Airline Schedule Recovery after Airport Closures: Empirical Evidence since September 11th*

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JEL Classification: L13, L93.

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* We thank Brian Meehan and several airline employees for clarifying various issues regarding airline/airport operations, and Gary Fournier, Julie Hotchkiss, Darin Lee, two anonymous referees, and participants in the Empirical Airlines Studies sessions at the 2003 Southern Economic Association meetings and a seminar at East Carolina University for helpful comments. Joe Bunting and Michael Hopkins provided valuable research assistance.

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Abstract

Since the September 11, 2001 terrorist attacks, repeated airport closures due to 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 empirically examine service quality during irregular airport operations. Our results indicate that economic considerations, particularly the potential revenue per flight, have predictable effects on service quality following airport closures. Airport concentration, hub destination and various logistical factors also significantly influence flight outcomes.

> "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, President Bush signed into law the Aviation and Security Transportation Act on November 19, 2001, shifting the burden of airline passenger security screening from private companies to the newly created Transportation Security Administration (TSA). One year later, the 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. There are a number of potentially competing objectives that the airlines could consider when determining how to best resume operations after a large scale unanticipated shutdown. First, carriers could maximize revenue by providing better service on higher revenue flights. This could involve avoiding cancellations of such flights to minimize short-term refund expenditures, or reducing delays to diminish the chance of disgruntlement and potential carrier-switching of high revenue passengers. Second, airlines could minimize the number of passengers who are adversely affected by the closure, and as a result possibly consider switching carriers, by providing better service for larger planes. Third, more competition among carriers at the route or airport level might bring about better service. Finally, airlines may opt to restore the flight network as quickly as possible by providing better service for flights to or from their hubs.

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. Suzuki (2000) proposes a theoretical model, calibrated with aggregate U.S. DOT data, which suggests that passengers switch airlines after experiencing a flight delay. If passengers are more likely to switch carriers after experiencing a flight delay or cancellation, then airline losses may extend beyond the immediate impact of the event.[1] As a result, when closures occur, flight operations personnel are under pressure to make real-time cancellation and delay decisions that will return the airline to the original schedule as quickly as possible upon reopening. In addition, information on how the aviation system as a whole recovers and which of these four airline schedule recovery hypotheses holds after a high-profile disruption in service might be useful for policymakers.[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 longer delays for hub destination flights, though this is smaller than the hub origination effect, as well as better on-time performance in more concentrated airports. Brueckner (2002) 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 and indicate that delays are more frequent for flights originating in carriers' hubs. Mazzeo (2003) reports more frequent and longer arrival delays on airline routes served by monopolists. Rupp, Owens and Plumly (2003) find that hub carriers have both more frequent and longer arrival delays. Rupp and Holmes (2004) report lower cancellation rates for carriers that offer fewer daily scheduled flights and for flights by hub carriers that travel to and from their hubs. Mayer and Sinai (2003b) also examine flight schedules and find that carriers systematically underestimate travel time. They report that more route competition both slightly reduces scheduled travel time and slightly increases departure delays. At the same airport, hub carriers have longer departure delays than non-hub carriers.

We examine the impact 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 economic, competition, and logistical measures at the airport and route level. Our analysis is novel in that, to our knowledge, it is the first to study the impact of potential revenue per flight, formed by multiplying average one-way airfare by the seating capacity of the aircraft, on service quality.[4] We find a significant positive effect of potential revenue on the likelihood of on-time departure for flights scheduled to depart after the airport reopens. Moreover, the probability and length of delay is significantly lower for higher revenue flights regardless of whether the flight is scheduled to depart during or after the closure. Thus, economic considerations matter to airlines when they attempt to recover flight schedules after a security-related airport or terminal closure.[5] However, holding potential revenue constant, larger planes experience more frequent and longer delays, which likely signifies that the logistical impact of loading additional passengers onto a plane outweighs long-term motivations to minimize the number of passengers who are delayed. We also investigate the link between competition and service quality by considering both route competition (effective competitors on a route) and airport competition (hub airports and airport concentration). In addition, the regressions control for logistical factors at the aircraft, airline, and event level. Logistical variables such as route distance and minutes of closure after a scheduled departure play a role in determining service quality.

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.[6]

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

Our data consist primarily of individual flight information from the Bureau of Transportation Statistics (BTS).[7] 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 U.S. carriers, which accounted for more than 90 percent of 2001 domestic revenues.[8] Though these ten 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. For each flight, exactly one of these indicators (canceled, delayed, or on time) equals one, while the other two equal zero. This paper adopts the Department of Transportation's (DOT) convention that a flight is considered on time if it departs no more than 15 minutes after its scheduled departure. This on-time measure is the industry standard. Indeed, media outlets report airline on-time performance using the DOT measure, and these on-time averages also appear in company advertisements and public relations media. Passengers are likewise likely to use this as the measure of service quality of the flight (or airline). Delays for flights originally scheduled to depart during the airport closure are measured relative to when the airport reopens, so that scheduled departures during an airport closure are considered "on time" if the flight departs within 15 minutes of an airport reopening.[9]

Compared to the 2001 national average, 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 constructed from the BTS data. These include measures that represent the level of competition both along the route and at the airport. We use the number of effective competitors on a given route to measure route level competition. 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.[10] We also calculate the airport concentration, which equals the Herfindahl index (sum of the squared carrier shares as a percentage of all daily flights) at the airport.

To determine if carriers attempt to provide better service to and from a carrier's hub airport, we include indicator variables for both hub origination and hub destination flights.[11] Hub flights are especially important for carriers given that consumer demand is higher for airlines with large operations from an origin city (Morrison and Winston, 1989).

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.[12] Two binary variables, indicating whether one of these airports was the origin or destination airport, are included as regressors. 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). We also control for the total number of flights for the carrier that were scheduled to depart during the shutdown.

Flights that were already loaded (or loading) at the time of the airport closure, but have not yet taken off, may also experience delays because passengers have to be de-planed and re-run through security. To distinguish these flights and measure this effect we include an indicator of flights that were scheduled to depart within 20 minutes after the airport closed. To measure whether airlines, airports, or the Transportation Security Administration are becoming more efficient in handling airport closures over time, we create the variable “event date” which re-normalizes the airport closure date between 0 (September 11th, 2001) and 1 (September 11th, 2002).[13]

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.[14] This “hours to clear queue” 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 the airport shutdown.[15]

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 one-way trip fare in 2001 from the Department of Transportation's *Origin and Destination Survey.*[16] The distance measure is included as an explanatory variable in the regressions. We multiply the average one-way fare by the number of seats in the aircraft to obtain the potential revenue per flight, which serves as the main economic variable in our analysis. Potential revenue provides an accurate proxy for flight revenue if flights following a shutdown depart 100% full, an assumption that may not be too unrealistic given the high cancellation rates surrounding airport security closures (see Figure 1).[17]

Summary statistics, separated for whether the flight is scheduled to depart during or after the shutdown, appear in Table II. The primary distinction between the during and after periods is the improved service quality for flights scheduled after the shutdown. The average flight distance is about 900 miles. Upon reopening, airports would have to operate at capacity for an average of 3.5 hours in order to clear the queue of departures scheduled during closures. Means of 178 for seating capacity and $196 for one-way airfare lead to an average potential revenue per flight of approximately $35,000, which represents the mean revenue lost to a carrier from canceling a full flight and refunding the airfare to ticketed passengers. The average time until the next flight on the same route by the same carrier is about 2 hours. The sample is heavily weighted toward hub airlines, as two-thirds of scheduled flights originate from a carrier's hub airport while one-third have hub destinations.[18] Security-related closures last slightly over three hours on average, which is likely shorter than some weather-related closures (e.g. ice or snow storms) but longer than others (e.g. lightning). 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 about 0.50.

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.[19] 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 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 44 percent is more than ten times the 2001 average of four 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 about 14 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 patterns for these two periods differ considerably. As a consequence, we separately analyze flights scheduled to depart during and after airport shutdowns.[20] 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.

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.[21] From the time the airport closes until sometime after airport reopening, the agent is 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 scheduled 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

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

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.[22] 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.[23] Examples of the two feasible sequencing possibilities are displayed in Figure 2. In the left panel (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.[24] In the right panel (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.[25]

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:

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

Calculating the probability of choosing each outcome j is now a three-step process:[26]

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:

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

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

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

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:

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

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

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

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

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 scheduled 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.[27] Meanwhile, the combination of low 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 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. However, Vuong’s (1989) model selection tests suggest the “cancel first” and “ontime first” models are indistinguishable (with *t*-statistics of 0.36 and 0.07 and for departures scheduled during and after shutdowns, respectively). Therefore, we select our preferred model specification for each time frame based on theory, the results of the likelihood ratio tests against the multinomial logit specification, and discussions with airline employees. 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.

To determine the factors that contribute to extended delays, we also estimate, for both the during- and after-shutdown periods, OLS regressions of delay length, in minutes, on the same set of explanatory variables that we use in the nested logit regressions. This is potentially informative to the extent that the nested logit model does not distinguish between delays of, say, 20 minutes and three hours, even though the latter clearly imposes higher costs on passengers. The samples for the delay length regressions omit canceled flights, but include flights classified as on time in the nested logit regressions.

4. Results

Flights scheduled after an airport reopens

Table III 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. Using the same set of explanatory variables, the right panel presents OLS estimates of the minutes of departure delay regression. The lower panel shows that both nested logit models fit the data significantly better than the multinomial logit model, though the log likelihood of our preferred specification ("On time 1st") is only slightly larger than that of the alternative nested model ("Cancel 1st").

We begin by examining the first hypothesis, that carriers provide better service on flights with higher potential revenue (average fare multiplied by seating capacity). Table III shows that for flights scheduled to depart after the shutdown ends, potential revenue affects service quality in a predictable manner controlling for other factors such as route and airport competition, flight distance, seats in the aircraft, and whether the airport serves as a carrier's hub. Though potential revenue does not impact the cancellation decision, it does significantly increase the likelihood that a flight departs on time rather than late. Specifically, an increase in potential revenue of $18,000, which is roughly equal to one standard deviation, increases the probability that a flight departs on time by 6.1 percentage points (i.e. 18 percent) and reduces the probability of delay by 8.1 percentage points (i.e. 15.6 percent). The right panel of Table III indicates that the same increase in potential revenue significantly shortens the departure delay by 13 minutes. Therefore, we find considerable support for the hypothesis that carriers provide better service on higher revenue flights.

This is the first paper of which we are aware that explicitly specifies potential revenue of the flight as a determinant of flight service quality.[28] These results show 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 due to service disruptions by avoiding delays on higher revenue flights.[29] If the theoretical model proposed by Suzuki (2000) is correct and passengers are more likely to switch carriers after experiencing a flight delay, then airline losses may extend beyond the immediate impact of the event.[30] To the extent that 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. These results suggest that business travelers provide a positive externality to their fellow passengers because flights with more business travelers have higher revenues and hence get priority in the queue. Moreover, given the similarities between pre- and post-shutdown service quality patterns (as displayed in Figure 1), this result suggests that economic factors play an important role in decisions regarding the delay and cancellation of flights under standard operating conditions.

We next examine the hypothesis that airlines minimize the number of passengers inconvenienced by providing better service quality for larger planes. Our rationale for categorizing seating capacity as an economic variable is that each passenger who switches away from a carrier as a result of a closure-induced flight cancellation or delay represents long run revenue lost to the carrier. On the other hand, seating capacity also has a logistical element, as flights with more seats take longer to load and thus face a greater likelihood of delay and longer delays. Table III shows that although seating capacity has no effect on flight cancellations, larger planes experience more flight delays and fewer on-time departures after an airport reopens. This combination of effects is consistent with a logistical effect, particularly since we would expect no logistical effect of seating capacity on the likelihood of cancellation. A longer load time for larger planes is not surprising, especially since the effect of an additional seat on potential revenue is already held constant. For instance, United Airlines has adopted a "departure on ready" policy[31] that takes precedence over the actual schedule, which implies that upon airport reopening, smaller planes, which need less time to load, will push back from the gate more quickly than larger planes. In sum, we find that the logistical effect of seating capacity on service quality dominates the potential economic effect for flights scheduled after airports reopen.

Turning to the third hypothesis that carriers provide better service quality on competitive routes and at competitive airports, we find that airport competition has a larger impact on service quality than route level competition. Table III shows that controlling for potential revenue, flight operation decisions are not related to the number of effective competitors on a route. However, highly concentrated (i.e. less competitive) airports experience more flight cancellations. For example, a one-tenth of a point increase in airport concentration (roughly the difference between Denver International, 0.55, and Chicago Midway, 0.66) increases the expected cancellation rate by four percentage points. We find no effect of airport concentration on the occurrence of flight delays. In comparison, Brueckner (2002) presents a theoretical model and some empirical evidence that concentrated airports have fewer flight delays since the dominant carrier fully internalizes costs of airport congestion.

In examining the fourth and final hypothesis that carriers restore flight networks as quickly as possible by providing better service to and from a carrier's hub airport, we interpret the hub variables as a measure of a carrier's flight network, since most passengers who make connections do so at a hub (Morrison and Winston, 1995). Flights that originate from a carrier's hub airport may be better positioned for departures with minimal delays given the availability of replacement aircraft, crews, and equipment. The results indicate that scheduled departures from a carrier's hub are neither more nor less likely to be canceled or delayed than non-hub carriers. Likewise, the length of the flight delay is not significantly different for hub carriers compared to their non-hub carrier counterparts. However, we find that departures that are destined for a carrier's hub experience significantly longer delays (about 10 minutes). Therefore, we find little support for the fourth hypothesis regarding better service being provided at hub airports.

Some logistical variables are also important for flights scheduled after an airport reopens. These include: number of flights shutdown for carrier, flight distance, departures from slot controlled airports, hours after airport reopening before scheduled departure, last flight of the day, and event date. The harder a carrier is hit by the shutdown, the more likely that the carrier will have to cancel a post-shutdown flight. One possible explanation for this is that scarce resources (e.g. gate agents) constrain the ability of carriers with a large airport presence to recover flight operations. Long distance flights are more likely to be delayed and hence less like to push back from the gate on time. Given that Mazzeo (2003) reports shorter arrival delays for longer flights, this suggests that pilots can make up time while airborne in order to partially offset a delayed departure. A larger proportion of flights scheduled at slot-controlled airports are canceled, which is likely due to the limited time (30 to 60 minutes) in which slot holders have to get flights airborne before losing their departure slot. It is not surprising, therefore, that flights from slot-controlled airports are more likely to depart on time and experience less frequent and shorter delays. 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 as depicted by Figure 1. Consequently, the last flight of the day is more likely to depart on time and less likely to be delayed. Getting the last flight to its destination also provides a networking benefit since it enables carriers to set themselves up for normal operations the following day. In contrast, on normal travel days, the last flight of the day is typically delayed (Mayer and Sinai, 2003a). Finally, the further removed the airport closure is from September 11th, the less drastic the impact upon service quality. This result may be due to a variety of factors including the transfer of airport security responsibilities from private firms to the Transportation Safety Agency, airlines (and airports) becoming more efficient at handling and recovering from airport closures due to security breaches, and airlines reacting to a perceived reduction in patience on the part of travelers the further removed they are from September 11th.

Flights scheduled during shutdowns

Table IV displays results for flights scheduled during airport shutdowns. The left panel reports estimates for the nested logit model in which the cancellation decision precedes the delay decision, and the right panel reports estimates for the OLS minutes of departure delay regression. Since no departures occur during the airport shutdown period, the departure delay is the number of minutes after the airport reopens before the plane pushes back from the gate. Note that the log likelihood for our preferred model (Cancel 1st) in Table IV represents a significant improvement (p-value = 0.04) over that of the multinomial logit model. This provides further empirical support for our hypothesized decision ordering during the shutdown period. We now examine each of the four potential hypotheses regarding airline schedule recovery for these flights.

Regarding the potential revenue hypothesis, the results indicate that departure delays are less frequent (nested logit) and shorter (OLS) for flights with higher potential revenue. Specifically, a one standard deviation increase in potential revenue of $18,000 reduces the probability of delay by 7.9 percentage points (i.e. 15.8 percent) and the length of delay by about 16 minutes (i.e. 17.2 percent). Hence, even for flights scheduled during the airport shutdown, we find support for the hypothesis that higher potential revenue flights receive better service quality. It is notable that there is a pronounced economic effect in both regimes (during and after the shutdown) despite the different underlying decision-making processes.

For seating capacity, we again find that the logistical effect dominates the potential economic effect. In particular, planes with more seating capacity have both more frequent and longer departure delays. An additional 57 seats (one standard deviation) increases the probability of delay by 7.5 percentage points and lengthens the delay by about 18 minutes.

We find that the number of effective carriers serving a route has no bearing on either the flight operations decision or the length of flight delays. At the airport level, we also find no link between airport concentration and service quality. Therefore, for flights scheduled during the airport closure, we find no evidence to support the third hypothesis that links service quality and competition.

Carriers operating out of their hub airports perform neither better nor worse than their non-hub airline counterparts. We find that hub destination flights are 12 percentage points less likely to be canceled and 16 percentage points more likely to be delayed. Clearly there exists a trade-off between cancellations and delays, in that providing better service quality by not canceling hub destination flights comes at a cost of worse service quality in the form of more frequent and longer departure delays. In sum, for our fourth and final hypothesis, we find no linkage between service quality and hub origination and mixed evidence that hub destination flights receive preferential treatment.

For flights scheduled to depart during airport closures, several logistical variables are relevant to the flight operations decision process. Long distance flights have fewer cancellations yet more delays. A potential explanation is the limited interchangeability of flight crews across plane types used to fly routes of various lengths: fewer substitute crews are available for long distance flights, which are less prevalent than short distance flights, making delays preferable to cancellations.[32] In addition, crews on longer distance flights are more likely to be constrained by the 16 hour on-duty limit than those on short flights, since the upcoming flight would have to be completed within the time limit.[33] Another important logistical variable is the amount of time that the airport is closed after the scheduled departure, increases in which reduce the likelihood and length of delays at the expense of more frequent cancellations. The cancellation of a large block of early flights enables carriers to clear the queue of scheduled departures and hence reduce the occurrence and magnitude of departure delays for the non-canceled flights. As with flights scheduled after shutdowns, delay lengths decrease over time, although other outcomes do not improve as time passes. Flights that were scheduled to depart within 20 minutes of the shutdown face longer delays, predicated by the likelihood that these flights were in the midst of loading and hence require passengers to deplane and pass through security again. Finally, as the duration of time until the next flight on the same route increases, delay lengths increase slightly.

Interestingly, the effects for each significant variable appear to represent a virtual one-to-one transfer between cancellation and delay, with little effect on the frequency of on-time departures. 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.

Normal operations

To determine if these results are generalizable to normal operations days, we compare whether the same factors that are important during irregular operations are also relevant during normal operations. To track performance during "normal days" we collect data on all flights seven days prior to the airport closure.[34] To collect matching sets of flights, we limit the normal operations sample to only those flights scheduled after the time of the corresponding closure (i.e. if a closure occurs at 8:15 a.m., then the normal operations data include only those flights scheduled to depart after 8:15 a.m. seven days previously).[35] The nested logit "On time 1st" model for the normal operations sample reveals many of the same results as found for the post shutdown period, including effects of potential revenue, number of seats, effective competitors, slot origination and destination and time until the next flight on the same route. In sum, our post shutdown are broadly applicable given that many of the factors that matter for recovering flight schedules after airport closures are also important on normal travel days.[36]

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 different service quality patterns for flights scheduled during and after airport shutdowns: cancellations occur for nearly half of flights scheduled during airport shutdowns but only one in seven flights scheduled after the airport reopens. Despite these different service quality patterns, we find that regardless of when they are scheduled relative to the shutdown, flights with greater potential revenue have significantly better service quality, in that they experience less frequent and shorter delays. This is consistent with the hypothesis that carriers maximize revenue when making flight operations decisions in response to security-related closures. To put this finding in perspective, our estimates suggest that for flights scheduled after an airport reopens, an increase in potential revenue of one standard deviation (or just over 50 percent from the mean) has an effect on delay length equal to that of a 25 percent increase in the number of flights scheduled during the shutdown for the carrier, an effect on the likelihood of delay equal to that of a 65 seat increase in plane size, and an effect on the likelihood of departing on time equal to that of being scheduled an additional 96 minutes after an airport reopens. In addition, we find competitive effects at the airport level for flights scheduled after airports reopen and with regard to flights scheduled during shutdowns that are destined for hubs.

The potential revenue results suggest two airline pricing implications. First, high-fare business travelers provide a positive externality to lower-fare leisure passengers. Second, air travelers may be more willing to pay higher fares if they know that carriers provide better service quality on higher revenue flights. We find that low-revenue flights on large planes from less competitive airports experience the worst service quality following a security closure. The trade-off between delays and cancellations that is most prevalent for flights scheduled during airport shutdowns implies that it is important to analyze flight outcomes simultaneously rather than individually, which most previous work has done. Finally, the steady improvement in service quality in the year after September 11, as reflected by the results for the event date variable, implies that airports and airlines have gradually improved their abilities to deal with the residual effects of unanticipated service disruptions, so that outside intervention for the purpose of making post-shutdown airport operations more efficient might be unnecessary.

Our potential revenue results confirm that airlines respond to economic incentives. This suggests that policymakers could use economic incentives to promote efficiency in the airline industry in such areas as airport access (gate and slot utilization) and allocation of system access during weather disruptions. In 2001, the Department of Transportation requested proposals for potential market-based solutions to relieve airport congestion and delays, particularly at slot-controlled LaGuardia Airport, which, prior to September 11th was heavily congested.[37] Our results provide some empirical support for a congestion based fee approach to allocate takeoffs and landings since it appears that carriers may be willing to pay more for schedule reliability for particular flights. In addition, a similar congestion-based market valuation approach could be implemented during severe weather conditions, which reduce an airport's capacity (for example, when instrument flight rules are in effect). Firms that want to pay more for bad weather access during limited airport operations could do so and as a result provide better service.

Both airports and the Transportation Security Administration have taken steps to prevent future security breaches and reduce the impacts of those that do occur. The Aviation and Security Transportation Act (2002) 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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Endnotes

[1] Although customers may at least partially blame the Transportation Security Agency, it is likely that at least some customers will attribute the cancellation or delay to the particular airline, thus providing airlines incentive to pay attention to service quality even after security-related airport closures.

[2] We do not study weather-related airport closures because their dynamics differ from those of security-related closures. 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).

[4] For round-trip itineraries, we divided the total ticket price in half to obtain the one-way airfare.

[5] 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."

[6] 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.

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

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

[9] We find similar results using other on time measures such as within 30, 60, or 90 minutes of scheduled departure (for post-shutdown flights) or airport reopening (for during shutdown flights).

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

[11] We use the airline hub definition of Mayer and Sinai (2003a) that an airport is considered a hub for the airline if the carrier has 26+ connecting flights.

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

[13] For example, the New York City area airport closures of November 12, 2001, which is 62 days after September 11, 2001, event date equals 62/365 or 0.170.

[14] 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.

[15] We set hours to clear queue equal to zero for all flights from Chicago Midway (MDW) and Louisville (SDF), 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. Other airports in the sample (e.g. Cincinnati) also have hours to clear queue equal to zero, indicating that the zeroes for MDW and SDF are not outliers. Results without these two airports are qualitatively similar, and the parameter estimates and implied marginal effects for potential revenue, our explanatory variable of primary interest, are nearly identical.

[16] The survey is available at http://ostpxweb.ost.dot.gov/aviation/aptcomp/aptcomp2001.htm.

[17] The alternative revenue construct is average revenue, which multiplies average monthly load capacity by average quarterly fare. This revenue measure makes the unrealistic assumption that following an airport security closure, flights are no more full than usual.

[18] 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%). In comparison, Mayer and Sinai (2003a) use the same hub definition and report that originations from a carrier's hub airport account for 40% of flights between 1988 and 2000.

[19] Recall that flights scheduled during the airport shutdown are considered "on time" if the plane departs (i.e., pushes back from the gate) within 15 minutes of the airport reopening.

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

[21] Discussions with airline employees indicate that security personnel determine whether an airport is opened or closed, while airlines decide whether an individual flight departs on-time, late, or not at all. The only exception is at slot-controlled airports, where carriers that fail to use a departure slot are forced to cancel the corresponding flight.

[22] More generally, the decision regarding which plane is the next to depart once the airport reopens depends on the characteristics of every flight that is waiting to depart. However, it is nearly impossible to incorporate this interaction among flights into the econometric framework. Models that do so are unable to include characteristics that do not vary across carriers within an event, such as those of the originating airport, rely on the questionable independence of irrelevant alternatives assumption, and ultimately are empirically unstable.

[23] 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.

[24] This paper focuses on departures, not arrivals, because arrivals can continue to land during closures. Hence, not only do arrivals not face the issue of limited runway spots that confronts departures when the airport reopens, but further arrival decisions are sometimes made before the security event and thus cannot be incorporated into our nested logit model.

[25] 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.

[26] For more details regarding these steps, see Greene (2000). We implement the model in a full information maximum likelihood framework, which is more efficient than the process described here.

[27] Moreover, by canceling, rather than delaying, flights scheduled to depart during closures, carriers minimize dissatisfaction of customers not directly affected by the closure.

[28] Since seating capacity is held constant in the regressions, changes in potential revenue are identified by changes in average fare. An advantage of specifying potential revenue rather than average fare as a regressor is that the estimated effect of seating capacity does not reflect changes in potential revenue. Explicitly including average fare instead of potential revenue in the regressions yields estimates that are slightly weaker statistically but comparable economically. The finding of a potential revenue effect is more notable given that flight-specific measures are proxied by quarterly averages, which presumably biases our estimated effects towards zero.

[29] 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).

[30] Passengers will switch carriers following an airport closure only if they attribute the poor service quality to an individual airline rather than the airport or the Transportation Security Administration.

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

[32] 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 is not allowed (Thengvall, Yu and Bard, 2001.

[33] The 16 hour limit was introduced by the FAA’s “Whitlow letter” of November, 2000.

[34] Seven days prior is preferred to the previous day because flight schedules might change for a weekend versus a weekday.

[35] Due to scheduling changes, the sample sizes are slightly different: n = 2,054 for “normal days” compared to the n=2,141 in our airport closure sample.

[36] A topic for future research is whether our results, particularly for potential revenue, generalize to the more common occurrence of weather-related airport closures.

[37] See, for example, U.S. Department of Transportation (2001b, 2001c) for airport congestion and managing capacity at LaGuardia Airport.

Figure 1: Mean Flight Outcomes by Renormed Scheduled Departure Time

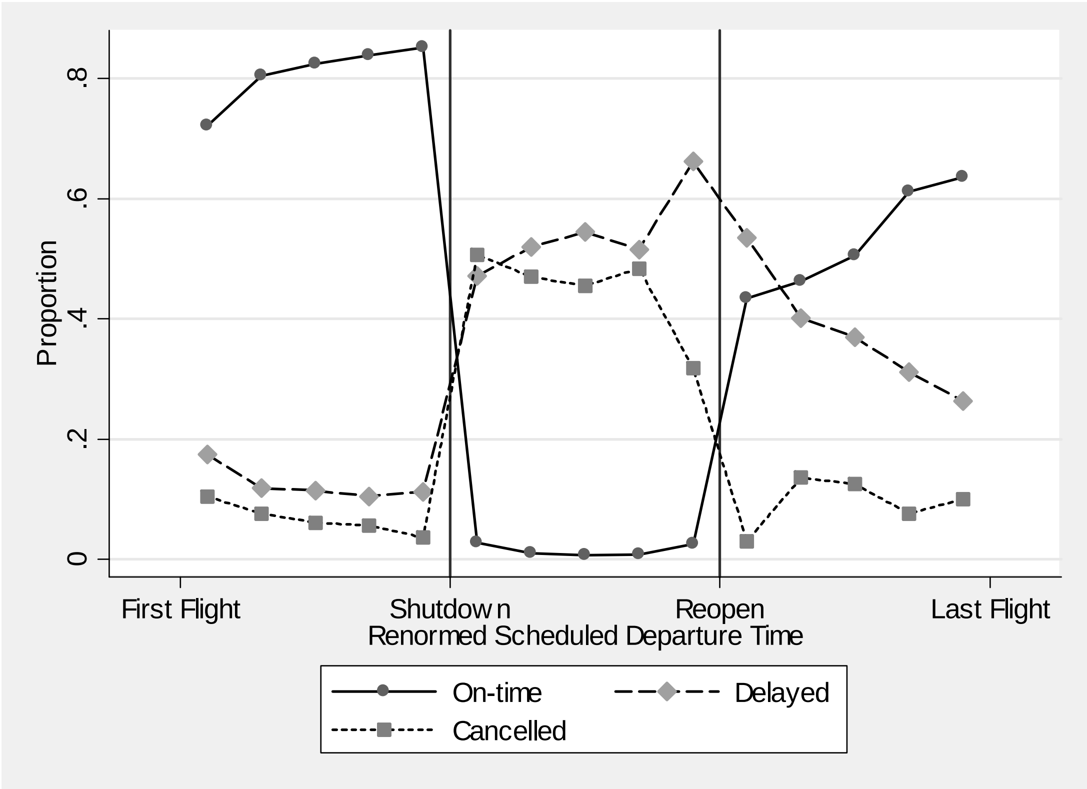

Figure 2: Schematic of Flight Operations Decision Process

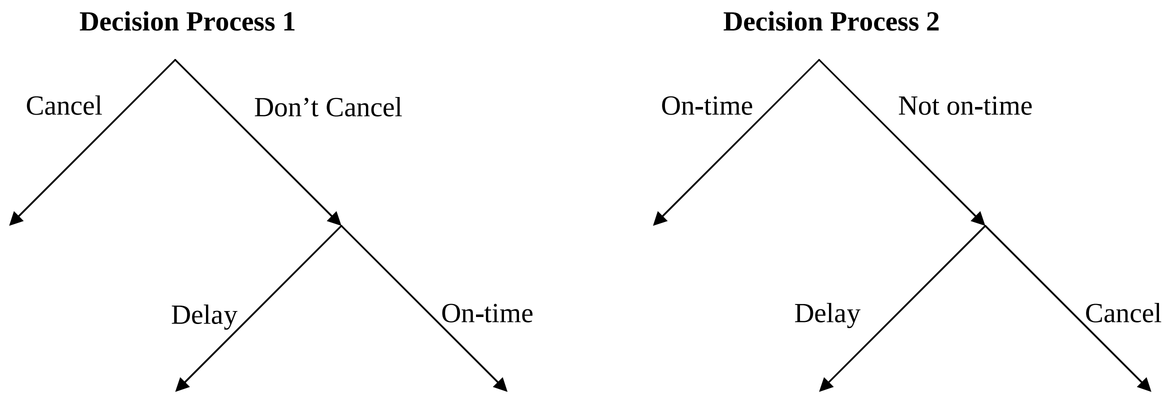

Table I: U.S. Airport and Terminal Closures due to Security Breaches during the twelve months following September 11th, 2001.

Date	Airport	Time of Closure[1]	Length of Closure[1]	Obs	Percent During Shutdown	Percent Delayed[2]	Percent Canceled	Average Delay[3] (minutes)	Airport or Terminal Closure?	Shutdown Reason
9/14/2001	Chicago (MDW)	13:16	3:29	79	42%	75%	24%	136.9	Airport	FBI questions three suspected terrorists
11/1/2001	New York (JFK)	16:56	0:49	13	23%	69%	8%	73.3	Terminal	Screeners not following proper procedure
11/12/2001	New York (JFK)	8:57	9:47	66	89%	33%	55%	52.8	Airport	AA Flight 587 crashes in Queens, NY
11/12/2001	Newark (EWR)	9:16	5:12	197	41%	45%	39%	67.1	Airport	AA Flight 587 crashes in Queens, NY
11/12/2001	New York (LGA)	9:00	5:25	176	47%	14%	55%	18.1	Airport	AA Flight 587 crashes in Queens, NY
11/16/2001	Atlanta (ATL)	12:05	3:43	405	31%	53%	45%	186.0	Airport	Passenger runs by security checkpoint
11/24/2001	Seattle (SEA)	8:45	2:45	165	21%	79%	1%	69.5	Airport	Unplugged metal detector
12/18/2001	Charlotte (CLT)	10:46	1:48	233	19%	52%	25%	75.8	Airport	Unplugged metal detector
12/18/2001	Baltimore (BWI)	14:00	2:32	22	45%	64%	0%	39.0	Terminal	Suspicious image on X-ray scanner
2/19/2002	Louisville (SDF)	6:41	2:21	45	24%	38%	0%	21.2	Airport	Sleeping security screener
2/24/2002	Salt Lake City (SLC)	22:36	3:07	15	100%	73%	7%	61.5	Airport	Luggage-screening machine malfunction
2/28/2002	Los Angeles (LAX)	6:30	1:50	151	15%	69%	1%	56.9	Terminal	Metal detector malfunction
3/4/2002	Los Angeles (LAX)	6:15	3:00	30	13%	43%	7%	39.1	Terminal	Grenade found in carry-on luggage
5/12/2002	Cincinnati (CVG)	9:29	2:37	117	9%	35%	2%	18.2	Airport	Passenger claims to have small knife
6/29/2002	Washington (IAD)	19:19	2:13	11	82%	73%	0%	40.5	Airport	Passenger with a knife clears security
7/27/2002	Los Angeles (LAX)	12:53	2:07	73	36%	73%	4%	80.2	Terminal	Man bypasses security checkpoint
8/26/2002	Denver (DEN)	7:07	1:49	343	10%	49%	1%	35.2	Airport	Woman bypasses security screening
	Total	11:24	3:12	2141	28%	51%	22.6%	71.4		

[1]Time of closure (military time) and length of closure are 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 and After U.S. Airport and Terminal Closures

Scheduled Flight: Variable	During Shutdown Mean	During Shutdown Std. Dev.	After Reopening Mean	After Reopening Std. Dev.
Percent canceled	0.437	0.496	0.142	0.349
Percent delayed	0.502	0.500	0.518	0.500
Percent on-time	0.061	0.239	0.340	0.474
Potential Revenue per Flight ($1,000's)	35.003	21.370	34.819	17.817
Distance (100's miles)	9.333	6.745	8.713	6.166
Seats in aircraft (100's)	1.786	0.573	1.777	0.573
Hours to clear queue	4.174	2.670	3.177	2.550
Hours of shutdown after scheduled departure	1.966	1.647	--	--
Hours after reopening before scheduled departure	--	--	3.833	3.339
Hours until next flight	2.406	2.092	1.602	1.880
Last flight of day	0.131	0.338	0.372	0.484
Number of Flights Shutdown for Carrier	34.437	35.377	33.477	34.767
Origination slot	0.238	0.426	0.072	0.258
Destination slot	0.102	0.303	0.093	0.291
Origination hub	0.594	0.491	0.706	0.456
Destination hub	0.389	0.488	0.329	0.470
Airport concentration (at departure)	0.478	0.222	0.528	0.238
Effective competitors (on route)	1.516	0.588	1.449	0.591
Departure Delay[1] (minutes)	92.376	71.924	65.932	84.910
Airport market share of largest carrier (percent)	0.601	0.250	0.653	0.249
Scheduled departure is within 20 minutes of shutdown	0.097	0.296	--	--
Event date[2]				
Observations	609		1,532	

[1]For flights scheduled to depart during the airport closure, departure delay is the number of minutes after the airport reopening before the plane pushes back from the gate. Flight cancellations are excluded.

[2] Event date is a renormalization of the airport closure date between 0 (9/11/2001) and 1 (9/11/2002).

Table III: Marginal Effects: Flights Scheduled After Airport Reopens - "Ontime" 1st Decision

Model	Nested Logit			OLS
Outcome	Cancel	Delayed	On time	Minutes of Departure Delay[1]
Economic Variables				
Potential revenue per flight ($1,000's)	0.0011	-0.0045*	0.0034**	-0.722**
	(0.0010)	(0.0019)	(0.0013)	(0.193)
Seats in aircraft (100's)	-0.0214	0.123*	-0.1016**	17.598**
	(0.0333)	(0.0506)	(0.0325)	(4.838)
Competition Variables				
Effective competitors (on route)	-0.0023	-0.0204	0.0227	1.727
	(0.0173)	(0.0275)	(0.0214)	(3.216)
Airport concentration (at departure)	0.3958**	-0.1850	-0.2109	7.144
	(0.1220)	(0.1488)	(0.1978)	(13.115)
Origination hub	-0.0095	0.1090	-0.0995	-4.346
	(0.0333)	(0.1004)	(0.0967)	(5.402)
Destination hub	0.0185	-0.0571	0.0386	9.823*
	(0.0242)	(0.0469)	(0.0371)	(4.783)
Logistical Variables				
Number of flights shutdown for carrier	0.0014**	-0.0022	0.0007	1.529**
	(0.0003)	(0.0039)	(0.0039)	(0.093)
Distance (100's miles)	-0.0007	0.0102*	-0.0095**	2.3424**
	(0.0023)	(0.0047)	(0.0033)	(0.402)
Hours to clear queue	0.0107	0.0069	-0.0176	-1.309
	(0.0099)	(0.0199)	(0.0162)	(1.290)
Hours after reopening before	-0.0137	-0.0239**	0.0377**	-5.612**
scheduled departure	(0.0071)	(0.0073)	(0.0039)	(0.594)
Hours until next flight	0.0008	0.0070	-0.0078	-0.506
	(0.0089)	(0.0103)	(0.0106)	(1.215)
Event date	-0.4519**	-0.2879**	0.7397**	-85.575**
	(0.1391)	(0.0787)	(0.1587)	(7.902)
Last flight of day	0.0169	-0.107*	0.0901*	-12.496*
	(0.0272)	(0.0454)	(0.0407)	(5.214)
Origination slot	0.1494**	-0.8566*	0.7073*	-52.528**
	(0.0514)	(0.3736)	(0.3378)	(8.329)
Destination slot	-0.0036	0.0355	-0.0320	-6.502
	(0.0246)	(0.0448)	(0.0431)	(6.197)
Sample Average	14.2%	51.8%	34.0%	65.9
Log-likelihood		-1,096.36		--
N		1,532		1,314
R-squared		--		0.50
Log-likelihood (MNL)[2]		-1,104.99		--
Log-likelihood (Cancel 1st)		-1,097.11		--

Cell entries are estimated marginal effects with bootstrapped standard errors in parentheses.
* and ** indicate significance at the 5% and 1% level, respectively.
[1]Departure delay is the number of minutes after the scheduled departure before the plane pushes back from the gate. Flight cancellations are excluded.
[2]"Log-likelihood (MNL)" is the classiscal multinomial logit model which imposes independence of irrelevant alternatives.

Table IV: Marginal Effects: Flights Scheduled During Airport Shutdown - "Cancel" 1st Decision

Model	Nested Logit			OLS
Outcome	Cancel	Delayed	On time[1]	Minutes of Departure Delay[2]
Economic Variables				
Potential revenue per flight ($1,000's)	0.0027	-0.0044*	0.0017	-0.886*
	(0.0021)	(0.0022)	(0.0012)	(0.359)
Seats in aircraft (100's)	-0.1023	0.1315*	-0.0293	31.042**
	(0.0654)	(0.0650)	(0.0312)	(10.130)
Competition Variables				
Effective competitors (on route)	0.0589	-0.0538	-0.0051	-1.981
	(0.0426)	(0.0404)	(0.0184)	(6.967)
Airport concentration (at departure)	0.2041	-0.0890	-0.1151	46.211
	(0.7858)	(0.5969)	0.2484	(24.759)
Origination hub	-0.0692	0.1321	-0.0630	7.178
	(0.6283)	(0.7313)	(0.1485)	(11.228)
Destination hub	-0.1222	0.1573**	-0.0351	5.676
	(0.0654)	(0.0609)	(0.0317)	(9.649)
Logistical Variables				
Number of flights shutdown for carrier	0.0021	-0.0017	-0.0004	0.181
	(0.0033)	(0.0027)	(0.0010)	(0.187)
Distance (100's miles)	-0.0132**	0.018**	-0.0048	1.950*
	(0.0045)	(0.0049)	(0.0038)	(0.828)
Hours to clear queue	0.0370	-0.0228	-0.0141	3.248
	(0.0393)	(0.0331)	(0.0130)	(2.208)
Hours of shutdown after	0.0625**	-0.066**	0.0035	-24.211**
scheduled departure	(0.0164)	(0.0156)	(0.0138)	(3.419)
Hours until next flight	0.0092	-0.0126	0.0034	4.211*
	(0.0122)	(0.0113)	(0.0046)	(1.994)
Event date	-0.4994	0.4799	0.0195	-52.757**
	(0.4602)	(0.4183)	(0.0843)	(14.784)
Last flight of day	0.0217	-0.0796	0.0578	-10.089
	(0.0777)	(0.0797)	(0.0364)	(12.203)
Scheduled to depart within	-0.0835	0.0371	0.0464	24.893*
20 minutes of shutdown	(0.2651)	(0.2401)	(0.0344)	(11.847)
Origination slot	0.2934	-0.3277	0.0343	-17.626
	(2.4615)	(2.4074)	(0.0770)	(14.612)
Destination slot	0.0370	-0.0404	0.0034	-0.347
	(2.2945)	(1.8278)	(0.5236)	(14.005)
Sample Average	43.7%	50.2%	6.1%	92.4
Log-likelihood		-347.33		--
N		609		343
R-squared		--		0.25
Log-likelihood (MNL)[3]		-349.39		--
Log-likelihood (On time 1st)		-349.34		--

Cell entries are estimated marginal effects with bootstrapped standard errors in parentheses.
* and ** indicate significance at the 5% and 1% level, respectively.

[1]Flights scheduled during the airport shutdown are considered "on time" if the plane departs (i.e., pushes back from the gate) within 15 minutes of the airport reopening.

[2]Departure delay (minutes after airport reopening before departure) excludes flight cancellations.

[3]"Log-likelihood (MNL)" is the multinomial logit model which imposes independence of irrelevant alternatives.