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AIRLINE SCHEDULE RECOVERY
AFTER AIRPORT CLOSURES:
EMPIRICAL EVIDENCE SINCE SEPTEMBER 11TH

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ABSTRACT

Since the September 11, 2001 terrorist attacks, repeated airport closures due to potential security breaches have imposed substantial costs on travelers, airlines, and government agencies in terms of flight delays and cancellations. Using data from the year following September 11th, this study examines how airlines recover flight schedules upon reopening of airports that have been closed for security reasons. As such, this is the first study to examine service quality during irregular operations. Our results indicate that while outcomes of flights scheduled during airport closures are difficult to explain, a variety of factors, including potential revenue per flight and logistical variables such as flight distance, seating capacity and shutdown severity, significantly predict outcomes of flights scheduled after airports reopen. Given the likelihood of continued security-related airport closings, understanding the factors that determine schedule recovery is potentially important.

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"Last week I announced a crackdown by special agents of the FAA and DOT's Inspector General focused on lapses in the security system currently operated by the airlines. Since then we have stopped flights; closed, searched and reopened concourses at nine major airports; and emptied airplanes to re-screen all passengers when we found that the airlines' security screeners had not followed proper procedures." (*U.S. Transportation Secretary Norman Mineta*, November 5, 2001).

1 Introduction

Airport security has attracted considerable attention since the terrorist attacks of September 11, 2001. Subsequent audits of airport security by the Office of Inspector General have revealed numerous security shortcomings that have resulted in frequent airport and terminal closures. For instance, in the six months following September 11th, 156 terminal or concourse evacuations in U.S. airports led to 2,395 flight delays or cancellations (Power, 2002). Due to airport security concerns, Congress passed the Aviation and Security Transportation Act on November 19, 2001, to shift the burden of airline passenger security screening from private companies to the newly created Transportation Security Agency (TSA). As of one year later, TSA had deployed federal screeners at all 429 U. S. commercial airports.

The purpose of this paper is to determine how carriers make flight operations decisions following security-related airport and terminal closures. Closures resulting from security concerns, and subsequent reopenings, serve as a natural experiment for studying how airlines recover flight schedules. Since the airline industry is highly capital-intensive, carriers seek to minimize time spent on the ground. For instance, the typical time at the gate between flights for a Southwest Airlines plane is just 20 minutes. A single cancellation or extended delay can cause ripple effects throughout the rest of the day. Even a short closure, therefore, is bound to result in some delays. Furthermore, security issues can keep airports closed for hours, forcing hundreds of flight cancellations. Airport closures are thus costly for airlines because of losses in both revenue and consumer goodwill, to the extent that airlines are blamed. Because passengers who experience delays are more likely to switch carriers (Suzuki, 2000), these losses extend beyond the immediate impact of the event.[1] As a result, when closures occur, flight operations personnel are under pressure to

[1] The loss in goodwill may be minimal if the consumers blame the Transportation Security Agency, rather than the airline, for the security-related airport closure.

make real-time cancellation and delay decisions that will return the airline to the original schedule as quickly as possible upon reopening. From a public policy perspective, it is also interesting to analyze how the aviation system as a whole recovers from a high-profile disruption in service.[2]

This work is the first to empirically examine service quality during irregular operations.[3] Several related studies have investigated flight delays and cancellations under normal operating conditions. Mayer and Sinai (2003a) find that in a given airport, hub carriers experience longer flight delays than non-hub carriers, and attribute this to the clustering of flights around peak travel times by hub airlines attempting to minimize passenger wait times between flights. They also report a positive effect of hub destination on delay, though this is smaller than the hub origination effect, as well as better on-time performance in more concentrated airports. Brueckner (2003) posits a theoretical model in which airports with one dominant carrier have fewer delays because the dominant carrier acts as a monopolist and fully internalizes the costs of airport congestion. He also presents empirical results that support this prediction of the model and indicate that delays are more frequent for flights originating in carriers' hubs. Mazzeo (2002) finds that monopolistic routes have more frequent and longer flight delays. Rupp, Owens and Plumly (2002) examine scheduled arrival times and find hub carriers have both more frequent and longer delays. Yet, hub carriers are less likely to cancel flights to and from their hubs (Rupp and Holmes, 2003). Rupp and Holmes also find higher cancelation rates for carriers that offer more daily scheduled flights. Mayer and Sinai (2003b) also examine flight schedules and find that carriers systematically underestimate travel time.

We examine the impacts on service quality, in the form of flight delays and cancellations, of three classes of explanatory factors. Following the previously-cited literature, we estimate regressions that include various logistical and competition measures at the airport and route level, along with logistical factors at the aircraft, carrier, and event level. Although a few logistical variables, such as route distance, aircraft and airport capacity, and event severity, play a role in

[2]We do not study weather-related airport closures because their dynamics differ from those of security-related closures for several reasons. While improved weather forecasting often enables airlines to adjust flight schedules in advance of pending bad weather, security-related closings are unanticipated. Moreover, whereas airports commonly operate at reduced capacity levels upon reopening after a weather-induced closure, after a security problem has been resolved airports can reopen without further capacity constraints. Finally, in contrast to severe weather events, which are concentrated in the Northeast U.S., security breaches are geographically unconstrained and thus occur at a random set of airports.

[3]For a theoretical networking-type model of irregular airline operations, see Thengvall, Bard, and Yu (2000).

determining service quality, these two groups of variables are largely unimportant. Our third category is a single variable of potential revenue per flight, formed by multiplying average round-trip airfare by the seating capacity of the plane. This study is novel in that, to our knowledge, it is the first to study the impact of potential revenue per flight on service quality. We find a significant effect of potential revenue per flight on whether post-shutdown flights depart on time and are delayed that persists even in the presence of airline fixed effects. Thus, economic considerations matter to airlines when they attempt to recover flight schedules after a security-related airport or terminal closure.[4]

The remainder of the paper is organized as follows. The next section discusses the data that we analyze. Section 3 outlines our econometric model, and section 4 presents the results of estimating the model. Section 5 concludes the paper.

2 Data

We examine how flight schedules were recovered after 17 security-related terminal closures that took place in the 12 months following the September 11, 2001 terrorist attacks. We identified airport closures by searching the ProQuest General Reference newspaper database, which includes the *Wall Street Journal*, *New York Times*, and *USA Today*, using keyword combinations of airport (or terminal) and closure (or closed or shutdown or security breach). For a closure to be included, either the entire airport had to close, as in 11 of the 17 events, or a terminal or concourse closure had to affect 100 percent of a carrier's fleet, as in the other six events.[5]

Table I lists various details for these closures. The average closure lasts more than three hours. Most closings are triggered by security breaches, ranging from sleeping security screeners and unplugged metal detectors to a replica grenade found in carry-on luggage and passengers running past security checkpoints. An FBI interrogation of three suspected terrorists closed Chicago's Midway Airport for three and a half hours on September 14, 2001. The three major

[4] We consider potential revenue rather than profit because we lack cost data. But McCartney (2002) acknowledges the importance of revenue considerations, noting that American Airlines "operated 14 different types of jets, each pegged for a specific mission to maximize revenue."

[5] We exclude instances like the (November 3, 2001) evacuation of Concourse B at Baltimore-Washington International Airport, used by Southwest Airlines, because Southwest continued flight operations from Concourse C.

airports serving New York City closed for several hours on November 12, 2001, as a precautionary measure after an American Airlines jet crashed shortly after taking off from JFK Airport.

Our data consist primarily of individual flight information from the Bureau of Transportation Statistics (BTS).[6] All carriers with revenues from domestic passenger flights of at least one percent of total industry revenues are required to report on-time performance information for individual flights. Data are thus available for all nonstop domestic flights for the ten largest, commonly referred to as "major," U.S. carriers, which accounted for more than 90 percent of 2001 domestic revenues.[7] Though these major carriers are required to report on flight operations in only 32 U.S. airports, since 1995 each has reported on all domestic operations.

For each of the 17 closures, our sample includes every domestic departure scheduled by major carriers from the time the airport closes through the rest of the day (including flights scheduled to depart after midnight), for a total of 2,141 flights. About one-fourth of the sample flights were scheduled to depart during the closure, with remaining flights scheduled to depart after the time the airport reopened.

We analyze the determinants of whether flights were canceled, delayed, or on time. This paper adopts the Department of Transportation's convention that a flight is considered on time if it departs no more than 15 minutes after its scheduled departure (or after airport reopening for flights scheduled to depart during the closure). For each flight, exactly one of these indicators equals one, while the other two equal zero. Compared to the 2001 national average, after an airport closure cancellations are six times more likely (22.6 percent versus 3.9 percent) and delays are twice as likely in our sample. On-time departures occur for just one-fourth of the sample. The average non-canceled flight departs 71 minutes after its scheduled departure time.

Many of the explanatory variables in our regression analysis are likewise taken or constructed from the BTS data. These include four measures that represent the level of competition between carriers at the airport or on the route in question. Two of these are binary indicators of whether the flight originates from or is destined for a carrier's hub. The third is a measure of airport concentration, which equals the Herfindahl index (sum of the squared carrier shares as a percentage

[6] The BTS data are available at http://www.bts.gov/oai/.

[7] These are Alaska, America West, American, Continental, Delta, Northwest, Southwest, Trans World (through December 31, 2001), United and US Airways.

of all daily flights) at the airport. The inclusion of these three variables is motivated by the finding of Morrison and Winston (1989) that consumer demand is higher for airlines with large operations from an origin city. The fourth competition variable represents the number of effective competitors on a given route. This variable, discussed in Morrison and Winston (1995), is the inverse of the sum of the squared market shares (as a percentage of all daily flights) on the route.[8]

We also include a variety of logistical measures as explanatory variables in the regressions. Several of these also come from the BTS data. Four U.S. airports are slot-controlled (a regulated number of takeoffs and landings) during the sample period: NY LaGuardia, NY JFK, Washington Reagan National, and Chicago O'Hare.[9] Two binary variables, indicating whether one of these airports was the origin or destination airport, are controlled for in the regressions. Four additional variables relating to the scheduled departure time of the flight are also included: the time (in hours) until the next scheduled departure for the same carrier and route, an indicator of whether the flight is the last flight of the day for that carrier and route, the time (in hours) until the airport reopens (for flights scheduled during the closure), and the time (in hours) elapsed between the reopening of the airport and the scheduled departure (for flights scheduled after the closure). Finally, we control for the total number of flights for the carrier that were scheduled to depart during the shutdown.

To these data we merge information from three additional sources. From the 2001 FAA Airport Capacity Benchmark Report, we obtain information on airport capacity, measured as the number of additional (or fewer) flights that would have to be scheduled at a given time interval (in 15 minute increments) for the airport to operate exactly at capacity. From this measure and information on the number of flights scheduled during the closure, we calculate the number of hours after reopening that the airport would have to operate at capacity in order to clear the backlog of scheduled departures.[10] This variable, which is specific to the closure and the time of day at 15 minute intervals, is included in the regression equations as a measure of the severity of

[8]An alternative measure, the route market share for the carrier on the day of the airport closure, performs similarly.

[9]Our variables account for the elimination of slot restrictions at O'Hare as of July 1, 2002.

[10]For example, if 14 flights were scheduled during a closure, and the airport that had closed was scheduled to operate at two flights below capacity in each 15 minute interval for the remainder of the day, the airport could accommodate two additional flights each 15 minutes, so that it would take 7 such intervals, or 1.75 hours, to clear the backlog of flights that could not depart during the closure.

the airport shutdown.[11]

The FAA Aircraft Registry database contains the number of seats in each type of aircraft. We match this by the tail number of the aircraft scheduled to make each flight and include it as a regressor.

Finally, for each pair of origination and destination airports, we obtain the flight mileage between the airports and average round trip fare in 2001 from the Department of Transportation's *Origin and Destination Survey*.[12] The distance measure is included as an explanatory variable in the regressions. We multiply the average round trip fare by the number of seats in the aircraft to obtain the potential revenue per round trip flight, which serves as the main economic variable in our analysis.

Summary statistics appear in Table II. Flight mileage averages 889 and varies from 72 (Denver-Colorado Springs) to 4,962 (Newark-Honolulu). Upon reopening, airports would have to operate at capacity for an average of nearly 3.5 hours in order to clear the queue of departures scheduled during closures. Means of 178 for seating capacity and $196 for round trip airfare lead to an average potential revenue per round trip flight of $34,871, which represents the mean revenue lost to a carrier from canceling a full flight and refunding the round trip airfare to ticketed passengers. The average time until the next flight on the same route by the same carrier is 2.6 hours. Two-thirds of scheduled flights originate from a carrier's hub airport while one-third have hub destinations.[13] Slot-controlled originations and destinations comprise 12 and 10 percent, respectively, of the sample. On average, routes have 1.5 effective competitors and the departure airport concentration is 0.51.

Figure 1 plots the proportion of flights that are canceled, delayed, and on time for each of three periods: before, during, and after the airport closures. These periods correspond to the left, middle, and right segments of the figure, respectively. Because airport closures occur at various times of day and last for varying amounts of time, we divide each period of each event into quintiles and, after combining the data across events, calculate mean outcomes for each quintile

[11] We set this variable equal to zero for all flights from Chicago Midway and Louisville, because these two airports are not are not among the nation's 31 busiest and therefore are not included in the aforementioned FAA capacity report.

[12] The survey can be accessed at http://ostpxweb.ost.dot.gov/aviation/aptcomp/aptcomp2001.htm.

[13] The sample consists of four possible types of routings: hub to hub (219 flights, or 10%), non-hub to hub (522, 24%), hub to non-hub (1,225, 57%), and non-hub to non-hub (175, 8%).

of each period. For example, quintiles of the during-shutdown period consist of 42 minutes for Chicago Midway, which closed for 210 minutes, but only 20 minutes for Denver International, which closed for 100 minutes.

Despite the normalization process, clear service quality patterns emerge within each of the three periods. Before the shutdowns, 81 percent of flights depart on time, slightly more than the 2001 average of 73 percent for domestic flights by major carriers. This suggests that airports operated under standard conditions before security breaches occurred. Not surprisingly, closures result in a sharp jump in the flight cancellation rate, from five percent in the last pre-shutdown quintile to 40 percent in the first during-shutdown quintile. Though cancellations decrease somewhat for flights scheduled during the later portions of shutdowns, the mean during-shutdown cancellation rate of 42 percent is more than ten times the 2001 average of 3.9 percent. Moreover, the decline in cancellations for flights scheduled later in the closure period is associated with a large rise in delays that results in a decrease in the proportion of flights that depart on time (i.e., within 15 minutes after the airport reopens). Upon airport reopening, the cancellation rate immediately falls to twelve percent, which is close to the pre-closure average rate of six percent. Meanwhile, the delay rate peaks in the first quintile and declines monotonically thereafter, while the on-time departure rate climbs steadily throughout the post-shutdown period.

Since our goal is to examine how flight schedules are recovered after a service disruption, we ignore flights that departed (or were scheduled to depart) before airports were closed and focus on the periods during and after airport closures. Figure 1 suggests that outcomes patterns for these two periods differ considerably. As a consequence, we separately analyze flights scheduled to depart during and after airport shutdowns.[14] The patterns displayed in Figure 1, particularly regarding cancellation rates for flights scheduled during and after airport closures, also determine an important aspect of the econometric specification, to which we now turn.

[14]Formal specification tests unequivocally reject pooling of data from these two periods.

3 Econometric Model

Consider the profit maximization problem facing the agent managing air traffic for a representative airline on the day of a security-related airport closure.[15] From the time the airport closes until sometime after airport reopening, the agent is typically confronted with an excess of flights scheduled relative to the number that can feasibly depart. Of course, during the airport shutdown no flights are allowed to depart. This creates a backlog of schedule departures once an airport (or terminal) reopens. The agent must integrate the flights that were scheduled to depart during the airport closure with the flights that were scheduled to depart after the airport reopening given the existing airport capacity limitations. Frequently after an airport closure, the backlog of scheduled departures exceeds the number of opportunities for flights to depart at the current time. The agent thus must decide between three possible outcomes for each affected flight: cancellation, delay, or on-time departure.

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 having outcome j, incorporating both short-term (e.g., rebooking costs) and long-term (e.g., service quality reputation) effects can be 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. Assuming that $\pi_j(X_i)$ can be approximated by a linear function of X_i, 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

[15] Discussions with airline personnel indicate that security personnel determine whether an airport is opened or closed, while airlines decide whether an individual flight departs on-time, late, or is canceled. The only exception is at slot-controlled airports, where carriers that fail to use a departure slot are forced to cancel the flight.

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

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),

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

where identification requires $\beta_k \equiv 0$ for one of the three outcomes. A well-known embedded assumption of the multinomial logit model is 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., departing on time) 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.

The IIA assumption might be unreasonably restrictive. An alternative discrete choice specification that relaxes the IIA assumption is the nested logit model. One way to motivate the nested logit model in our context is by postulating that the decision between these three outcomes occurs as a sequence of two binary choices: the first option is either chosen or not chosen, and if the first option is bypassed, then one of the other two options is chosen.[16] Examples of the two feasible sequencing possibilities are displayed in Figure 2. In the left panel, labeled Decision Process 1, the agent first decides whether to cancel the flight. Then, for flights not canceled, she decides whether the flight should depart on time or be delayed. In the right panel, labeled Decision Process 2, the agent first decides whether the flight should depart on time, and then, for flights that do not depart on time, she decides whether the flight will be delayed or canceled.[17]

[16] 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.

[17] It seems unlikely that the third possible ordering, in which the agent first decides whether to delay and then decides whether non-delayed flights depart on time or are canceled, would represent a rational decision process.

Next we outline the econometric method involved in estimating the nested logit model in the case of Decision Process 1 (the method for Decision Process 2 is analogous). Define the inclusive value I_i as the natural log of the sum of (exponentiated expected) profits from not canceling:

(5) $$I_i = \ln \sum_{k=ONTIME,DELAY} e^{X_i \beta_k}$$

Calculating the probability of choosing each outcome j is now a three-step process[18]:

1. Conditional on not canceling, the probability that a flight is on time (rather than delayed) is estimated equivalently to a standard (binary choice) logit using only the non-canceled flights:

   (6) $$\Pr_i(\text{ ONTIME } | \text{ CANCEL=0}) = \frac{e^{X_i \beta_{ONTIME}}}{1 + e^{X_i \beta_{ONTIME}}}$$

   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

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

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

   (8) $$\Pr_i(\text{ CANCEL }) = \frac{e^{X_i \beta_{CANCEL} + \tau I_i}}{1 + e^{X_i \beta_{CANCEL} + \tau I_i}}$$

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

[18]For more details regarding these steps, see Greene (2000).

The unconditional probabilities of on-time and delayed departure are straightforward to compute. Because the estimated β and τ parameters are difficult to interpret, we report marginal effects

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

along with standard errors that are estimated by 100 replications of a non-parametric bootstrap.

The question remains whether Decision Process 1 or 2 in Figure 2 more closely reflects the actual decision sequencing that airline agents utilize for flights scheduled during and after security-related airport closures. The choice between these two processes for each of the two periods, during and after the shutdowns, is driven by theory and supported empirically. In theory, one might expect that once an airport reopens, carriers would attempt to adhere as closely as possible to their original timetables for flights that were not yet scheduled to depart and thus had not (yet) been delayed or canceled. But maintaining the post-shutdown flight schedule would require limiting the number of flights originally scheduled during the shutdown, and thus already delayed, to be rescheduled after airport reopening. This implies that Decision Process 1 applies to flights scheduled during the shutdown, as airlines must first decide which flights to attempt to reschedule while minimizing the impact on post-shutdown flights not yet affected, and then find a slot in which to send off the rescheduled flights. In contrast, Decision Process 2 would govern flights scheduled after airport reopening: flights that could not depart on time would be delayed with the intent to eventually depart if possible.

The patterns depicted in Figure 1 are consistent with these conjectures. The uniformly higher rates of cancellation for flights during airport closures, coupled with the virtually immediate return to pre-closure cancellation rates upon reopening, implies that different decision processes are used for flights scheduled during and after closures. The fact that cancellation rates are substantially higher than pre-closure rates, and cancellation rates exceed delay rates for the majority of the closure period, is consistent with the premise that the cancellation decision is made before the delay decision for flights scheduled *during* closures.[19] Meanwhile, the combination of low

[19]Moreover, by canceling flights scheduled to depart during closures, carriers minimize customer dissatisfaction if passengers blame the security breach rather than the carriers for the closure.

cancellation rates and only gradual decline of the delay rate as the on-time rate increases towards its pre-closure level upon airport reopening suggests that flights scheduled after closures are only canceled after the decision not to depart them on time. This logic implies that Decision Process 2 is the "natural" order of the delay vs. cancellation decision that is followed during normal operations.

Ideally, we could confirm our hypotheses regarding which decision process governs each period by estimating the nested logit model implied by both decision orderings and comparing the performance of the two. There is, however, no easily-constructed criterion by which to choose between two non-nested models. Since the log-likelihoods of the regressions are informative in some cases, we present these, along with the log-likelihood of the more restrictive multinomial logit model, for each specification in Tables III and IV, which are discussed below.[20]

4 Results

4.1 Flights scheduled during shutdowns

Table III displays results for the nested logit model with the cancellation decision preceding the delay decision for flights scheduled during airport shutdowns. Specification (2), in the right panel, includes airline fixed effects, while specification (1), in the left panel, does not. For each model, the bottom panel shows that the log likelihood of the alternative feasible nested logit model, in which the on-time decision is made before the cancellation decision, is statistically identical to that of the multinomial logit model, while the log likelihood for the models estimated in Table III represent significant improvements over those of the multinomial logit models. This provides further empirical support for our hypothesized decision ordering during the shutdown period.

Although adding airline fixed effects substantially improves the fit of the model, specifications (1) and (2) yield similar results. In each, carriers appear to make cancellation decisions with regard to only a few competitive and logistical factors. Notably, potential revenue per flight does

[20]For both the during and after closure periods, results for both the alternative feasible nested logit and multinomial logit models are comparable to those presented in Tables III and IV. Nested logit coefficients and standard errors (as opposed to the marginal effects shown in Tables III and IV) are available upon request. Furthermore, as an alternative robustness test, we applied the discrete factor method (Heckman and Singer, 1984) to the multinomial logit model. This method specifies a discrete approximation to the error structure rather than assuming a specific form. Results are quite similar to those reported below and are also available upon request.

not have a significant effect on cancellations or delays of flights scheduled during airport closures.

Two competitive variables are significant determinants of cancellations and delays during shutdowns, though only in the presence of airline fixed effects. Flights destined for a hub airport of the airline are 18 percentage points less likely to be canceled and 19 percentage points more likely to be delayed. Since a majority of passengers make connections at a hub (Morrison and Winston, 1995), canceling hub destination flights is more inconvenient for connecting passengers and potentially more costly for airlines since tickets must be reissued for each missed connection. Hub destination cancellations also increase the probability that connecting passengers do not make their destinations on the scheduled day, which is clearly a major inconvenience. In addition, after an airport closure (which averages over three hours) and subsequent flight delay (which averages over an hour), some flight crews might be approaching the 16 hour on-duty limit. Since replacement crews are more accessible at hubs, carriers have an incentive to not cancel hub destination flights, or at least might be more able to avoid such cancellations.

In contrast, an additional effective competitor on a route increases cancellations by eight percentage points while reducing delays by seven percentage points. Both pairs of effects, particularly that for destination hubs, are large relative to the during-shutdown averages of 42 percent for both flight cancellations and delays. Similar findings have been documented by Rupp and Holmes (2003) and Rupp, Owens and Plumly (2003). A potential explanation is that excess capacity increases with the competitors on a route, enabling carriers to more effectively consolidate flights.[21]

In both specifications, two logistical variables significantly affect cancellation and delay decisions. As flight distance increases by 500 miles, the likelihood of cancellations decreases, and that of delays increases, by about nine percentage points when airline fixed effects are included. A potential reason that cancellations of longer distance flights might hurt schedule recovery efforts is the limited interchangeability of flight crews across plane types used to fly routes of various lengths. Since there are many more short-haul than long-haul flights, fewer substitute crews are available for the latter.[22] Another possibility is that this result arises from the mandate that

[21]Morrison and Winston (2000) report that it is common, in response to new entrants onto a route, for the incumbent major carrier to not only reduce fares but to also increase capacity.

[22]For example, according to Continental personnel, a DC9-30 aircraft can substitute for a Boeing 737-200 but not for a MD-80 or a Boeing 737-300, and a Boeing 737-300 can substitute for a Boeing 737-200 while the reverse

flights cannot leave the gate when it is known that the expected flight time will result in pilots exceeding the maximum 16 hours during which they can remain on duty. Longer distance flights will be more likely to encounter the constraint than shorter distance flights, and locating a replacement crew may disproportionately delay longer flights.[23]

Also, for every additional hour that an airport is closed after the scheduled departure, cancellation is seven percentage points more likely while delay is eight percentage points less likely. This suggests that carriers cancel flights scheduled early in the shutdown period and re-book displaced passengers onto later flights.

A third logistical variable, the number of seats in the aircraft, significantly increases the chance of delay when airline effects are excluded, yet the significance is wiped away with the inclusion of airline effects.

Overall, the results suggest that in the struggle to maintain flight schedules after an unexpected airport shutdown, airlines make decisions regarding flights scheduled during the shutdown that are affected to some extent by certain competitive and logistical factors that are essential to minimizing disruptions but are otherwise somewhat haphazard. Interestingly, the effects for each significant variable appear to represent a virtual one-to-one transfer between cancellation and delay, with no effect on the on-time departures (this includes the number of seats, although the cancellation effect is insignificant). This pattern provides further evidence that cancellation decisions are made first for flights scheduled during shutdowns, with flights more vital to maintaining the schedules of airlines and customers being delayed rather than canceled.

4.2 Flights scheduled after an airport reopens

Table IV displays results for the nested logit model with the on-time decision preceding the cancellation decision for flights scheduled to depart after an airport reopens. Analogous to the previous table, specification (3) in the left panel omits airline fixed effects while specification (4) in the right panel includes them. The lower panel again reveals that both nested logit models fit the data significantly better than the multinomial logit model. While the log likelihood of the

is not allowed (Thengvall, Yu and Bard, 2001).

[23] The 16 hour limit was introduced by the FAA's "Whitlow letter" of November 2000. We thank an anonymous United Airlines pilot for bringing this to our attention.

specification (3) model is substantially greater than is that of the alternative feasible nested logit model, the specification (4) log likelihood is not significantly different from that of the alternative nested model ("Cancel" 1^{st}).

The main result from this table is that for flights scheduled to depart after the shutdown ends, potential revenue affects service quality in a predictable manner. Though potential revenue does not impact the cancellation decision, it does significantly increase the likelihood that a flight departs on time rather than late. Without airline fixed effects, a $10,000 increase in potential revenue increases the probability that a flight departs on time by seven percentage points (or 14 percent), with an offsetting effect on the probability of delay (of 17 percent). With airline fixed effects added, the impact of potential revenue on the likelihoods of on-time and delayed departure are roughly halved, but still statistically significant.

This result shows that economic considerations impact schedule recovery strategies. There are likely both short and long-term elements to the relationship between potential revenue and service quality. Carriers can avoid costly reimbursements to passengers who abort their trips because of service disruption by avoiding delays on higher revenue flights.[24] Perhaps more importantly, Suzuki (2000) reports that passengers are more likely to switch carriers after experiencing flight delays. To the extent that current high-revenue flight passengers will fly with the carrier in the future, carriers have an incentive to minimize high-revenue flight delays in order to keep high-revenue flight passengers from becoming dissatisfied and switching carriers. Moreover, given the similarities between pre- and post-shutdown service quality patterns (as displayed in Figure 1), this result suggests that economic factors play a role in decisions regarding the delay and cancellation of flights under standard operating conditions.

Competition appears to have only a small impact on schedule recovery after airport reopening. Increased airport concentration results in cancellations of flights that would otherwise depart on time, with a one-tenth point increase in airport concentration (roughly the difference between Denver International, 0.55, and Chicago Midway, 0.66) increasing the cancellation rate by seven percentage points. This suggests that when the bulk of flights affected by a shutdown are for a

[24]On September 25, 2001, Norman Strickland, Assistant Director for the Office of Aviation Enforcement and Proceedings, opined that "refunds should be provided upon request to passengers who wish to cancel their trips as a result of a flight cancellation or significant schedule change made by the carrier" (airconsumer.ost.dot.gov/rules/20010925.htm).

single carrier, service quality suffers, as airline personnel (e.g. gate agents) are scarce resources that constrain the recovery ability of carriers with a large airport presence. But these effects are not robust to the addition of airline indicators. Similar to during shutdowns, flying to a hub has an effect only when airline effects are included. In contrast to the during-shutdown case, flights destined for hubs are less likely to be on time.

Carriers confront a trade-off between cancellations and flight delays with fewer cancellations during an airport shutdown contributing to more flight delays after an airport reopens. Logistical variables are more important for flights scheduled after reopening than for those scheduled during shutdowns. The effect of distance, particularly compared to that in the previous table, is reminiscent of that just discussed for flying to a hub, except that it holds whether or not airline effects are included. In particular, longer distance flights are again more likely to be delayed, but the delayed flights are ones that would otherwise have been on time, rather than canceled as was the case for flights scheduled during shutdowns. Mazzeo (2002) reports better on-time arrival rates for longer flights, which suggests that pilots can make up time while airborne in order to at least partially offset a delayed departure. This pattern suggests that certain types of flights — to a hub and long-distance — must depart in order to maintain flight schedules.

Both with and without airline fixed effects, planes with greater seating capacity are more likely to be delayed at the expense of departing on time. An additional 100 aircraft seats reduces the probability of an on-time departure by 9-14 percentage points and raises the probability of delay by 13-16 percentage points. This might be merely because larger planes take longer to load. For instance, United Airlines has adopted a "departure on ready" policy that takes precedence over the actual schedule.[25] If this policy is followed after a security breach, smaller planes, which load more quickly, should push back and thus take off before larger planes upon airport reopening. The lack of both robustness of this effect and offsetting decline in the on-time rate for flights scheduled during airport shutdowns provides further evidence that the decision process differs during and after the shutdown.

With increases in shutdown severity relative to airport capacity, as measured by the number of airport capacity operation hours to clear the queue of flights backlogged from the closure, flights

[25] See http://aerosite.net/tower.htm.

are less likely to leave on schedule and more likely to be delayed, regardless of airline fixed effects inclusion. The on-time effect is larger in magnitude than the delay effect because some flights that would otherwise depart on time are instead canceled, but this increase in cancellations is no longer significant when airline effects are included.

Several additional logistical factors matter. As each hour passes after airport reopening, airports gradually revert to normal operations, with more flights departing on time and fewer being delayed or canceled, though only the on-time effect is robust to the inclusion of airline fixed effects. The last flight of the day is more likely to depart on time and less likely to be delayed (in the absence of airline fixed effects), showing that operations generally return to normal by the end of the day. Getting this last flight to its destination also allows carriers to set themselves up for normal operations the following day. The harder a carrier is hit by the shutdown, as represented by the number of flights by the carrier that were scheduled during the airport closure, the more likely that the carrier will have to cancel a post-shutdown flight. As the length of time until the next carrier/destination-specific flight increases, the probability of delay increases when airline fixed effects are included. Finally, when the closed airport is slot-controlled, delays are less likely while cancellations and on-time departures are more likely, an apparent contradiction possibly explained by the fact that slot holders have a limited time (30-60 minutes) to get flights airborne before they must be canceled. But airline indicators render all three of these effects insignificant.

5 Conclusion

Since September 11, 2001, many airports have been closed because of security breaches. These closures have provided a natural experiment on how airlines recover flight schedules following a major service disruption. The data reveal substantially different patterns in service quality for flights scheduled during and after airport shutdowns. Carriers ultimately cancel nearly half of flights scheduled during airport shutdowns. Consequently, only a few variables affect the performances of these flights: hub destination, route competition, timing of scheduling during the shutdown, and flight distance.

In correspondence with improved service quality that ensues upon airport reopening, several additional factors affect departure performance of flights scheduled after closures end. Notably, flight-specific potential revenue has no impact on departures scheduled during shutdowns, but impacts performance in a predictable way for flights scheduled after airports reopen. In particular, flights with higher potential revenue are significantly more likely to depart on time and less likely to be delayed. Once normalcy begins to return to airport operations, economic considerations play an important role in flight schedule recoveries following security-related airport closures. Moreover, though route competition no longer matters, hub destination and flight timing and distance continue to have an effect, and several logistical variables that were inconsequential for flights scheduled during shutdowns become relevant.

Both airports and the Transportation Security Agency have taken steps to prevent future security breaches and reduce the impacts of those that do occur. The Aviation and Security Transportation Act reassigned the responsibility for airport safety from private companies to the federal government in an effort to improve safety and minimize the possibility of a breach. Airport security managers are now required to obtain permission from supervisors before evacuating concourses following a breach (Morrison, 2002). And Los Angeles International Airport, for example, has created many separate and smaller security zones within its airport by closing some tunnels that connect terminals. Still, Transportation Secretary Norman Mineta's "zero-tolerance" policy towards airport security lapses suggests that security-related airport closures will continue to occur. The results of this study provide insight into the factors dictating flight schedule recovery following such closures.

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Figure 1: Mean Flight Outcomes by Renormed Scheduled Departure Time

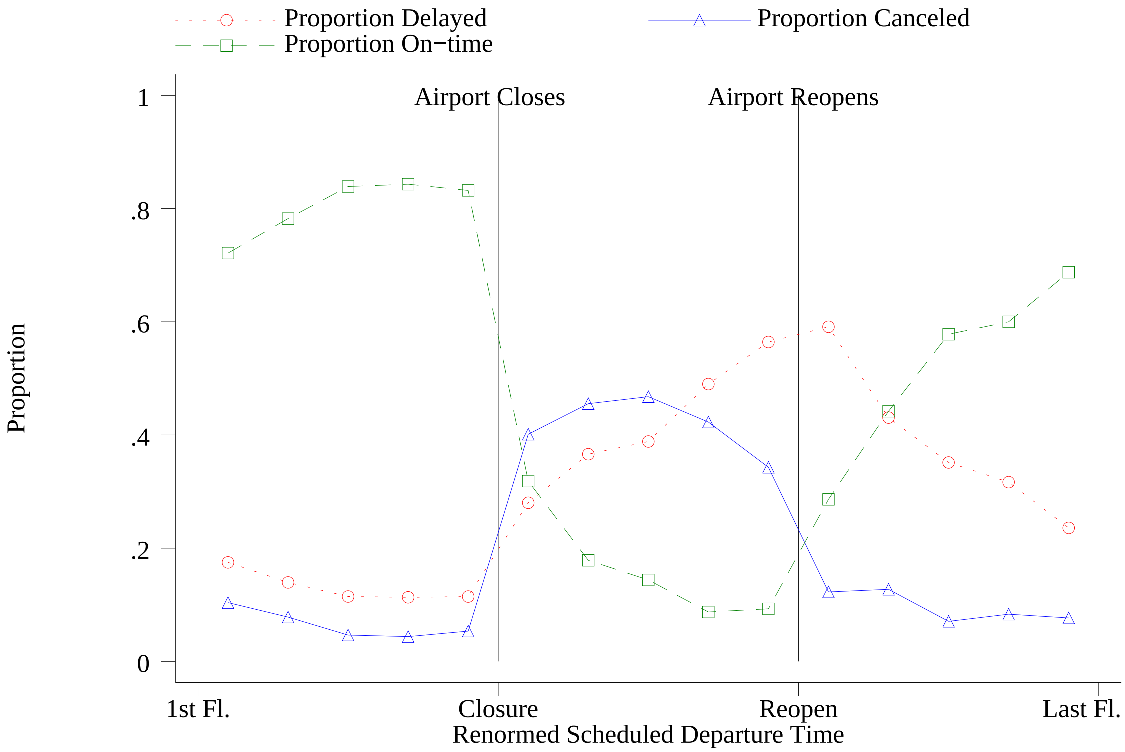

Figure 2: Schematic of Airline Operation Decision Processes

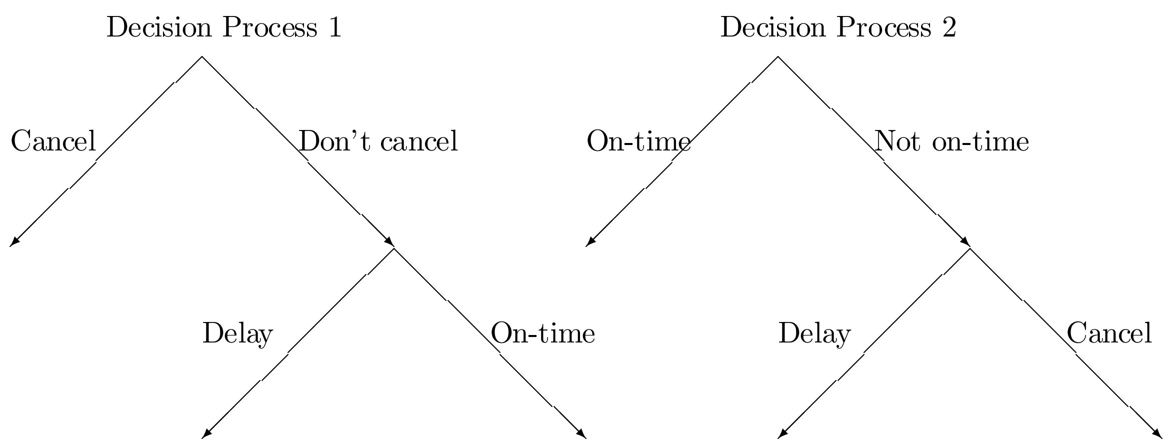

Table I: U.S. Airport and Terminal Closures due to Security Breaches during the twelve months following September 11th, 2001.

Date	Airport	Length of Closure[1]	Observations	Percent During Shutdown	Percent Delayed[2]	Percent Canceled	Average Delay[3] (minutes)	Shutdown Reason
9/14/2001	Chicago (MDW)	3:29	79	42%	75%	24%	136.9	FBI questions three suspected terrorists.
11/1/2001	New York (JFK)	0:49	13	23%	69%	8%	73.3	Screeners not following proper procedure.
11/12/2001	New York (JFK)	9:47	66	89%	33%	55%	52.8	AA Flight 587 crashes in Queens, NY.
11/12/2001	Newark (EWR)	5:12	197	41%	45%	39%	67.1	AA Flight 587 crashes in Queens, NY.
11/12/2001	New York (LGA)	5:25	176	47%	14%	55%	18.1	AA Flight 587 crashes in Queens, NY.
11/16/2001	Atlanta (ATL)	3:43	405	31%	53%	45%	186.0	Passenger runs past security checkpoint.
11/24/2001	Seattle (SEA)	2:45	165	21%	79%	1%	69.5	Unplugged metal detector.
12/18/2001	Charlotte (CLT)	1:48	233	19%	52%	25%	75.8	Unplugged metal detector.
12/18/2001	Baltimore (BWI)	2:32	22	45%	64%	0%	39.0	Suspicious image on X-ray scanner.
2/19/2002	Louisville (SDF)	2:21	45	24%	38%	0%	21.2	Sleeping security screener.
2/24/2002	Salt Lake City (SLC)	3:07	15	100%	73%	7%	61.5	Luggage-screening machine malfunction.
2/28/2002	Los Angeles (LAX)	1:50	151	15%	69%	1%	56.9	Metal detector malfunction.
3/4/2002	Los Angeles (LAX)	3:00	30	13%	43%	7%	39.1	Grenade found in carry-on luggage.
5/12/2002	Cincinnati (CVG)	2:37	117	9%	35%	2%	18.2	Passenger claims to have small knife.
6/29/2002	Washington (IAD)	2:13	11	82%	73%	0%	40.5	Passenger with a knife clears security.
7/27/2002	Los Angeles (LAX)	2:07	73	36%	73%	4%	80.2	Man bypasses security checkpoint.
8/26/2002	Denver (DEN)	1:49	343	10%	49%	1%	35.2	Woman bypasses security screening.
	Total	3:12	2141	28%	51%	22.6%	71.4	

[1]Length of closure is denoted as hours:minutes.

[2]Flight delay and cancellation numbers are only for the ten major domestic carriers: America West, American Airlines, Alaska, Continental, Delta, Northwest, Southwest, TWA (before 12/31/2001), United, US Airways.

[3]Average departure delay (minutes) is the difference between actual and scheduled departure time minus the unavoidable length of closure delay. Canceled flights are excluded in this departure delay calculation.

Table II: Summary Statistics for Scheduled Flights During U.S. Airport and Terminal Closures (n = 2,141)

Variable	Mean	Std. Dev.	Min	Max
Percent canceled	0.226	0.418	0	1
Percent delayed	0.513	0.500	0	1
Percent on-time	0.261	0.439	0	1
Potential Revenue per Flight ($1,000's)	34.871	18.891	4.353	138.166
Distance (100's miles)	8.889	6.341	0.72	49.62
Seats in aircraft (100's)	1.779	0.573	0.160	4.950
Hours to clear queue	3.461	2.623	0	8.5
Hours after reopening before scheduled departure[1]	1.966	1.647	0.017	9.733
Hours until next flight	2.629	1.873	0.017	15.333
Last flight of day	0.304	0.460	0	1
Number of Flights Shutdown for Carrier	33.750	34.936	0	106
Origination slot	0.119	0.324	0	1
Destination slot	0.096	0.294	0	1
Origination hub	0.674	0.469	0	1
Destination hub	0.346	0.476	0	1
Airport concentration (at departure)	0.514	0.235	0.213	0.838
Effective competitors (on route)	1.468	0.591	1	4
Departure Delay[2] (minutes)	71.406	83.064	-12	573
Airport market share of largest carrier (percent)	0.668	0.234	0.269	0.914

[1]For flights scheduled to departure after airport reopens.
[2]Departure delay excludes flight cancellations.

Table III: Marginal Effects: Flights Scheduled During Airport Shutdown—"Cancel" 1^{st} Decision

Model		(1)			(2)	
Outcome	**Cancel**	**Delayed**	**On-time**	**Cancel**	**Delayed**	**On-time**
Potential Revenue per Flight (1000's)	0.001	-0.003	0.002	0.002	-0.003	0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Logistical Variables						
Distance (100's Miles)	-0.011*	0.017**	-0.006	-0.017**	0.019**	-0.002
	(0.006)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)
Seats in Aircraft (100's)	-0.102	0.138*	-0.036	-0.069	0.085	-0.016
	(0.061)	(0.057)	(0.034)	(0.065)	(0.061)	(0.030)
Hours to Clear Queue	0.048	-0.034	-0.014	0.069	-0.047	-0.022
	(0.027)	(0.022)	(0.015)	(0.048)	(0.043)	(0.013)
Hours After Scheduled Departure	0.070**	-0.078**	0.008	0.059**	-0.057**	-0.003
Before Airport Reopening	(0.015)	(0.016)	(0.012)	(0.015)	(0.015)	(0.012)
Hours Until Next Flight	0.004	-0.008	0.004	0.005	-0.006	0.001
	(0.010)	(0.010)	(0.005)	(0.011)	(0.011)	(0.004)
Last Flight of Day	-0.000	-0.069	0.069	0.046	-0.056	0.009
	(0.071)	(0.077)	(0.039)	(0.082)	(0.082)	(0.028)
Number of Flights	0.002	-0.002	0.000	0.001	-0.001	0.000
Shutdown for Carrier	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
Origination Slot	0.354	-0.384	0.031	0.318	-0.340	0.022
	(0.373)	(0.425)	(0.074)	(0.230)	(0.236)	(0.053)
Destination Slot	0.029	-0.043	0.014	0.022	-0.024	0.002
	(4.829)	(3.394)	(1.474)	(3.997)	(2.838)	(1.203)
Competition Variables						
Origination Hub	-0.064	0.117	-0.053	-0.103	0.133	-0.029
	(0.142)	(0.142)	(0.045)	(0.207)	(0.190)	(0.054)
Destination Hub	-0.105	0.132	-0.027	-0.176*	0.186**	-0.010
	(0.076)	(0.071)	(0.034)	(0.070)	(0.068)	(0.031)
Airport Concentration	0.322	-0.199	-0.123	0.586	-0.216	-0.371
	(0.560)	(0.320)	(0.324)	(0.428)	(0.396)	(0.201)
Effective Competitors	0.058	-0.052	-0.006	0.082*	-0.073*	-0.009
	(0.038)	(0.036)	(0.018)	(0.038)	(0.036)	(0.019)
Airline Fixed Effects?		No			Yes	
Sample Average	41.6%	41.8%	16.6%	41.6%	41.8%	16.6%
Log-likelihood		-358.40			-318.60	
N		609			609	
Log-likelihood (MNL)		-360.13			-337.67	
Log-likelihood (On-time 1^{st})		-360.06			-337.57	

Cell entries are estimated marginal effects with bootstrapped standard errors in parentheses.

**: Significant at 1%; *: Significant at 5%

"Log-likelihood (MNL)" is the classical multinomimal logit model which imposes independence of irrelevant alternatives.

Table IV: Marginal Effects: After Airport Reopens — “Ontime” 1^{st} Decision

Model		(3)			(4)	
Outcome	**Cancel**	**Delayed**	**On-time**	**Cancel**	**Delayed**	**On-time**
Potential Revenue per Flight (1000's)	0.001	-0.007**	0.007**	-0.000	-0.003*	0.004**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Logistical Variables						
Distance (100's Miles)	0.001	0.012**	-0.014**	-0.003	0.018**	-0.015**
	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)
Seats in Aircraft (100's)	-0.017	0.155**	-0.138**	-0.036	0.127**	-0.091*
	(0.035)	(0.043)	(0.041)	(0.030)	(0.037)	(0.039)
Hours to Clear Queue	0.035**	0.045*	-0.080**	0.018	0.045*	-0.063**
	(0.013)	(0.020)	(0.015)	(0.013)	(0.022)	(0.019)
Hours After Reopening	-0.013**	-0.025**	0.038**	-0.014	-0.012	0.026**
Before Scheduled Departure	(0.005)	(0.009)	(0.008)	(0.008)	(0.010)	(0.007)
Hours Until Next Flight	-0.006	0.005	0.001	-0.008	0.024*	-0.016
	(0.008)	(0.010)	(0.011)	(0.009)	(0.010)	(0.011)
Last Flight of Day	0.005	-0.087*	0.083*	-0.022	-0.055	0.077*
	(0.024)	(0.036)	(0.035)	(0.023)	(0.041)	(0.036)
Number of Flights	0.002**	0.002	-0.003	0.003**	0.003	-0.005
Shutdown for Carrier	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
Origination Slot	0.236*	-0.821*	0.585*	0.029	-0.276	0.248
	(0.115)	(0.332)	(0.241)	(0.094)	(0.172)	(0.204)
Destination Slot	-0.001	0.033	-0.032	0.029	-0.015	-0.014
	(0.022)	(0.054)	(0.044)	(0.023)	(0.043)	(0.041)
Competition Variables						
Origination Hub	0.042	0.032	-0.074	-0.062	0.156	-0.094
	(0.057)	(0.053)	(0.059)	(0.103)	(0.126)	(0.119)
Destination Hub	0.038	-0.026	-0.012	0.002	0.070	-0.072*
	(0.026)	(0.042)	(0.034)	(0.028)	(0.041)	(0.035)
Airport Concentration	0.718**	0.076	-0.794**	0.073	0.224	-0.297
	(0.147)	(0.180)	(0.203)	(0.195)	(0.224)	(0.169)
Effective Competitors	0.002	-0.035	0.032	-0.018	0.038	-0.020
	(0.025)	(0.031)	(0.023)	(0.022)	(0.030)	(0.024)
Airline Fixed Effects?		No			Yes	
Sample Average	9.9%	40.3%	49.8%	9.9%	40.3%	49.8%
Log-likelihood		-1,171.47			-1,099.03	
N		1532			1532	
Log-likelihood (MNL)		-1,179.15			-1,100.43	
Log-likelihood (Cancel 1^{st})		-1,175.25			-1,098.02	

Cell entries are estimated marginal effects with bootstrapped standard errors in parentheses.

**: Significant at 1%; *: Significant at 5%

“Log-likelihood (MNL)” is the classical multinomimal logit model which imposes independence of irrelevant alternatives.