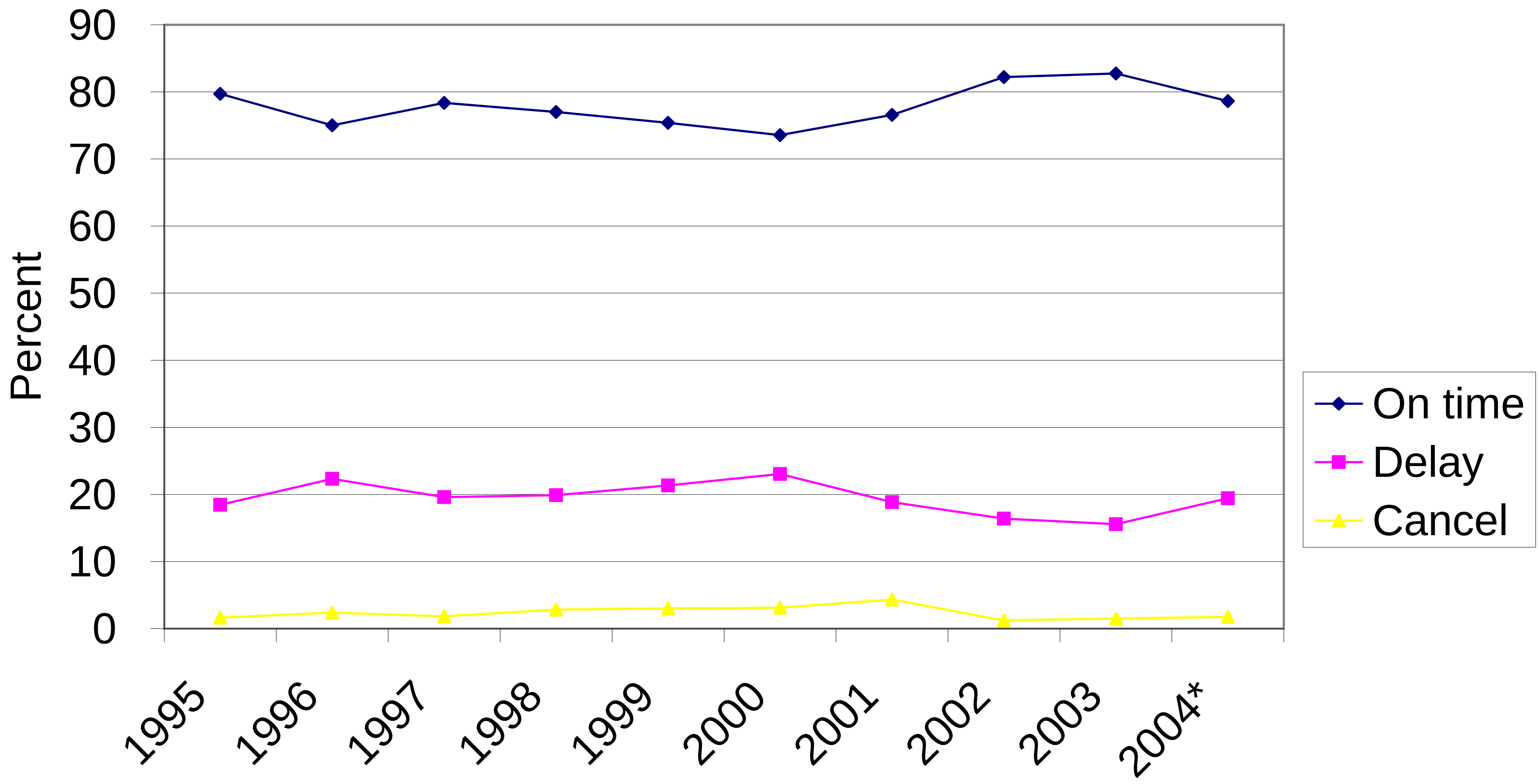


Figure 2: Domestic Flight Arrivals for U.S. Carriers



*Note: 2004 data represents the first ten months.

Figure 3: Domestic Flight Cancellations: LGA vs. All U.S. Airports

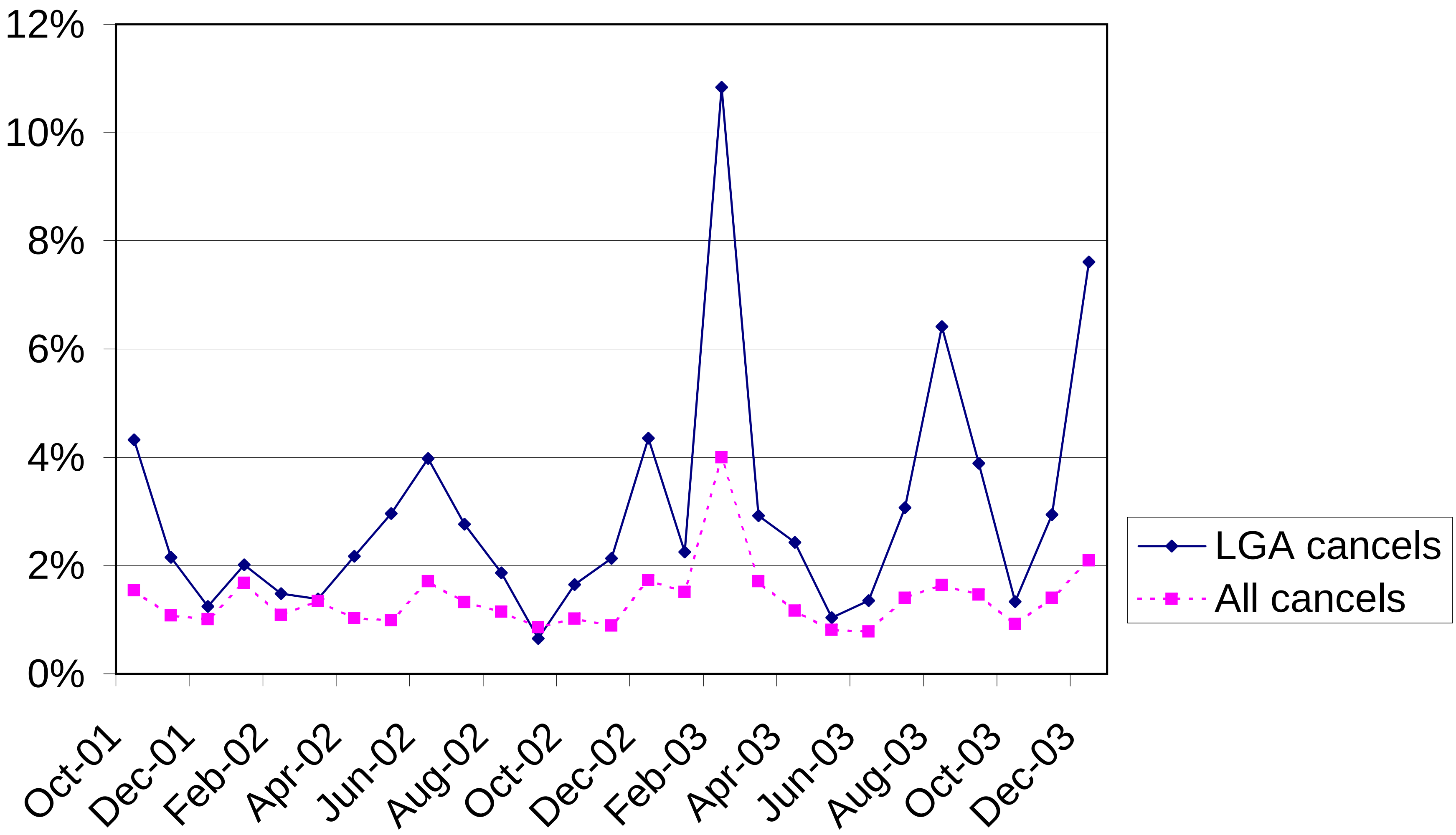


Figure 4: Ontime Domestic Arrivals: LGA vs. All U.S. Airports

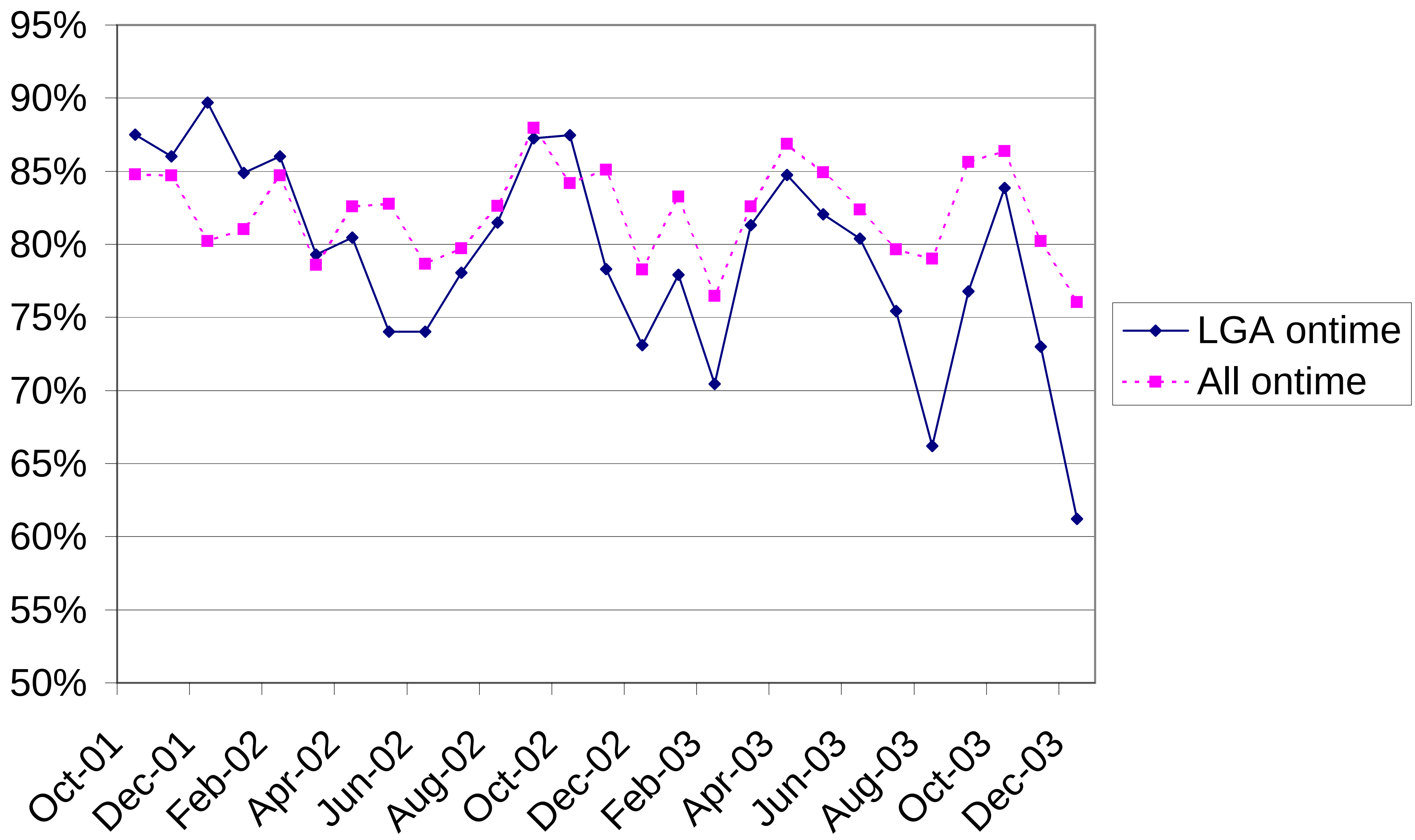


Figure 5: U.S. domestic flight cancellations Oct. 2001-Dec. 2003

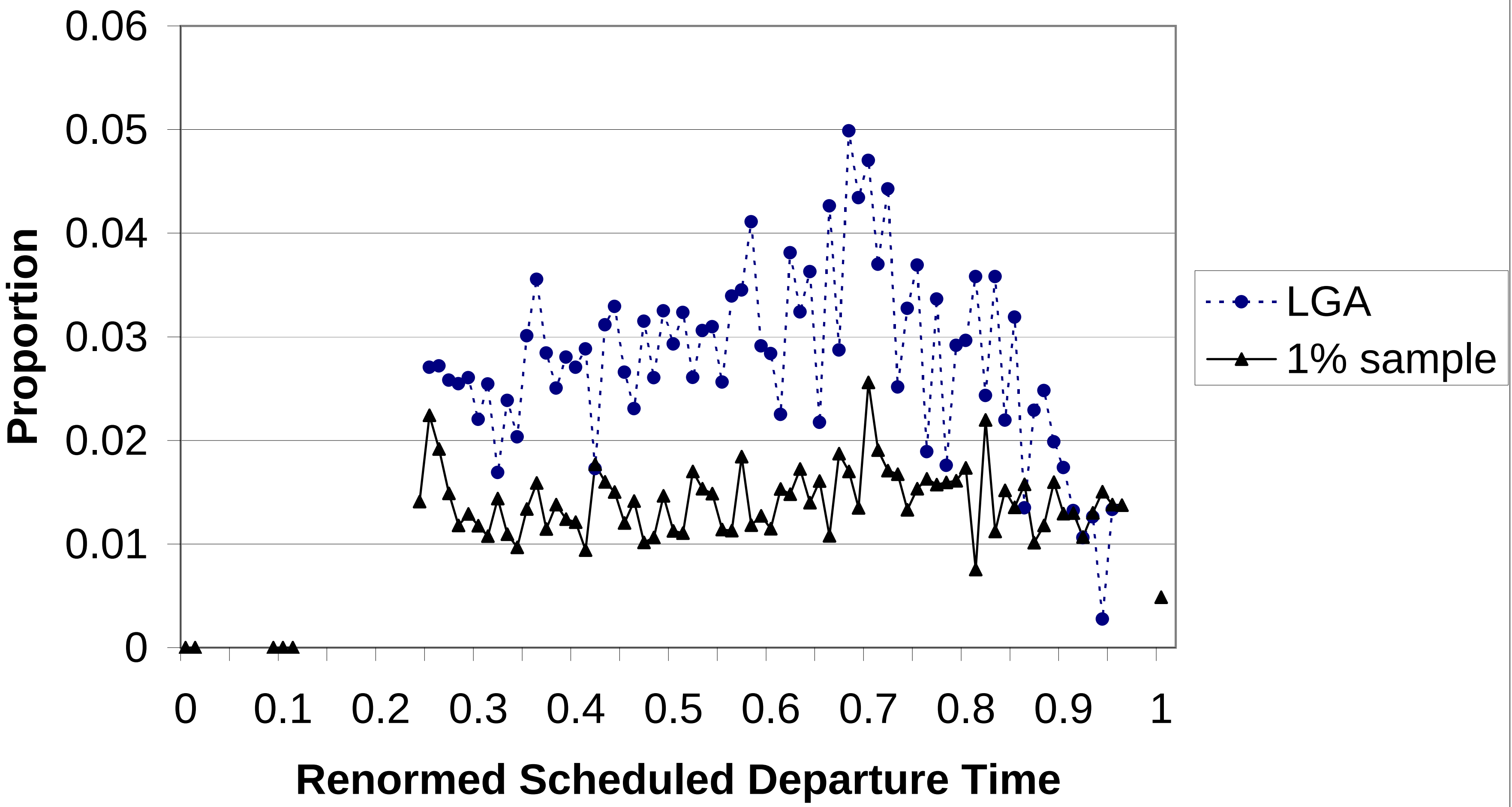


Figure 6: U.S. domestic flight delays Oct. 2001-Dec. 2003

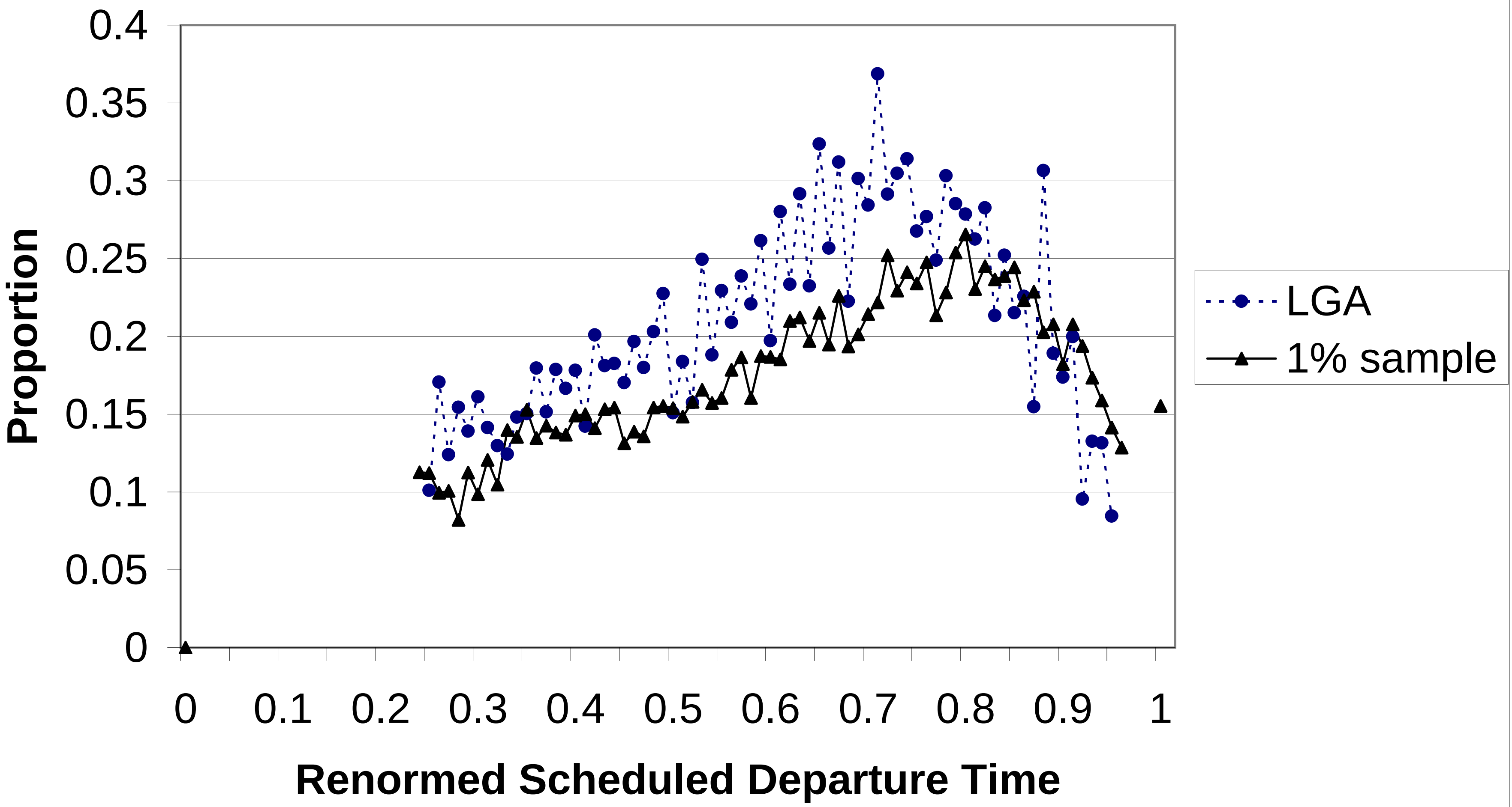


Table I: Summary of U.S. Carriers On-time Performance for Domestic Flights[1]

Year	Scheduled Flights	On-Time Arrivals	Late Arrivals	Flights Canceled	Flights Diverted	Pecent On-time Arrivals	Pecent Late Arrivals	Percent Canceled
1995	4,458,656	3,554,452	822,735	72,945	8,524	79.72	18.45	1.64
1996	4,460,898	3,346,474	996,137	106,659	11,628	75.02	22.33	2.39
1997	4,528,214	3,548,102	887,251	82,821	10,040	78.36	19.59	1.83
1998	4,493,094	3,460,205	893,727	128,190	10,972	77.01	19.89	2.85
1999	4,602,990	3,470,355	982,209	138,519	11,907	75.39	21.34	3.01
2000	4,734,758	3,483,158	1,091,662	147,978	11,960	73.57	23.06	3.13
2001*	5,120,525	3,920,828	965,678	222,368	11,651	76.57	18.86	4.34
2002	4,429,210	3,641,385	726,771	54,112	6,942	82.21	16.41	1.22
2003	5,404,874	4,471,915	840,959	82,430	9,570	82.74	15.56	1.53
2004**	5,937,929	4,669,595	1,153,654	103,316	11,364	78.64	19.43	1.74
Average	4,817,115	3,756,647	936,078	113,934	10,456	77.92	19.43	2.37

[1] Source: Bureau of Transportation Statistics, Airline On-Time Data, accessed 4 December 2004.

*The 2001 cancellations reflect the shutdown of the air transportation system as a result of the terrorist attacks of 11 September 2001.

Table II: Comparing 1% sample U.S. domestic flights vs. all LGA flights Oct. 2001-Dec. 2003 by major carriers

Sample & observations:	1% sample (n=120,543)		LGA (n=211,632)	
	Mean	Standard Deviation	Mean	Standard Deviation
Flight Arrivals				
Proportion ontime[1] (<15 min late)	0.823	0.381	0.792	0.406
Proportion ontime (<30 min late)	0.899	0.301	0.859	0.348
Proportion ontime (<45 min late)	0.931	0.253	0.895	0.307
Proportion canceled	0.014	0.117	0.031	0.172
Minutes of arrival delay	3.524	30.459	4.234	36.913
Economic Variables				
Average one-way air fare (quarterly)	155.942	64.599	170.142	62.950
Average revenue (in $10,000s)	1.561	1.155	1.667	0.990
Potential revenue (in $10,000s)	2.288	1.561	2.575	1.336
Yield (average revenue passenger mile)	0.338	0.306	0.362	0.214
Route load factor (monthly average)	0.671	0.129	0.633	0.142
Proportion local passengers	0.394	0.267	0.675	0.209
Seating capacity of aircraft (in 100's)	1.429	0.597	1.522	0.582
Aircraft seating capacity < 71 passengers	0.170	0.376	0.156	0.362
Route Competition Variables				
Effective competitors	1.487	0.604	1.727	0.660
Monopoly	0.524	0.499	0.347	0.476
Large duopoly carrier	0.244	0.430	0.316	0.465
Small duopoly carrier	0.102	0.303	0.160	0.366
Airport Competition Variables				
Airport concentration at origination	0.413	0.207	0.406	0.209
Airport concentration at destination	0.413	0.231	-	-
Airline hub origination	0.416	0.493	0.513	0.500
Small airline hub origination	0.123	0.329	0.092	0.289
Medium airline hub origination	0.130	0.336	0.187	0.390
Large airline hub origination	0.163	0.370	0.234	0.423
Airline hub destination	0.418	0.493	-	-
Small airline hub destination	0.122	0.327	-	-
Medium airline hub destination	0.134	0.340	-	-
Large airline hub destination	0.162	0.369	-	-
1997 non-hub/small hub airport origination	0.112	0.315	0.034	0.182
Slot origination airport	0.057	0.232	0.154	0.361
Slot destination airport	0.057	0.232	-	-
Logistical Variables				
Distance (in 100's miles)	7.32	5.70	6.59	4.07
Hours until next flight	6.16	6.27	4.20	5.34
Renormed scheduled departure time	0.56	0.19	0.57	0.19
Daily total carrier flights on route	6.09	5.76	9.43	5.08
Daily total origination airport flights (100's)	6.59	5.57	7.84	6.00
Daily total destination airport flights (100's)	6.58	5.57	5.44	0.63
Weather Variables				
Rain origination (inches)	0.10	0.32	0.12	0.35
Rain destination (inches)	0.09	0.31	0.13	0.35
Minimum temperature origination (Farenheith)	49.28	17.38	48.48	18.14
Minimum temperature destination (Farenheith)	49.25	17.44	48.27	16.23
Frozen precipitation origination (inches)	0.01	0.05	0.01	0.06
Frozen precipitation destination (inches)	0.01	0.05	0.01	0.07

Note: All variables are constructed from the original data set of every domestic flight by major carriers.

[1] Ontime flights push back from the gate within 15 minutes of their scheduled departure time.

Table III: Logit estimations of flight arrivals for 1% sample of U.S. domestic flights Oct.2001-Dec.2003.

		Model (1)			Model (2)	
		Ontime			Cancel	
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.
Economic Variables						
Average revenue (in $10,000s)	-0.0748 **	0.0169	0.0102	0.2310 **	0.0627	0.0020
Local passengers	-0.3338 **	0.0534	0.0073	0.4268 **	0.0909	0.0037
Route load factor (monthly average)	-0.4703 **	0.0769	0.0104	-2.2405 **	0.2564	-0.0193
Seating capacity of aircraft (in 100's)	0.0995 **	0.0353	0.0050	-0.6710 **	0.1376	-0.0058
Aircraft seating capacity < 71 passengers	-0.3699 **	0.0402	0.0064	0.3515 *	0.1407	0.0034
Seating capacity*hub destination	-0.0313	0.0281	0.0040	0.1232	0.0933	0.0011
Route Competition Variables						
Monopoly	-0.0211	0.0304	0.0041	0.1002	0.0979	0.0009
Large duopoly carrier	-0.0254	0.0277	0.0038	0.0265	0.0898	0.0002
Small duopoly carrier	0.0131	0.0334	0.0045	0.2097 *	0.1042	0.0020
Airport Competition Variables						
Airport concentration at origination	-0.1524 **	0.0471	0.0064	0.4866 **	0.1406	0.0042
Airport concentration at destination	-0.0287	0.0336	0.0046	0.0899	0.0860	0.0008
Airline hub origination	-0.1063 **	0.0258	0.0036	-0.2687 **	0.0906	-0.0023
Airline hub destination	0.0987 *	0.0498	0.0067	-0.1352	0.1500	-0.0012
1997 non-hub/small hub airport origination	-0.0401	0.0336	0.0047	-0.0210	0.1037	-0.0002
Logistical Variables						
Slot origination	-0.0879 *	0.0357	0.0051	0.3400 **	0.1009	0.0034
Slot destination	-0.0844 *	0.0356	0.0051	0.4596 **	0.0952	0.0049
Distance (in 100's miles)	-0.0039	0.0024	-0.0005	-0.0280 **	0.0095	-0.0002
Hours until next flight	0.0033 *	0.0016	0.0005	-0.0135 *	0.0062	-0.0001
Renormed scheduled departure time	-1.5658 **	0.0447	0.0060	0.4159 **	0.1533	0.0036
Daily total carrier flights on route	-0.0048 **	0.0010	0.0001	0.0539 **	0.0067	0.0005
Daily total origination airport flights (100's)	-0.0183 **	0.0022	-0.0025	0.0266 **	0.0073	0.0002
Daily total destination airport flights (100's)	-0.0254 **	0.0022	-0.0035	0.0335 **	0.0073	0.0003
Weather Variables						
Rain origination (inches)	-0.6388 **	0.0237	0.0030	0.5147 **	0.0471	0.0044
Rain destination (inches)	-0.6865 **	0.0246	0.0030	0.4534 **	0.0450	0.0039
Minimum temperature origination	0.0027 **	0.0007	0.0001	-0.0012	0.0027	0.0000
Minimum temperature destination	-0.0021 **	0.0007	0.0001	-0.0040	0.0026	0.0000
Frozen precipitation origination (inches)	-2.5726 **	0.1432	0.0200	3.6027 **	0.2075	0.0310
Frozen precipitation destination (inches)	-1.7484 **	0.1334	0.0180	3.1863 **	0.2028	0.0274
Constant	-0.6844	0.4171		-3.7901 **	0.3431	
Pseudo-R^2	0.0564			0.1140		
Observations	120,264			120,264		

Note: Robust standard errors are reported. Regressions include indicator variables for carrier, day of week and month. Marginal effects are the probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels. Ontime flights arrive at gate within 15 minutes of the scheduled arrival time.

Table IV: Nested Logit & OLS estimations of flight arrivals for 1% sample U.S. domestic flights Oct.2001-Dec.2003.

Estimation:	Model (3) - Nested Logit			Model (3) - Nested Logit			Model (4) - OLS	
Dependent Variable:	Ontime Arrival			Cancel			Minutes of Arrival Delay	
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.	Coeff	Std Error
Economic Variables								
Average revenue (in $10,000s)	-0.0726 **	0.0170	-0.0101	0.1730 **	0.0650	0.0028	0.6070 **	0.2050
Local passengers	-0.3352 **	0.0558	-0.0463	0.5699 **	0.2098	0.0101	2.8415 **	0.4846
Route load factor (monthly average)	-0.4985 **	0.0821	-0.0657	-2.7881 **	0.2612	-0.0278	8.5250 **	0.8383
Seating capacity of aircraft (in 100's)	0.0909 *	0.0357	0.0128	-0.4589 **	0.1366	-0.0063	0.3659	0.3830
Aircraft seating capacity < 71 passengers	-0.3674 **	0.0403	-0.0503	0.2100	0.1404	0.0062	2.5860 **	0.4844
Seating capacity*hub destination	-0.0320	0.0281	-0.0043	-0.0466	0.0990	-0.0002	0.3887	0.3429
Route Competition Variables								
Monopoly	-0.0221	0.0304	-0.0031	0.1376	0.1031	0.0018	0.1262	0.3460
Large duopoly carrier	-0.0304	0.0277	-0.0042	0.0181	0.0952	0.0005	-0.0557	0.3236
Small duopoly carrier	0.0148	0.0342	0.0018	0.2449 *	0.1109	0.0027	-0.3814	0.3903
Airport Competition Variables								
Airport concentration at origination	-0.1513 **	0.0472	-0.0210	0.3481 *	0.1520	0.0056	1.3985 **	0.5026
Airport concentration at destination	-0.0317	0.0341	-0.0044	0.0472	0.1491	0.0009	0.8613	0.4711
Airline hub origination	-0.1097 **	0.0264	-0.0147	-0.3860 **	0.0972	-0.0034	0.5289	0.2792
Airline hub destination	0.0958	0.0497	0.0130	0.1477	0.1632	0.0008	-0.8924	0.5696
1997 non-hub/small hub airport origination	-0.0366	0.0339	-0.0050	0.0476	0.1073	0.0009	0.4507	0.3846
Logistical Variables								
Slot origination	-0.0899 *	0.0357	-0.0126	0.3231 **	0.1060	0.0047	-0.9129 *	0.4350
Slot destination	-0.0879 *	0.0357	-0.0123	0.3091 **	0.1037	0.0045	0.4628	0.4925
Distance (in 100's miles)	-0.0033	0.0026	-0.0004	-0.0386 **	0.0105	-0.0004	-0.2556 **	0.0264
Hours until next flight	0.0043 *	0.0021	0.0006	-0.0093	0.0063	-0.0002	-0.0565 **	0.0192
Renormed scheduled departure time	-1.5862 **	0.0533	-0.2157	-1.0489 **	0.1705	0.0037	15.8231 **	0.4727
Daily total carrier flights on route	-0.0007	0.0060	-0.0002	0.0675 **	0.0079	0.0008	-0.0482	0.0298
Daily total origination airport flights (100's)	-0.0187 **	0.0023	-0.0026	0.0160 *	0.0077	0.0004	0.1713 **	0.0249
Daily total destination airport flights (100's)	-0.0258 **	0.0024	-0.0035	0.0081	0.0075	0.0004	0.1763 **	0.0260
Weather Variables								
Rain origination (inches)	-0.6519 **	0.0239	-0.0892	0.2386 **	0.0557	0.0094	10.0411 **	0.5653
Rain destination (inches)	-0.7012 **	0.0245	-0.0959	0.1238 *	0.0566	0.0086	9.7846 **	0.5278
Minimum temperature origination	0.0028 **	0.0007	0.0004	0.0019	0.0028	0.0000	-0.0155	0.0082
Minimum temperature destination	-0.0020 **	0.0007	-0.0003	-0.0065 *	0.0027	-0.0001	0.0124	0.0079
Frozen precipitation origination (inches)	-2.4658 **	0.1513	-0.3388	2.4770 **	0.2301	0.0543	47.6865 **	4.6769
Frozen precipitation destination (inches)	-1.6554 **	0.1415	-0.2279	2.1860 **	0.2321	0.0426	22.8090 **	3.0290
Log-likelihood/R^2	-58,143						0.0533	
Observations	361,629						118,642	

Note: Robust standard errors are reported. Regressions include a constant and indicator variables for carrier, day of week, month & year.
Marginal effects are the probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels.
Ontime flights arrive at gate within 15 minutes of the scheduled arrival time.

Table V: Nested Logit estimations of flight arrivals at New York's LaGuardia Airport Oct.2001-Dec.2003.

Estimation:	Model (5) - Nested Logit			Model (5) - Nested Logit			Model (6) - OLS	
Dependent Variable:	Ontime Arrival			Cancel			Minutes of Arrival Delay	
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.	Coeff	Std Error
Economic Variables								
Average revenue (in $10,000s)	-0.0023	0.0428	-0.0064	0.2000 **	0.0563	0.0058	0.2580	0.2470
Local passengers	0.0056	0.1032	-0.0084	0.3073	0.1865	0.0088	-0.7905	0.8505
Route load factor (monthly average)	-1.8261 **	0.6143	-0.1643	-3.2905 **	0.2521	-0.0598	14.4172 **	0.9126
Seating capacity of aircraft (in 100's)	-0.0385	0.0877	0.0131	-0.6205 **	0.1213	-0.0172	-0.6867	0.3652
Aircraft seating capacity < 71 passengers	-0.5090 **	0.0502	-0.0652	-0.2721 *	0.1128	0.0020	3.7270 **	0.5078
Route Competition Variables								
Monopoly	-0.2163 **	0.0376	-0.0375	0.2105	0.1245	0.0102	2.4685 **	0.3711
Large duopoly carrier	-0.0166	0.0430	-0.0152	0.4239 **	0.1434	0.0126	1.2425 **	0.2711
Small duopoly carrier	-0.0666	0.0503	-0.0135	0.1300	0.2166	0.0050	0.8888 **	0.3171
Airport Competition Variables								
Airport concentration at origination	-0.1569 *	0.0750	-0.0238	0.0374	0.2416	0.0041	0.8121	0.8488
Airline hub origination	-0.0825	0.0666	-0.0033	-0.2850 *	0.1356	-0.0066	-1.4919 **	0.4510
1997 non-hub/small hub airport origination	-0.1680 **	0.0550	-0.0307	0.2147	0.2122	0.0094	2.9801 **	0.6196
Logistical Variables								
Slot origination	0.0768	0.0446	0.0070	0.1344	0.0715	0.0024	-0.1751	0.2363
Distance (in 100's miles)	0.0103	0.0066	0.0026	-0.0367 **	0.0119	-0.0013	-0.2126 **	0.0478
Hours until next flight	0.0141 **	0.0024	0.0026	-0.0181 *	0.0091	-0.0008	-0.2560 **	0.0235
Renormed scheduled departure time	-2.0202 **	0.1525	-0.2764	-0.4977 **	0.1483	0.0246	23.2251 **	0.4398
Daily total carrier flights on route	0.0545 **	0.0083	0.0066	0.0414 **	0.0144	0.0001	-0.4765 **	0.0350
Daily total origination airport flights (100's)	-0.0404 **	0.0035	-0.0062	0.0108	0.0081	0.0011	0.4086 **	0.0370
Daily total destination airport flights (100's)	-0.5777 **	0.0489	-0.0807	-0.0869	0.1056	0.0086	8.4772 **	0.3095
Weather Variables								
Rain origination (inches)	-0.4553 **	0.0279	-0.0700	0.1440 **	0.0425	0.0129	6.5524 **	0.3487
Rain destination (inches)	-1.0063 **	0.0274	-0.1443	-0.0282	0.0596	0.0186	16.3953 **	0.3789
Minimum temperature origination	-0.0010	0.0009	-0.0002	0.0012	0.0020	0.0001	0.0294 **	0.0099
Minimum temperature destination	-0.0087	0.0052	-0.0006	-0.0221 **	0.0035	-0.0005	0.1017 **	0.0127
Frozen precipitation origination (inches)	-1.6568 **	0.2908	-0.2715	1.0810 **	0.4142	0.0632	28.1817 **	2.4094
Frozen precipitation destination (inches)	-1.8299	1.0824	-0.3575	3.1077 **	0.3455	0.1250	45.7265 **	2.9046
Constant	7.8576 **	1.2770		2.1750 **	0.6709		-72.0201 **	2.0074
Log-likelihood/R^2	-111,934						0.0867	
Observations	634,896						204,813	

Note: Robust standard errors are reported. Regressions include a constant and indicator variables for carrier, day of week, month & year.
Marginal effects are the probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels.
Ontime flights arrive at gate within 15 minutes of the scheduled arrival time.

Table VI: Nested Logit estimations of flight arrivals for 1% sample U.S. domestic flights Oct.2001-Dec.2003.

Model (7) - Ontime arrival (<30 min. late)	Ontime Arrival			Cancel		
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.
Economic Variables						
Average revenue (in $10,000s)	-0.1020 **	0.0217	-0.0087	0.1510 *	0.0713	0.0028
Local passengers	-0.4658 **	0.0771	-0.0397	0.5602	0.4027	0.0112
Route load factor (monthly average)	-0.0158	0.1392	-0.0011	-2.5504 **	0.2717	-0.0270
Seating capacity of aircraft (in 100's)	0.1913 **	0.0482	0.0163	-0.3741 **	0.1411	-0.0061
Aircraft seating capacity < 71 passengers	-0.2755 **	0.0545	-0.0235	0.2815 *	0.1422	0.0061
Seating capacity*hub destination	-0.0500	0.0364	-0.0042	-0.0904	0.1142	-0.0004
Route Competition Variables						
Monopoly	-0.0358	0.0384	-0.0031	0.0736	0.1073	0.0012
Large duopoly carrier	-0.0774 *	0.0359	-0.0066	-0.0830	0.0982	0.0000
Small duopoly carrier	-0.0386	0.0444	-0.0033	0.1510	0.1192	0.0020
Airport Competition Variables						
Airport concentration at origination	-0.1362 *	0.0616	-0.0116	0.3531 *	0.1592	0.0053
Airport concentration at destination	-0.0416	0.0366	-0.0035	0.0095	0.1668	0.0006
Airline hub origination	-0.1121 **	0.0387	-0.0095	-0.4289 **	0.1043	-0.0033
Airline hub destination	0.1161	0.0632	0.0099	0.2144	0.1953	0.0010
1997 non-hub/small hub airport origination	-0.1162 **	0.0439	-0.0099	-0.0142	0.1151	0.0012
Logistical Variables						
Slot origination	-0.0955 *	0.0445	-0.0082	0.3304 **	0.1138	0.0046
Slot destination	-0.1333 **	0.0434	-0.0114	0.2953 **	0.1082	0.0046
Distance (in 100's miles)	0.0036	0.0038	0.0003	-0.0378 *	0.0152	-0.0004
Hours until next flight	0.0025	0.0037	0.0002	-0.0070	0.0067	-0.0001
Renormed scheduled departure time	-1.8424 **	0.1204	-0.1566	-1.6213 **	0.1873	0.0034
Daily total carrier flights on route	-0.0067	0.0149	-0.0006	0.0706 **	0.0125	0.0008
Daily total origination airport flights (100's)	-0.0192 **	0.0031	-0.0016	0.0150	0.0089	0.0004
Daily total destination airport flights (100's)	-0.0309 **	0.0035	-0.0026	0.0008	0.0080	0.0004
Weather Variables						
Rain origination (inches)	-0.7080 **	0.0264	-0.0602	0.1446 *	0.0689	0.0095
Rain destination (inches)	-0.7171 **	0.0263	-0.0610	0.0053	0.0664	0.0081
Minimum temperature origination	0.0007	0.0010	0.0001	-0.0001	0.0029	0.0000
Minimum temperature destination	-0.0012	0.0010	-0.0001	-0.0059	0.0030	0.0000
Frozen precipitation origination (inches)	-2.8194 **	0.1996	-0.2400	2.0734 **	0.2555	0.0538
Frozen precipitation destination (inches)	-2.0332 **	0.1941	-0.1731	1.9018 **	0.2524	0.0431
Constant	4.4065 **	0.1751		0.4139	0.4629	
Log-likelihood/R^2	-40,910					
Observations	361,629					

Note: Robust standard errors are reported. Regressions include indicator variables for carrier, day of week, month & year. Marginal effects are probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels. Ontime flights arrive at gate within 30 minutes of the scheduled arrival time.

Table VII: Nested Logit estimations of flight arrivals for 1% sample U.S. domestic flights Oct.2001-Dec.2003

Model (8) - Ontime arrival (<45 min. late)	Ontime Arrival			Cancel		
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.
Economic Variables						
Average revenue (in $10,000s)	-0.0968 **	0.0276	-0.0057	0.1890 *	0.0937	0.0029
Local passengers	-0.5321 **	0.1139	-0.0315	0.5260	0.7726	0.0111
Route load factor (monthly average)	0.2200	0.3221	0.0107	-2.6539 **	0.2913	-0.0271
Seating capacity of aircraft (in 100's)	0.2158 **	0.0702	0.0126	-0.4375 **	0.1496	-0.0066
Aircraft seating capacity < 71 passengers	-0.2323 **	0.0824	-0.0137	0.3206 *	0.1499	0.0057
Seating capacity*hub destination	-0.0408	0.0461	-0.0025	-0.0876	0.1503	-0.0003
Route Competition Variables						
Monopoly	-0.0340	0.0455	-0.0020	0.0814	0.1172	0.0012
Large duopoly carrier	-0.0411	0.0451	-0.0025	-0.0560	0.1030	0.0000
Small duopoly carrier	-0.0312	0.0593	-0.0017	0.1636	0.1385	0.0019
Airport Competition Variables						
Airport concentration at origination	-0.1838 *	0.0842	-0.0108	0.3131	0.1661	0.0051
Airport concentration at destination	-0.0451	0.0398	-0.0028	-0.0565	0.1858	0.0000
Airline hub origination	-0.0250	0.0646	-0.0019	-0.4083 **	0.1199	-0.0035
Airline hub destination	0.0556	0.0759	0.0035	0.1881	0.2778	0.0011
1997 non-hub/small hub airport origination	-0.1025	0.0552	-0.0062	-0.0197	0.1231	0.0010
Logistical Variables						
Slot origination	-0.1250 *	0.0544	-0.0072	0.3305 **	0.1252	0.0045
Slot destination	-0.1462 **	0.0517	-0.0085	0.3078 **	0.1188	0.0046
Distance (in 100's miles)	0.0072	0.0044	0.0004	-0.0404	0.0277	-0.0005
Hours until next flight	0.0003	0.0066	0.0000	-0.0051	0.0071	-0.0001
Renormed scheduled departure time	-1.8331 **	0.3064	-0.1121	-1.9131 **	0.2055	0.0039
Daily total carrier flights on route	-0.0141	0.0308	-0.0008	0.0728 **	0.0248	0.0008
Daily total origination airport flights (100's)	-0.0201 **	0.0037	-0.0012	0.0172	0.0130	0.0004
Daily total destination airport flights (100's)	-0.0307 **	0.0055	-0.0019	-0.0015	0.0097	0.0003
Weather Variables						
Rain origination (inches)	-0.7152 **	0.0301	-0.0430	0.0878	0.0933	0.0092
Rain destination (inches)	-0.6979 **	0.0275	-0.0420	-0.0429	0.0716	0.0078
Minimum temperature origination	0.0003	0.0012	0.0000	0.0010	0.0034	0.0000
Minimum temperature destination	0.0006	0.0013	0.0000	-0.0046	0.0036	-0.0001
Frozen precipitation origination (inches)	-2.9610 **	0.3965	-0.1763	1.9756 **	0.3315	0.0532
Frozen precipitation destination (inches)	-2.1872 **	0.3786	-0.1299	1.8175 **	0.2936	0.0426
Constant	4.6685 **	0.3758		1.0614	0.6986	
Log-likelihood/R^2	-31,466					
Observations	361,629					

Note: Robust standard errors are reported. Regressions include indicator variables for carrier, day of week, month & year. Marginal effects are probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels. Ontime flights arrive at gate within 45 minutes of the scheduled arrival time.

Table VIII: Nested Logit estimations of flight arrivals for 1% sample U.S. domestic flights Oct.2001-Dec.2003.

Model (9) - Airline hub size	Ontime			Cancel		
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.
Economic Variables						
Average revenue (in $10,000s)	-0.0688 **	0.0171	-0.0095	0.1670 *	0.0658	0.0027
Local passengers	-0.3402 **	0.0570	-0.0470	0.5844 **	0.2113	0.0103
Route load factor (monthly average)	-0.4779 **	0.0820	-0.0628	-2.7833 **	0.2626	-0.0280
Seating capacity of aircraft (in 100's)	0.0891 *	0.0357	0.0125	-0.4248 **	0.1371	-0.0059
Aircraft seating capacity < 71 passengers	-0.3714 **	0.0407	-0.0509	0.2134	0.1419	0.0063
Seating capacity*small airline hub dest.	-0.0712	0.0416	-0.0096	-0.1277	0.1437	-0.0008
Seating capacity*medium airline hub dest.	0.0179	0.0450	0.0025	-0.0093	0.1515	-0.0003
Seating capacity*large airline hub dest.	-0.0312	0.0364	-0.0042	-0.1196	0.1263	-0.0011
Route Competition Variables						
Monopoly	0.0115	0.0321	0.0015	0.1347	0.1082	0.0015
Large duopoly carrier	-0.0089	0.0285	-0.0012	0.0128	0.0978	0.0002
Small duopoly carrier	0.0217	0.0343	0.0027	0.2426 *	0.1112	0.0026
Airport Competition Variables						
Airport concentration at origination	-0.1107 *	0.0496	-0.0155	0.4111 **	0.1550	0.0060
Airport concentration at destination	-0.0224	0.0336	-0.0030	-0.0443	0.1592	-0.0003
Small airline hub origination	-0.0930 **	0.0295	-0.0125	-0.2466 *	0.1070	-0.0020
Medium airline hub origination	-0.1478 **	0.0384	-0.0198	-0.4126 **	0.1444	-0.0034
Large airline hub origination	-0.2451 **	0.0450	-0.0331	-0.4812 **	0.1515	-0.0032
Small airline hub destination	0.1521 *	0.0683	0.0207	0.0802	0.2100	-0.0006
Medium airline hub destination	-0.0156	0.0801	-0.0024	0.3240	0.2567	0.0040
Large airline hub destination	-0.0014	0.0673	-0.0005	0.3410	0.2206	0.0040
1997 non-hub/small hub airport origination	-0.0246	0.0341	-0.0034	0.0516	0.1082	0.0009
Logistical Variables						
Slot origination	-0.0911 *	0.0358	-0.0127	0.3406 **	0.1062	0.0049
Slot destination	-0.0947 **	0.0357	-0.0132	0.2962 **	0.1041	0.0045
Distance (in 100's miles)	-0.0043	0.0026	-0.0006	-0.0376 **	0.0105	-0.0004
Hours until next flight	0.0042 *	0.0020	0.0006	-0.0092	0.0063	-0.0002
Renormed scheduled departure time	-1.5840 **	0.0530	-0.2154	-1.0341 **	0.1713	0.0039
Daily total carrier flights on route	-0.0007	0.0059	-0.0002	0.0685 **	0.0078	0.0008
Daily total origination airport flights (100's)	-0.0137 **	0.0026	-0.0019	0.0199 *	0.0089	0.0004
Daily total destination airport flights (100's)	-0.0224 **	0.0027	-0.0031	0.0017	0.0091	0.0002
Weather Variables						
Rain origination (inches)	-0.6508 **	0.0239	-0.0891	0.2391 **	0.0558	0.0094
Rain destination (inches)	-0.7012 **	0.0245	-0.0959	0.1250 *	0.0564	0.0086
Minimum temperature origination	0.0027 **	0.0008	0.0004	0.0012	0.0028	0.0000
Minimum temperature destination	-0.0021 **	0.0007	-0.0003	-0.0056 *	0.0027	0.0000
Frozen precipitation origination (inches)	-2.4674 **	0.1511	-0.3390	2.4675 **	0.2310	0.0541
Frozen precipitation destination (inches)	-1.6533 **	0.1414	-0.2276	2.2015 **	0.2328	0.0427
Constant	3.7957 **	0.1084		-0.5731	0.3852	
Log-likelihood	-58,127					
Observations	361,629					

Note: Robust standard errors are reported. Regressions include indicator variables for carrier, day of week and month. Marginal effects are the probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels. Ontime flights arrive at the gate within 15 minutes of the scheduled arrival time.

Appendix I: Nested Logit & OLS estimations of flight departure delays for 1% sample U.S. domestic flights Oct.2001-Dec.2003.

Estimation:	Model (3) - Nested Logit			Model (3) - Nested Logit			Model (4) - OLS	
Dependent Variable:	Ontime Departure			Cancel			Minutes of Departure Delay	
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.	Coeff	Std Error
Economic Variables								
Average revenue (in $10,000s)	-0.0851 **	0.0192	-0.0103	0.1540 *	0.0662	0.0027	0.3270	0.1740
Local passengers	-0.4003 **	0.0675	-0.0478	0.4002 *	0.1701	0.0089	2.6679 **	0.4225
Route load factor (monthly average)	-0.6525 **	0.0949	-0.0718	-2.9300 **	0.2667	-0.0265	7.2226 **	0.7032
Seating capacity of aircraft (in 100's)	0.1086 **	0.0403	0.0135	-0.4504 **	0.1393	-0.0063	0.4422	0.3212
Aircraft seating capacity < 71 passengers	-0.4630 **	0.0454	-0.0546	0.0792	0.1423	0.0059	2.4323 **	0.3991
Seating capacity*hub destination	-0.0710 *	0.0314	-0.0082	-0.0662	0.1004	0.0000	0.4241	0.2975
Route Competition Variables								
Monopoly	-0.0315	0.0330	-0.0038	0.0553	0.1046	0.0010	-0.0732	0.2859
Large duopoly carrier	-0.0300	0.0301	-0.0035	-0.0220	0.0962	0.0001	0.0563	0.2692
Small duopoly carrier	0.0170	0.0369	0.0016	0.2280 *	0.1128	0.0024	-0.2223	0.3244
Airport Competition Variables								
Airport concentration at origination	-0.1494 **	0.0505	-0.0182	0.3454 *	0.1541	0.0056	1.0261 *	0.4202
Airport concentration at destination	0.0292	0.0421	0.0033	0.0849	0.1517	0.0007	-0.1932	0.2905
Airline hub origination	-0.1163 **	0.0281	-0.0130	-0.4134 **	0.0964	-0.0035	1.0279 **	0.2356
Airline hub destination	0.1313 *	0.0546	0.0151	0.1732	0.1639	0.0006	-0.7139	0.4839
1997 non-hub/small hub airport origination	-0.0501	0.0366	-0.0059	0.0002	0.1109	0.0005	0.3349	0.3249
Logistical Variables								
Slot origination	-0.0245	0.0399	-0.0036	0.4149 **	0.1109	0.0050	-0.5180	0.3345
Slot destination	-0.0819 *	0.0393	-0.0103	0.3711 **	0.1064	0.0051	0.4775	0.3914
Distance (in 100's miles)	0.0066 *	0.0029	0.0008	-0.0304 **	0.0101	-0.0004	-0.0162	0.0218
Hours until next flight	0.0066 **	0.0021	0.0008	-0.0060	0.0064	-0.0001	-0.0299	0.0162
Renormed scheduled departure time	-2.1940 **	0.0639	-0.2551	-1.7656 **	0.1816	0.0034	13.9958 **	0.3931
Daily total carrier flights on route	0.0026	0.0056	0.0002	0.0699 **	0.0074	0.0008	-0.0743 **	0.0222
Daily total origination airport flights (100's)	-0.0244 **	0.0025	-0.0029	0.0092	0.0078	0.0004	0.1492 **	0.0207
Daily total destination airport flights (100's)	-0.0263 **	0.0026	-0.0031	0.0068	0.0078	0.0004	0.1611 **	0.0217
Weather Variables								
Rain origination (inches)	-0.6243 **	0.0243	-0.0738	0.2278 **	0.0586	0.0093	7.5251 **	0.5193
Rain destination (inches)	-0.4304 **	0.0239	-0.0511	0.2474 **	0.0558	0.0075	4.2634 **	0.3850
Minimum temperature origination	0.0007	0.0008	0.0001	-0.0004	0.0028	0.0000	-0.0085	0.0071
Minimum temperature destination	0.0009	0.0008	0.0001	-0.0042	0.0028	-0.0001	0.0064	0.0067
Frozen precipitation origination (inches)	-1.9508 **	0.1576	-0.2340	2.6267 **	0.2437	0.0510	26.2292 **	3.5954
Frozen precipitation destination (inches)	-1.5334 **	0.1521	-0.1842	2.2181 **	0.2491	0.0419	16.1680 **	2.4421
Log-likelihood/R^2	-58,143						0.0533	
Observations	361,629						118,642	

Note: Robust standard errors are reported. Regressions include a constant and indicator variables for carrier, day of week, month & year.
Marginal effects are the probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels.
Ontime flights arrive at gate within 15 minutes of the scheduled arrival time.

Appendix II: Nested Logit estimations of flight arrivals for 1% sample U.S. domestic flights Oct.2001-Dec.2003.

Estimation:	Nested Logit			Nested Logit		
Dependent Variable:	Cancel - 1st Decision[1]			Ontime - 2nd Decision		
	Coeff	Std Error	Marg.Eff.	Coeff	Std Error	Marg.Eff.
Economic Variables						
Average revenue (in $10,000s)	0.1960 **	0.0737	0.0029	-0.0646 **	0.0177	-0.0106
Local passengers	0.3137	0.2003	0.0061	-0.3236 **	0.0593	-0.0463
Route load factor (monthly average)	-2.4863 **	0.5098	-0.0282	-0.6866 **	0.0826	-0.0665
Seating capacity of aircraft (in 100's)	-0.5899 **	0.1442	-0.0081	0.0627	0.0366	0.0143
Aircraft seating capacity < 71 passengers	0.2150	0.2662	0.0049	-0.3398 **	0.0426	-0.0475
Seating capacity*hub destination	0.0711	0.0986	0.0012	-0.0373	0.0296	-0.0057
Route Competition Variables						
Monopoly	0.0880	0.1006	0.0013	-0.0208	0.0324	-0.0037
Large duopoly carrier	0.0134	0.0937	0.0004	-0.0351	0.0294	-0.0048
Small duopoly carrier	0.2179 *	0.1096	0.0026	0.0328	0.0355	0.0022
Airport Competition Variables						
Airport concentration at origination	0.4083 *	0.1617	0.0060	-0.1133 *	0.0509	-0.0192
Airport concentration at destination	0.0472	0.1156	0.0008	-0.0292	0.0358	-0.0044
Airline hub origination	-0.3569 **	0.1320	-0.0038	-0.1398 **	0.0273	-0.0150
Airline hub destination	-0.0467	0.1682	-0.0012	0.1010	0.0532	0.0139
1997 non-hub/small hub airport origination	-0.0213	0.1075	-0.0001	-0.0339	0.0359	-0.0043
Logistical Variables						
Slot origination	0.2866 *	0.1202	0.0042	-0.0722	0.0386	-0.0125
Slot destination	0.3709 **	0.1132	0.0052	-0.0630	0.0387	-0.0121
Distance (in 100's miles)	-0.0285 **	0.0100	-0.0004	-0.0031	0.0025	-0.0001
Hours until next flight	-0.0103	0.0074	-0.0002	0.0055 **	0.0018	0.0008
Renormed scheduled departure time	-0.3678	1.1394	0.0054	-1.6731 **	0.0500	-0.2193
Daily total carrier flights on route	0.0586 **	0.0099	0.0007	0.0095 **	0.0029	0.0007
Daily total origination airport flights (100's)	0.0176	0.0151	0.0003	-0.0194 **	0.0023	-0.0028
Daily total destination airport flights (100's)	0.0181	0.0192	0.0004	-0.0265 **	0.0024	-0.0037
Weather Variables						
Rain origination (inches)	0.3335	0.3424	0.0083	-0.6399 **	0.0247	-0.0887
Rain destination (inches)	0.2783	0.3506	0.0079	-0.6935 **	0.0252	-0.0953
Minimum temperature origination	-0.0010	0.0034	0.0000	0.0028 **	0.0008	0.0004
Minimum temperature destination	-0.0077 *	0.0034	-0.0001	-0.0025 **	0.0008	-0.0003
Frozen precipitation origination (inches)	2.6793 *	1.1488	0.0481	-2.1637 **	0.1572	-0.3154
Frozen precipitation destination (inches)	2.3713 **	0.8443	0.0391	-1.3409 **	0.1511	-0.2026
Constant	-1.5217	3.1921		4.0495 **	0.1105	
Log-likelihood	-58,165					
Observations	361,629					

Note: Robust standard errors are reported. Regressions include indicator variables for carrier, day of week and month. Marginal effects are the probability that the average flight is ontime or canceled. * and ** indicate 5% and 1% significance levels. Ontime flights arrive at the gate within 15 minutes of the scheduled arrival time.

[1] The cancel 1st decision is depicted as "Decision Process 2" in the Figure 1 schematic.