An Investigation Into the Determinants of Flight Cancellations[¤]

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Keywords: Service Quality, Flight Cancellations, Airlines
JEL Classi¯cation: L13, L93.

March 19, 2004

Abstract

This paper uses Bureau of Transportation data on 35 million domestic °ights between 1995 and 2001 to investigate the determinants of °ight cancellations. This paper is novel in two regards since it focuses exclusively on °ight cancellations and it explores the service quality and °ight revenue relationship. We ¯nd that carriers have some control over the occurrence of °ight cancellations given that cancellations are signi¯cantly less likely on Thursday, Friday, and Sunday and for the last °ight of day. There is only modest evidence that links cancellations with revenue.

[¤]We thank Joe Hopkins, Harumi Ito, Darin Lee, Chris Mayer, Ed Schumacher, Lester Zeager, several anonymous airline operations employees, and seminar participants at Appalachian State University, East Carolina University, International Industrial Organization Conference, and Southern Economic Association Conference for their helpful comments. Sherrine Ahmed and Jim Goodman provided research assistance.

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"Canceling a flight for economic reasons was totally taboo before, but we're seeing it now." (Robert Harrell, Vice President for American Express Travel Related Services, *Wall Street Journal*, 15 February 1991.)

1 Introduction

U.S. airline carriers had 665.5 million enplanements in 2000, which generated $93.6 billion in passenger revenue and employed 679,967 individuals (*Air Transport Association 2001 Annual Report*). Yet airlines have historically provided poor customer service: approximately one in four flights were delayed, canceled, or diverted between 1995 and 2002 (see Table 1). The most common consumer air travel complaint in 2000 was flight problems (e.g., cancellations, delays, and missed connections), an increase of 30 percent from 1999 (Air Travel Consumer Report, February 2001, p. 34), while revenue passenger miles increased only 6 percent over the same period.[1] Consumer frustration with airlines was typified by a Chicago businessman, who filed suit against United Airlines in 2000, seeking financial damages to cover ticket refunds, reimbursements for alternative transportation, compensation for emotional distress, lost vacation days, and missed business opportunities following a rash of cancellations due to unresolved contractual issues with United pilots (Carey, 2000). In 1999, due to poor airline service quality, U.S. Congressional hearings debated the merits of a passenger bill of rights. Ultimately, fourteen major domestic airlines voluntarily agreed in 1999 to the Airline Customer Service Commitment, which promised improved treatment of air travelers. In a follow-up study one year later, the U.S. Department of Transportation found that airlines were falling short of their promises due to extensive flight delays and long check-in lines (Heller, 2000).

This paper examines flight cancellations by using a sample of U.S. Bureau of Transportation Statistics (BTS) data for 35 million domestic flights in the U.S. by major carriers between January 1995 and August 2001. During this period there were more than one million flight cancellations. Moreover, cancellations became more frequent, increasing from 91,905 (in 1995) to more than twice that amount, 231,198 flights (in 2001), which corresponds to a cancellation rate of 1.73 and 2.79 percent, respectively, of all scheduled domestic flights. This study is novel in two aspects. First, it is one of the first to investigate the determinants of flight cancellations.[2] Second, the paper explores the relationship between service quality and revenues during normal daily operations.

Related theoretical work on flight cancellations is provided by networking models, which determine the optimal aircraft recovery schedule following a hub closure (Yan and Yang, 1996; Thengvall et al. 2000; Thengvall et al. 2001). Previous empirical research on service quality primarily has focused on flight delays, instead of cancellations (e.g., Mayer and Sinai, 2003a & 2003b; Mazzeo, 2003).

In the first six months after the BTS began tracking causes of flight delays in August, 2003, the four most common delay causes (in order of relevance) are late arriving aircraft, air carrier delay, national aviation system delay, and extreme weather.[3] Hence this paper controls for each of these measures and we find many significant non-weather cancellation factors matter such as day of the week, departure time, and number of daily scheduled flights on a route. An analysis of flight cancellations is beneficial given that (i) cancellations are more inconvenient for passengers than flight delays (e.g., following a cancellation passengers who are fortunate enough to be re-booked on the carrier's next scheduled departure on the route wait an average of over five hours, whereas the typical delayed flight departs an average of 52 minutes late; (ii) airline performance is a high-priority issue for travelers, airlines, and lawmakers; and (iii) recent consolidation (American Airlines acquired TWA in 2001), bankruptcy filings (US Airways and United Airlines declared bankruptcy in 2002), and scheduling cut-backs since the September 11th terrorist attacks (Carey and McCartney, 2001) may affect cancellations. Hence this paper investigates the link between flight cancellations and competition at both the route and airport level.

This paper examines four potential flight operation objectives originally proposed by Rupp et al. (2003), that carriers might pursue. There are a number of different competing objectives that carriers could follow in making daily flight operation decisions in order to maintain existing flight schedules. First, carriers may opt to maximize revenues by providing better service quality on higher revenue routes. Second, carriers may choose to minimize the number of passengers displaced by a service interruption by conducting fewer cancellations of larger and fuller planes. Third, route and airport competition may motivate carriers to improve service quality. Fourth, carriers may choose to maintain their flight network by providing better service to and from their hubs.

We examine the effect of four classes of explanatory variables on flight cancellations. Following the previously cited literature, our regressions include economic, competitive, logistical, and weather measures at the route, airport, and aircraft level. We find that route competition improves service quality, however, at the airport level, flight cancellations are independent of airport concentration. Finally, we find significantly fewer flight cancellations at hub airports, which highlights the importance of hub flights in maintaining a flight network. We find limited evidence linking revenue with flight cancellations. In the next section, we examine four potential flight operation objectives. We then describe the econometric specification used in the empirical analysis. The data are discussed in section 3, and findings are presented in section 4. We conclude the paper with some public policy implications for flight cancellations.

2 Flight Operation Objectives

We envision two types of cancellations. First, "stochastic cancels" are situations where the short run supply of available aircraft is exogenously decreased (e.g., severe weather limits airport operations, or an equipment failure/maintenance repair is necessary before the aircraft is operational). Second, "strategic cancellations" are situations in which the airline cancels a flight for strictly economic reasons (e.g., low passenger bookings). Note that economic factors can still play an important role even when stochastic cancels occur since airlines may prioritize high-profit flights over low-profit flights.

2.1 Revenue Maximization

Neoclassical economic theory assumes that airlines maximize profits. Since route-level profitability figures are unavailable and costs are likely more constant across routes than revenue, we use route revenue as a profit proxy. There are likely to be both short-term and long-term aspects of the relationship between revenue and service quality. In the short-term carriers might want to avoid canceling a high revenue flight to prevent costly passenger reimbursements. If the theoretical switching model, proposed by Suzuki (2000) and calibrated with aggregate US DOT data, is accurate and passengers who experience poor service quality are more likely to switch carriers, then the effect of a flight cancellation may also be felt long-term by the carrier. This may be especially true if travelers blame flight cancellations on the carrier rather than a problem that is beyond the carrier's control (i.e., severe weather). Hence our first hypothesis is that carriers provide better service quality on more profitable (high revenue) routes.

We consider three alternative revenue measures including *average revenue* (quarterly average one-way passenger fare multiplied by the monthly average number of occupied seats on the plane), *potential revenue* (quarterly average one-way passenger fare multiplied by seating capacity of the plane), and *yield* (dollars per revenue passenger mile). Note that these revenue measures are monthly/quarterly averages for a route and hence are not the revenue for an individual flight. Flight-specific revenue varies by many factors, such as the load capacity, number of seats, and class of fare purchased, but such fine detail are not available.

This paper is one of the first to link route revenue with flight service quality. Rupp et al. (2003) find that higher potential revenue flights receive better service quality (fewer cancellations and delays) after an airport reopens following a security-related airport closure. During irregular operations, *potential revenue* may be the preferred revenue measure since every seat is likely to be taken after an airport reopens due to the large number of flight cancellations. During normal operations, however, *average revenue* may be a better measure of lost revenue from a flight cancellation since *average revenue* does not assume that all seats are occupied. Instead, this revenue measure assumes that the flight has the monthly average passenger load. Finally, we include *yield* as an alternative route revenue/profitability measure. Although our examination of the revenue and service quality relationship is novel, previous studies on airline prices have used *yield* (Windle and Dresner, 1999; Lee and Ito, 2004). Given that *yield* decreases as flight length increases, all estimations control for flight length by including non-stop distance blocks between airports for *short flight* (<400 miles) and *middle distance* (400 to 800 miles) flights.

2.2 Minimize Passenger Inconvenience

The second hypothesized carrier objective is that carriers provide better service for the largest number of passengers possible to minimize passenger inconvenience from a service disruption. Minimizing inconvenience is related to the first hypothesized objective (revenue maximization) since the number of passengers is also a component in the revenue calculation. We use three variables to measure the magnitude of passenger inconvenience – *load capacity, seating capacity,* and *last flight of day.* First, *load capacity* is the monthly average proportion of total seats that are occupied by passengers for carrier j on route r. *Load capacity* is an alternative profit proxy since routes with higher *load capacity* are also likely to be more profitable. Carriers can minimize passenger inconvenience from a service disruption by canceling flights with lighter passenger loads. Second, if carriers are minimizing passenger inconvenience, then we should find fewer cancellations for planes with larger *seating capacity.* Third, carriers can also reduce passenger inconvenience by not canceling the *last flight of the day* for carrier j on route r.[4] Getting the last flight to its destination also by-passes some costly alternatives such as issuing refunds, rebooking passengers on a competitor's flight, and/or paying for overnight accommodations for displaced passengers.[5]

2.3 Competition

Kranton (2003) presents a model where price competition in a market can eliminate the incentive for firms to produce a high-quality good when consumers cannot observe the quality of the good prior to purchase. Empirical research in a variety of industries such as public schools (Hoxby, 2000), health care (Kessler and McClellan, 2000) and surface freight transportation (Ellig and Kelley, 2002) have found that competition improves service quality, yet the competitive effects on service quality in the airline industry remain unclear. Mazzeo (2003) finds more competitive routes have better service quality in terms of less frequent and shorter flight delays.[6] Mayer and Sinai (2003b), however, report the opposite result that less competitive routes provide better service. Oum et al. (2000) find mixed evidence of how competition affects service quality in their examination of global airline alliances and international flight delays. At the airport level, Brueckner (2002) and Mayer and Sinai (2003a) find more concentrated (less competitive) airports have fewer flight delays. Given that the competitive effects on airline service quality are ambiguous, this paper hopes to provide some insight into how one measure of airline service, flight cancellations, is affected by both route and airport level competition.

We explore five different variables to characterize route competition. First, we count the daily number of *carriers* serving route r. Second, *effective competitors* is the inverse of the Herfindahl index for all carriers serving route r each day. Morrison and Winston (1995) argue that *effective competitors* provides a better representation of the competitive environment than *carriers*, since a carrier count makes no distinction between carriers with a large or small presence on a route. Third, since more than half of the sample involves routes served by a single carrier, we examine *monopolist* routes to see if less competitive routes have worse service quality. Fourth, *market share,* the proportion of daily scheduled flights on route r provided by carrier j, provides a continuous measure of route-level competition. Finally, we track the performance of routes served by two carriers to determine if performance differs for large and small duopolists. Following Mayer and Sinai (2003b), the carrier with a larger (smaller) route market share is the *large (small) duopoly carrier*.

We also examine the competitive influences on service quality at the airport level by including airport concentration at both the origination and destination airports. *Airport concentration origination* (*destination*) is the sum of squared daily *market share* for all carriers serving the origination (destination) airport. Highly concentrated airports provide air travelers with fewer choices. Hence the third potential operations objective is that carriers provide better service quality on competitive routes and airports in order to retain passengers.

2.4 Flight Network

The fourth and final hypothesis suggests that carriers give priority to hub origination and destination flights to maintain their flight network. We define *airline hub origination (destination)* as carriers with 26 or more connections at the origination (destination) airport. By not canceling hub origination flights, carriers can keep their network intact. In addition, hub origination flights may have fewer cancellations than non-hub flights due to some supply-side issues. Maintenance and/or staffing issues can be more easily addressed for flights originating at a carrier's hub airport due to the greater availability of spare parts, replacement aircraft, mechanics, ground personnel, and flight crews. For example, Northwest Airlines has pilot bases and flight attendant bases at all three of its U.S. hub airports (Memphis, Minneapolis/St. Paul, and Detroit) and Northwest operates two U.S. maintenance bases in Minneapolis and Duluth, MN.

Hub destination flights may have fewer flight cancellations than non-hub destination flights due to demand side issues - carriers need these flights to arrive in order to keep their network intact and to enable connecting passengers to reach their next flight. Morrison and Winston (1995, p. 44) report that at a typical hub a majority of passengers make connections. In addition, flights destined for hubs are more likely to haul passengers making international connections. Canceling a hub destination flight is more inconvenient for both domestic and international connecting passengers. Discussions with flight operation employees of mainline U.S. carriers confirm that carriers are concerned about getting passengers to international destinations.

We further explore this flight network hypothesis by distinguishing the size of an airline's hub. Similar to Mayer and Sinai (2003a), we define airline hub size based on the number of connecting flights at the origination airport, such that airlines having 71 or more connections are *large airline hub origination*, between 46 and 70 connections *medium airline hub origination*, and between 26 and 45 connections *small airline hub origination*. Hub airline operations at destination airports are defined in a similar manner. We expect that the flight network effect is most pronounced for *large airline hub origination* & *destination*.

2.5 Econometric Specification

We now specify the empirical model. Due to the presence of a discrete dependent variable (flight cancellation), we employ a probit model to estimate our parameters of interest:

$$L_{it} = [\Phi(X_{it}\beta)]^{z_{it}} [1 - \Phi(X_{it}\beta)]^{1-z_{it}} \tag{1}$$

where $z_{it} = 1$ if the i^{th} flight on day t is canceled and 0 otherwise and X_{it} is a vector of carrier, route, airport, weather, and time period characteristics. In addition, for a baseline of comparison with previous flight delay studies, we present one estimation for the occurrence of a flight departure delay. Hence $z_{it} = 1$ if the i^{th} flight on day t departs more than 15 minutes after its scheduled departure time and 0 otherwise.

Given that we consider five different route competition measures, we compare the results of the models using binary tests for model selection due to Davidson and MacKinnon (1993) and Vuong's (1989) non-nested test.[7] Results of these tests, along with the comparisons of log-likelihood values, suggest that models using *monopoly* as the route competition measure are better specified. Hence *monopoly* is the default variable for route competition. Overall, the estimates of the effect of competition on the cancellation rate are similar regardless of the route competition measure.

All flight cancellation and delay models control for individual carrier, month, year, and day of week effects by using indicator variables.[8] We do not present the estimated effects for day of week, month, and specific carriers because they are intended as control variables, not as independent variables interesting on their own. Nonetheless, the appendix reports coefficients, standard errors, and marginal effects for these indicator variables for three estimated flight cancellation models (models 4-6) which are representative of the indicator variable effects.[9]

2.6 Correlation Issues

We are concerned about correlation between the unobserved terms in three dimensions. First, *intertemporal correlation within a route* may exist. For example, airport-specific shocks (such as less experienced employees or airport construction) may lead to this condition. Second, a similar argument would suggest correlation *across carriers within the same route*. Furthermore, airlines may be more willing to offer poor service on a route if the competition also offers poor service on the same route. Third, correlation *within carrier across "opposite" routes* may exist. That is, if a flight from airport A to airport B is canceled, then the flight from B to A may also be cancelled. The prototypical example is if a flight from a hub to an outlying airport is canceled, then there is no aircraft in the outlying airport, so the return flight is canceled by default.

We deal with the first two correlation types by estimating standard errors via block bootstrapping (Härdle et al. 2002). We find that the bootstrapped standard errors are, on average, approximately 50% larger than the standard errors assuming independence. We deal with the third correlation issue by randomly selecting flights in one direction only, either "A to B" or "B to A", but not both.

3 The Data

3.1 The Sample

Our data and a majority of the variables are constructed from individual flights obtained from the U.S. Bureau of Transportation Statistics (BTS) TranStats database (www.transtats.bts.gov). Airlines with at least 1 percent of domestic scheduled passenger revenues are required to submit monthly performance reports to the BTS. Hence these flight data cover all nonstop scheduled-service domestic flights by the ten largest mainline or "major" U.S. carriers,[10] which account for more than 85 percent of domestic revenues in 2000 (Air Travel Consumer Report, January 2001). The ten major carriers are required to report flight operations in 29 U.S. airports. Beginning in 1995, every major airline has voluntarily reported all domestic operations to the BTS. Prior to 1995, carriers did not report flight delays or cancellations due to mechanical difficulties. The result is the best source of airline cancellation rates and on-time performance data. Covering the period 1995-2002, Table 1 summarizes annual flight operations. The table shows that the percentage of late arrivals has generally increased since 1995, reaching a peak in 2000 of 27 percent, and a dramatic reduction in flight delays in 2002. Cancellation rates exhibit a similar pattern, increasing each year between 1997 and 2001 with the highest cancellation rate of 3.3 percent occurring in 2000. Most recently, cancellation rates have fallen in 2001 and 2002. The percentage of flights diverted has remained relatively constant, around 0.2 percent. Finally, on-time performance improved substantially in 2002 with on-time arrival rates exceeding 80 percent and flight cancellations dropping to 1.2 percent.

[Place Table 1 about here]

We obtained every domestic flight in the U.S. between January 1995 and August 2001 from the BTS TranStats database. We restrict our attention to the pre-September 11th period since we expect a massive structural shift around this period (rendering pooling unappealing) and more data is available in the pre-period than the post-period.[11] Since there are approximately 35 million individual flights during this period, to obtain a more manageable data set we are forced to reduce the sample size. As mentioned previously, the sample is reduced by 50% to avoid correlation between routes serving the same two airports. Specifically, the sample only includes flights in one direction, either from airport A to airport B or from B to A. We also omit days in which a carrier cancels more than 95% of their scheduled domestic daily flights. This criterion drops days in which a labor strike prohibits flight operations. Next, we randomly select ten percent of the remaining flights, resulting in a sample size of 1,447,095 individual flights.

All variables are constructed from the original data set, with only the estimations using the smaller randomly selected sample. Individual flight data provide efficiency gains over monthly aggregate cancellation data if the individual flight characteristics (e.g., departure time or daily precipitation), contribute to the cancellation rate. Daily flight data enable us to control for day of the week effects. In fact, we find significantly fewer flight cancellations for weekend flights (Thursday, Friday, and Sunday) compared to Wednesday flights (see Appendix). Friday and Sunday are busy travel days given the surge of leisure travelers on the weekends. Hence canceling such flights would be especially costly for carriers and inconvenient for passengers. The *Sunday* marginal effect of -0.0055 from model (4) suggests that the cancellation rate for *Sunday* is 0.55 percentage points lower than *Wednesday*. This percentage point reduction corresponds to *Sunday* flights being approximately 21 percent less likely to be cancelled, compared to *Wednesday* flights, given that the average flight cancellation rate in the sample is 2.56 percent. This result suggests that flight cancellations may not be entirely random. Consequently, all estimations include day-of-the-week indicators to control for important day of the week effects.

The average number of major *carriers* serving a route is 1.65, while the average number of *effective competitors* is 1.46. Descriptive statistics for the sample appear in Table 2.

[Place Table 2 about here]

About two-fifths of the sample (41 percent) involve flights which originate at a carrier's hub. Carriers provide an average of seven non-stop *daily scheduled flights* on a route. Five of every six flights are on routes with limited competition. Specifically, monopoly and duopoly routes comprise 53 and 30 percent of the sample, respectively. One in nine flights (11 percent) originate from a slot-controlled airport (i.e., New York LaGuardia (LGA), New York JFK, Washington Reagan National (DCA), and Chicago O'Hare (ORD)). A 'slot' provides the carrier with a short window (typically 60 or 90 minutes) in which an aircraft is allowed to land or take-off. Slots cannot be transferred nor can they be saved (i.e., the carrier either uses the slot or loses it).

We match the tail numbers provided by the BTS to the FAA Aircraft Registry database, which enables us to obtain aircraft characteristics such as *seating capacity* (the number of available seats on the aircraft), manufacturer (i.e., *McDonnell-Douglas*, *Airbus, etc.),* and *aircraft age* (the number of years since the aircraft was manufactured). Since we are unable to match tail numbers to the FAA registry database for approximately half of the sample flights,[12] only model (9) includes aircraft specific characteristics.

We also match individual flights to quarterly passenger fare data from the Airline Origin and Destination Survey, which is a 10% sample of airline tickets from reporting carriers, collected by the U.S. Office of Airline Information of the Bureau of Transportation Statistics and included in the TranStats database. These fare data enable us to estimate the revenue of a particular flight. The sample *average fare* of $166 reflects the nominal quarterly average one-way airfare for carrier j on route r. For round-trip itineraries, the total ticket price is divided by two to obtain the one-way airfare. *Average revenue* is found by multiplying *average fare* by the monthly average number of occupied seats for carrier j on route r, which is obtained from the Air Carrier Statistics database (also known as T-100 data bank and available at TranStats). The typical plane size is 162 seats with a *potential revenue* per flight of approximately $31,000. Since the average load is two-thirds of capacity, the *average revenue* per flight is about $21,000. Finally, *yield* is the carrier's total quarterly revenue on route r divided by the total quarterly revenue passenger miles on route r.

We obtain *load capacity* from the TranStats database, which includes monthly downloadable T-100 domestic market data. This variable is the monthly average proportion of total seats that were occupied by passengers for carrier j on route r. *Load capacity* is multiplied by the *seating capacity* of the aircraft in order to obtain the monthly average number of occupied seats for the carrier. *Load capacity* is also used to construct *average revenue.*

One caveat for the above revenue and *yield* measures is that the BTS Origination and Destination Survey data only provide the average fare for a given quarter (monthly for *load capacity)*; hence we do not observe average fares paid on a particular day and flight. For example, within the same day there may be considerable variation in *load capacity* and day or time of departure. To partially account for the occurrence of cascading delays during the day (Mazzeo, 2003), we include a continuous time measure, *time01* which renormalizes the scheduled departure time to between 0 (midnight) and 1 (23:59). *Time01* and *day of the week* can partially, but not perfectly, control for these within day and between day differences. Nonetheless, in these data, quarterly revenue and *yield* measures and monthly capacity observations provide the smallest possible level of aggregation.

Since most airports are active weather reporting stations,[13] we obtain daily weather data at origination and destination airports from the U.S. National Oceanic & Atmospheric Administration (NOAA). These weather measures include temperature, rain, and freezing rain. *Minimum temperature origination (destination)* is the minimum daily temperature (in Fahrenheit) at the origination (destination) airport. *Rain origination (destination)* is the amount of daily precipitation (in hundredths of an inch) at the origination (destination) airport. Finally, *frozen precipitation origination (destination)* is daily rain origination (destination) multiplied by one if daily minimum temperature < 33, otherwise zero.[14]

The sample selection criteria drops days in which a carrier cancels 95% or more of its scheduled flights. Since labor issues may cause a carrier to cancel a portion of its flights, we use the ProQuest database to search the *Wall Street Journal* for keyword combinations of airline (or carrier) and labor (or strike or slow-down or sick-out or work-to-rules or CHAOS). Hence *labor unrest* is a binary variable, coded as one for the month in which the *Wall Street Journal* reports that a carrier is experiencing a previously mentioned labor issue and zero otherwise.

Since airport congestion is an important flight delay determinant (Mayer and Sinai, 2003a; Mazzeo, 2003), we include *daily airport operations origination (destination),* which is the total number of daily take-offs and landings at the origination (destination) airport. We also include monthly indicators in all estimations to control for both demand and seasonal fluctuations in cancellations which typically peak in January for cold weather airports.

4 Results

4.1 Which Flights are Canceled?

This paper examines various route and airport competition measures, aircraft characteristics, flight revenues, and airport size effects by estimating fourteen flight cancellation models and one flight delay model. The latter enables a comparison with the flight delay literature. All estimated models include carrier, day of the week, month, and year indicator variables. We also report marginal effects in Tables 3-8, which are defined as the effect on the probability that the average flight is canceled. We begin by examining the first hypothesis, that carriers maximize revenues.

We find weak evidence that higher *average revenue* flights have fewer cancellations since *average revenue* achieves statistical significance in just three of the twelve estimated cancellation models. We also consider an alternative measure of route revenue, *potential revenue*. Model 11 shows no relation between *potential revenue* and flight cancellations. *Average revenue* is our preferred flight revenue proxy since it assumes that the aircraft is carrying the average number of passengers for that route and carrier, whereas *potential revenue* represents an upper-bound of lost revenue from a flight cancellation due to the assumption that every seat is taken.

Finally, we consider a third revenue proxy, route *yield*. Model 12 reveals that routes with higher quarterly *yields* have significantly higher cancellation rates. This result may not be economically meaningful, however, since a 10 percent increase in *yield* (or 4 cents per mile) increases the cancellation rate by only 0.01 percentage points. This counter-intuitive statistical result may be due to shorter flights having higher *yields*. Short flights, however, are not necessarily more profitable due to the fixed costs of flight operations (i.e., take-offs, landings, booking costs and labor "preparation time"). While every model attempts to control for distance effects by including flight distance blocks, nonetheless, this is an imperfect technique of controlling for flight operation costs.

In sum, we find weak support for the hypothesis that carriers maximize revenues when making flight cancellation decisions. We are hesitant to reject this hypothesis outright, however, because of data limitations. While we observe individual flight outcomes, we do not observe individual flight revenues. Instead, we use the lowest level of revenue data aggregation available to us, quarterly averages of route revenue. Given this crude revenue proxy, it is somewhat surprising that we are able to detect any pattern at all between revenues and flight cancellations. Next, we turn our attention to the second hypothesis that carriers minimize passenger inconvenience.

[Place Tables 3-8 about here]

We find a couple of passenger inconvenience results that are robust across modeling specifications: fewer cancellations occur on routes with higher *load capacity* and on the *last flight of day.* This result for *load capacity,* a route-level measure of the proportion of occupied seats for a given carrier each month, suggests that carriers are reluctant to cancel flights on routes that have higher seat occupancy rates. Specifically, interpreting the -0.06 *load capacity* marginal effect from model (1) indicates that a 10 percentage point increase (about a one standard deviation) in a carrier's average monthly *load capacity* on a route reduces the cancellation rate by 0.6 percentage points (or 23 percent)**.** Better service quality in terms of fewer cancellations for planes with higher occupancy rates does come at a cost, since model 10 suggests that routes with fuller planes take longer to load and hence experience more frequent flight delays, a result consistent with Rupp et al. (2003). In sum, we find that full planes are more likely to be delayed yet less likely to be canceled.

Fewer cancellations for *last flight of day* highlights another distinction between flight delays and cancellations, since Mayer and Sinai (2003b) document more departure delays for *last flight of day.* This result suggests that carriers minimize passenger inconvenience by not canceling the last flight since this would force passengers to either rebook on a competing carrier or unexpectedly spend a night at the airport or departure city. Neither of these options is very appealing for the carrier, hence the lower cancellation rates for *last flight of day.* Alternatively, better performance for *last flight of day* could also be considered as evidence supporting the "flight network hypothesis" since getting the final daily flight to its scheduled destination sets the carrier up for regular operations the following day.

Carriers that offer more *daily scheduled flights* on a route are more likely to cancel a flight. We do not, however, attribute this result to congestion since the *daily total airport operations* at both origination and destination are co-variates and should control for airport congestion. Instead, we believe that canceling a flight on a route with frequent daily service minimizes passenger inconvenience since carriers have more opportunities to accommodate displaced passengers and hence reduce the waiting time until the next flight. Shorter waiting periods also discourage passengers from making the costly demand of being re-booked on another carrier. Using the estimated parameters from model 4, figure (1) graphs both the predicted and actual probability of a flight cancellation as a carrier schedules more daily flights on a route. This figure reveals that as the number of *daily scheduled flights* increases, holding all other characteristics constant, the probability of a flight cancellation also increases. Restricting the graph to routes in which a carrier schedules between 0 and 16 daily flights (95 percent of all flights in our sample are on routes with 16 or fewer daily flights), we find that the predicted cancellation rates mirror the actual rates.

[Place Figure 1 about here]

Model (9) reveals that planes with more *seating capacity* experience significantly fewer cancellations, even after controlling for aircraft age and manufacturer. In sum, we find considerable support for the second hypothesis that carriers minimize passenger inconvenience by providing better service for both larger and fuller planes and by not canceling the final flight of the day.

Let us now turn to the third hypothesis which proposes that competition improves service quality. We begin by considering route competition effects. The results are consistent with the third hypothesis since most route competition measures show that competitive routes have fewer flight cancellations. One exception, however, occurs in model (2) which suggests that no link exists between *effective competitors* and cancellations. More typically, model (3) reveals that routes with more *carriers* have significantly fewer flight cancellations. Likewise, *monopoly* routes also have significantly more cancellations. This result is robust across a variety of specifications since *monopoly* registers statistical significance in nine of ten estimated cancellation models. The magnitude, however, of the *monopoly* effect is rather small. For example, the marginal effect in model (4) indicates that *monopoly* routes have 0.24 percentage points higher cancellation rates which corresponds roughly to a 9% increase in flight cancellations. In other words, for a carrier that has seven daily scheduled flights on a route (or 2,555 scheduled flights a year), we estimate that a monopolist would cancel an additional six flights per year. In addition to more flight cancellations, we also find that *monopoly* routes have significantly more departure delays. This latter result is also consistent with a delay study by Mazzeo (2003).[15]

Higher flight cancellation rates for *monopoly* routes is especially interesting given that Borenstein and Netz (1999) find that monopolist carriers have easier to maintain flight schedules due to greater departure time differentiation which enables a monopolist to avoid peak travel congestion times. Borenstein and Netz report that routes served by multiple carriers, which operate the same total number of flights, have flight schedules with less departure-time differentiation (i.e., grouping departures around peak travel times) compared to a monopolist which operates the same number of flights. Despite these easier to satisfy flight schedules, we find that *monopoly* carriers have significantly more flight cancellations.

Model (5) reveals that a carrier's route level *market share*, a continuous measure of competition, is also linked to flight cancellations. We find that carriers with a larger market share provide worse service quality, a result consistent with the previously discussed findings for *monopoly* and *carriers*. Finally, model (6) examines the performance of both *monopoly* and *duopoly carriers*. We find that *monopoly* and *small duopoly carriers* have more cancellations. Surprisingly, *large duopoly carriers* are neither more likely nor less likely to cancel flights.

We next examine whether airport competition influences flight cancellations. Every estimated cancellation model reports the identical result, that neither *airport concentration origination* nor *destination* influences flight cancellations in a predictable manner. The departure delay estimation (model 10) indicates that the airport concentration variables have negative coefficients which is consistent with the hypothesis proposed by Brueckner (2002) that delays fall as airline market power increases, however, the coefficients are not statistically significant.[16] In contrast to the flight delay literature, which has documented fewer flight delays at more concentrated airports (Mayer and Sinai, 2003a), we do not find improved service quality, in terms of fewer cancellations, at concentrated airports. In sum, there is considerable support for part of the third hypothesis. Improvements in service quality from competition, however, are limited to route competition and not airport competition.

The fourth and final hypothesized airline objective is that carriers provide better service to and from their hub airports in order to maintain their flight network. All estimated cancellation models reveal a consistent and overwhelming result that *airline hub origination* and *destination* flights have significantly fewer cancellations. These results are attributed to the previously discussed demand and supply side issues. Carriers want to avoid canceling flights originating from their hubs to keep their flight network operating. The supply-side issues for fewer *airline hub origination* cancellations include better access to maintenance facilities, ground personnel, replacement flight crews, and spare parts. On the other hand, demand-side issues arise for fewer *airline hub destination* cancellations since carriers need these aircraft to arrive at the hub in order to maintain their flight network. In addition, *airline hub destinations* typically involve connecting passengers some of whom may be bound for an international destination. Hence canceling an *airline hub destination* flight is inconvenient for connecting passengers, and especially so for international bound travelers. We should also note that better service (i.e., fewer cancellations) for hub airlines is a stark contrast to the flight delay literature (Mayer and Sinai, 2003a & 2003b; Mazzeo, 2003) which has extensively documented worse hub service (i.e., both more frequent and longer delays) for hub origination and destination flights.

To further explore this flight network hypothesis, model (7) examines the size of an airline's hub. If this network hypothesis holds, then carriers should provide better service at *larger airline hubs*. In fact, we find that flight cancellations monotonically decrease as the size of a carrier's hub increases for both origination and destination airports. For example, the marginal effects for *large* (-0.009), *medium* (-0.008), and *small* (-0.003) *airline hub originations* correspond to a reduction in the flight cancellation rate of 35%, 31%, and 8% respectively. Hence there is overwhelming evidence to support the fourth and final hypothesis that carriers seek to maintain their flight networks.

We now briefly discuss other important logistical and weather variables. It is not surprising that airport congestion (measured by *daily total airport operations*) at both origination and destination is positively correlated with flight cancellations, since flight delays due to airport congestion have been well documented (Mayer and Sinai, 2003a; Mazzeo, 2003). This congestion result may explain why Southwest Airlines, the carrier with the best historical on-time performance record (*Air Travel Consumer Report*, March 2003), is reluctant to enter markets with congested airport facilities (Oh and Wiggins, 2001; Boguslaski et al.

2003). In addition, table (8) reveals that airport congestion-related flight cancellations are confined to large airports (>400 daily take-offs and landings). The problem of airport congestion is most acute at the nation's four slot-controlled airports. Model (8) shows that both *slot origination* and *destination airports* have significantly higher cancellation rates. This result is likely due to the nature of a slot, which entitles the carrier to use the slot (land/depart typically within a 60 minute window) or lose it.

Time01 registers significantly higher cancellation rates in ten of fourteen estimated models which suggests that flights scheduled later in the day are more likely to be canceled. A carrier may opt to cancel a flight rather than experience cascading delays (Mazzeo, 2003) for the remainder of the day. The airport size estimations in Table 8 indicate that the small airports experience the majority of late-in-the-day flight cancellations. For example, the marginal effect of 0.0149 for *time01* in model 15 suggests that the cancellation rate for an 8 p.m. departure at small airports is 0.75 percentage points (or 29 percent) higher than an 8 a.m. departure.

Flight cancellation decisions appear to be independent of flight length since a majority of the flight cancellation models have insignificant estimates for *short flight* and *middle distance*. Not surprisingly, carriers that are experiencing *labor unrest* have higher cancellation rates. Finally, as expected, severe weather (*rain* and *frozen precipitation*) at both origination and destination airports increases the likelihood of a flight cancellation with *frozen precipitation* causing a larger service disruption than *rain*. Interestingly, we find significantly fewer cancellations at the destination during cold weather. The combination of cold weather and precipitation (*frozen precipitation*), however, leads to the expected result of more cancellations.

5 Conclusion

This paper extends the literature on airline service quality by examining determinants of flight cancellations. Since the Airline Deregulation Act of 1978, airlines have attracted Congressional attention due to disgruntled passengers, employee strikes, proposed mergers, and financial concerns. This study proposes four possible airline flight operations objectives that carriers might pursue in order to satisfy existing flight schedules. We find only weak support for the revenue maximization objective since only a few models link *average revenue* with flight cancellations. Instead, minimizing passenger inconvenience appears to be a greater priority as we find fewer cancellations for larger planes and for planes with higher seat-occupancy rates. The *last flight of day* and routes with infrequent daily service also have fewer cancellations, which provides further support for the claim that carriers' minimize passenger inconvenience. We find that more competitive routes have lower cancellation rates. Flight cancellations rates appear independent of airport concentration. Finally, we find considerable support for the hypothesis that carriers maintain their flight network by canceling flights to and from their hubs less frequently. Moreover, this hub airline effect (for both origination and destination airports) is strongest for large hub operations.

We are now able to address the public policy question posed in the introduction: how might airline consolidation influence flight cancellations? If consolidation causes a reduction in route competition (i.e., more monopolist routes), then these estimates suggest that only a modest increase in flight cancellations would occur. Specifically, we estimate that a 10 percent increase in the number of monopoly routes in the U.S., holding everything else unchanged, would increase the cancellation rate by 0.024 percentage points (or about 1 percent).

More generally, what public policy implications can be gleaned from this analysis? Although severe weather events are clearly beyond the control of airlines, the findings that cancellation rates are significantly lower on Thursdays, Fridays and Sundays and on routes with infrequent daily service suggest that flight cancellations are not random events. Finally, given that we find considerable support for the hypothesis that carriers are minimizing passenger inconvenience in addition to maintaining their existing flight networks, we see little need for active government intervention to improve service quality. Instead, we advocate for greater transparency from the U.S. Department of Transportation on the causes of flight cancellations. Specifically, the DOT should begin collecting data on the causes of flight cancellations (much like they have done for flight delays since June, 2003) and publicize their findings in order to break the misperception that all flight cancellations are beyond the carriers' control. This news might motivate carriers to improve service quality and may help weary air travelers sleep a little easier.

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Notes

[1]This increase in the complaint rate in the last couple of years is a relatively recent development since Morrison and Winston (2000, p. 20) show that complaints against U.S. carriers per billion revenue passenger miles have been relatively constant between 1990 and 1998.

[2]We are aware of only two other studies examining cancellations. An earlier version of Mayer and Sinai (2003a) included one cancellation regression. This regression, however, was omitted in the final published version of the paper. Rupp et al. (2003) examine flight cancellations during irregular operations (i.e., security-related airport closures).

[3]http://www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp accessed March 2, 2004.

[4]A few flights (primarily red-eye flights from the West to the East coast of the U.S.) are scheduled to depart the following day, shortly after midnight. Hence flights scheduled before 3:00 a.m. are treated as the "same day" for the *last flight of day* designation.

[5]While there is no FAA regulation that requires airlines to assist displaced passengers, most carriers provide overnight accommodations if the cancellation is caused by events within the carriers' control (e.g., see the Customer Service Plan for American Airlines at www.aa.com).

[6]For related flight delay literature see Foreman and Shea (1999).

[7]The Davidson-MacKinnon test is comparable to the J-test commonly used in testing regression models.

[8]Since the revenue measures are defined at the route level, we exclude indicator variables for route effects.

[9]The full set of indicator variable results and the results for *market share, carriers* and *effective competitors* are available upon request of the authors.

[10]The major carriers include Alaska, America West, American, Continental, Delta, Northwest, Southwest, TWA, United, and US Airways. In 2001, two additional major carriers were added: Aloha and American Eagle. These data exclude commuter airlines such as US Airways Express or Delta Connection.

[11]See Lee and Ito (2004) for an analysis of how the September 11th terrorist attacks impacted U.S. airline demand.

[12]This is due to (i) missing tail numbers, (ii) incorrectly recorded tail numbers, and (iii) tail numbers that are no longer active in the FAA registry database. In situations where the tail number (and hence *seating capacity*) is unknown, *seating capacity* is found by substituting the median value of seats on comparable flights (i.e., same flight number, route, carrier, month, and year).

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

[14]Since many NOAA weather stations do not report wind speed and daily snowfall totals, we must exclude wind as a weather variable. We construct our own snowfall measure by interacting the more commonly reported weather variables: temperature and precipitation.

[15]Mayer and Sinai (2003b), however, use a sample of 3 million flights between 1988 and 2000 and find better on-time performance for monopoly routes.

[16]Brueckner (2002) also reports that airport concentration (i.e., airport Herfindahl index) does not achieve standard statistical levels in both airport delay regressions which use this measure.

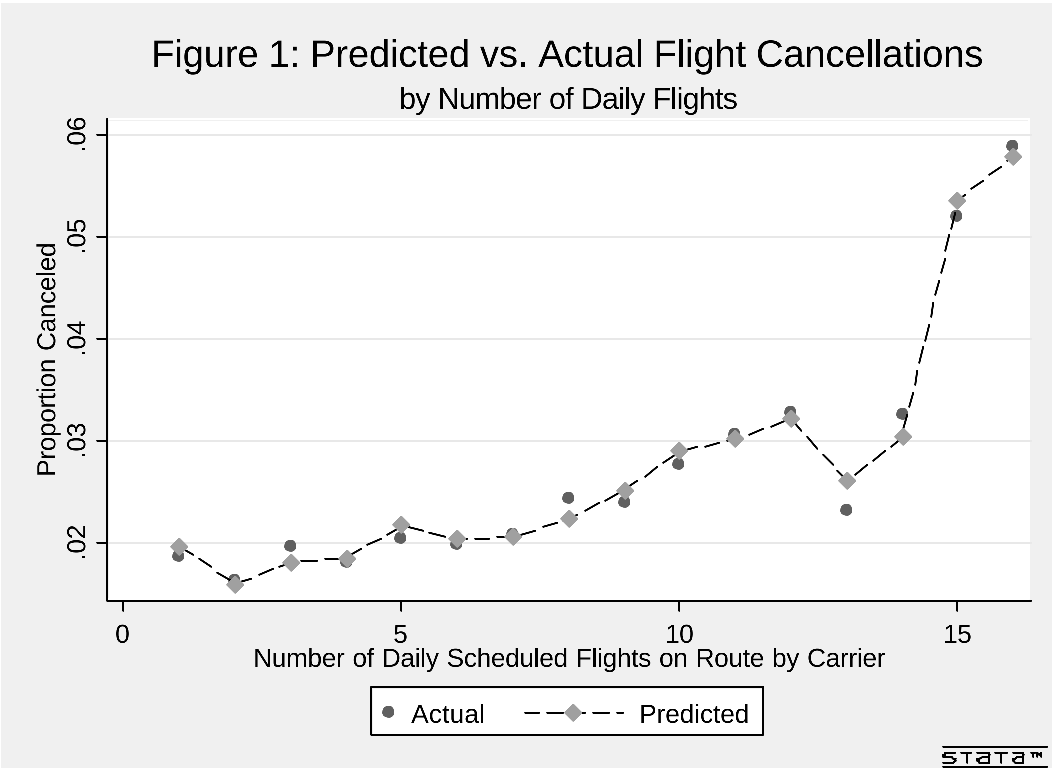
Figure 1: Predicted vs. Actual Flight Cancellations
by Number of Daily Flights
Proportion Canceled
.02
.03
.04
.05
.06
0
5
10
15
Number of Daily Scheduled Flights on Route by Carrier
Actual
Predicted

Table 1: Summary of Major Carriers On-time Performance[1], 1995-2002

Year	Scheduled Flights	Flights Canceled	Pecent On-time	Percent Late	Percent Canceled	Percent Diverted
1995	5,327,435	91,905	76.65	21.43	1.73	0.20
1996	5,351,983	128,536	71.87	25.46	2.40	0.26
1997	5,411,843	97,763	75.91	22.06	1.81	0.22
1998	5,384,721	144,509	74.27	22.80	2.68	0.24
1999	5,527,884	154,311	73.07	23.89	2.79	0.25
2000	5,683,047	187,490	69.04	27.41	3.30	0.25
2001	5,967,780	231,198	73.07	23.89	2.79*	0.25
2002	5,267,770	64,981	80.75	17.86	1.23	0.16
Average	5,490,308	137,587	74.33	23.10	2.34	0.23

[1]Source: Bureau of Transportation Statistics (www.bts.gov/oai/on_time_2002/), accessed 1/30/2004. Major carriers include: Alaska, America West, American, Continental, Delta, Northwest, Southwest, TWA, United, US Airways.

*Because of the shutdown of the air transportation system as a result of the terrorist attacks on September 11, 2001, the BTS granted air carriers waivers that we would not count the forced cancellations against the air carriers' on-time performance ratings. Hence, the "Percent Canceled" does not reflect these forced cancellations. For historical purposes, however, the number of "Flights canceled" includes all cancellations regardless of reason.

Table 2: Descriptive Statistics: 5% sample of all daily domestic flights by major U.S. carriers, January 1995 to August 2001

Variable	Obs	Mean	Std. Dev.
Proportion Canceled	1,545,085	0.0256	0.1578
Proportion Delayed	1,545,085	0.1857	0.3889
Economic Variables			
Potential Revenue (in $10,000s)	1,447,095	0.3054	0.2145
Load Capacity (Monthly Average)	1,545,085	0.6702	0.1253
Yield (dollars per mile)	1,544,653	0.3541	0.3283
Average One-way Fare (Quarterly Average)	1,544,653	165.9045	79.3885
Average Revenue (in $10,000s)	1,447,095	0.2073	0.1589
Route Competition Variables			
Effective Competitors	1,545,085	1.4576	0.5833
Number of Carriers	1,545,085	1.6511	0.8351
Monopoly Route	1,545,085	0.5288	0.4992
Route Market Share	1,545,085	0.7809	0.2681
Small duopoly carrier	1,545,085	0.1012	0.3016
Large duopoly carrier	1,545,085	0.2036	0.4027
Airport Competition Variables			
Airline Hub Origination	1,545,085	0.4052	0.4909
Large Airline Hub Origination	1,545,085	0.1680	0.3738
Medium Airline Hub Origination	1,545,085	0.1306	0.3370
Small Airline Hub Origination	1,545,085	0.1066	0.3087
Airline Hub Destination	1,545,085	0.4579	0.4982
Large Airline Hub Destination	1,545,085	0.1921	0.3940
Medium Airline Hub Destination	1,545,085	0.2056	0.4042
Small Airline Hub Destination	1,545,085	0.0601	0.2377
Airport Concentration Origination	1,545,085	0.0143	0.0822
Airport Concentration Destination	1,545,085	0.0156	0.0886
Slot Origination	1,545,085	0.1116	0.3148
Slot Destination	1,545,085	0.1659	0.3720
Aircraft Characteristics			
Aircraft Age	1,042,056	11.1812	7.1492
Airbus	1,123,649	0.0443	0.2057
McDonnell-Douglas	1,123,649	0.2072	0.4053
Seating Capacity of Aircraft	1,060,197	162.2064	51.3258
Logistical Variables			
Daily Total Airport Operations Orig.	1,545,085	6.1891	4.4511
Daily Total Airport Operations Dest	1,545,085	6.7667	5.0148
Daily Scheduled Flights	1,545,085	7.0840	4.7813
Last Flight of Day	1,545,085	0.1776	0.3822
Time01	1,545,085	0.5660	0.1974
Short Flight (< 400 miles)	1,545,085	0.4419	0.4966
Middle Distance (400 to 800 miles)	1,545,085	0.3429	0.4747
Labor Unrest	1,545,085	0.0585	0.2346
Weather Variables			
Minimum Temperature Origination	1,545,085	51.1134	17.1647
Minimum Temperature Destination	1,545,085	49.7770	18.3997
Rain Origination	1,545,085	9.6895	31.6288
Rain Destination	1,545,085	9.8150	32.3273
Frozen Precipitation Origination	1,545,085	0.6169	5.0238
Frozen Precipitation Destination	1,545,085	0.7420	5.5027

Table 3: Probit Estimations of Flight Cancellations - The Effect of Route Competition

Dependent Variable: Flight Cancellations for Major U.S. Carriers, January 1995 - August 2001.

Model	(1)			(2)			(3)		
	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.
Route Competition Variables									
Effective Competitors				-0.0134	0.0101	-0.0006			
Number of Carriers							-0.0384 **	0.0073	-0.0017
Airport Competition Variables									
Airline Hub Origination	-0.1200 **	0.0127	-0.0052	-0.1250 **	0.0125	-0.0054	-0.1417 **	0.0126	-0.0061
Airline Hub Destination	-0.1125 **	0.0132	-0.0050	-0.1196 **	0.0136	-0.0053	-0.1428 **	0.0136	-0.0063
Airport Concentration Origination	0.0329	0.0335	0.0015	0.0330	0.0335	0.0015	0.0327	0.0335	0.0015
Airport Concentration Destination	0.0286	0.0315	0.0013	0.0288	0.0314	0.0013	0.0286	0.0314	0.0013
Economic Variables									
Average Revenue (in $10,000s)	-0.0156	0.0402	-0.0007	-0.0095	0.0396	-0.0004	0.0066	0.0407	0.0003
Load Capacity (Monthly Average)	-1.3556 **	0.0387	-0.0604	-1.3606 **	0.0383	-0.0606	-1.3741 **	0.0385	-0.0611
Logistical Variables									
Daily Total Airport Operations Orig.	0.0014	0.0012	0.0001	0.0022	0.0014	0.0001	0.0034 **	0.0013	0.0002
Daily Total Airport Operations Dest	0.0058 **	0.0011	0.0003	0.0068 **	0.0014	0.0003	0.0080 **	0.0012	0.0004
Daily Scheduled Flights	0.0388 **	0.0010	0.0017	0.0383 **	0.0011	0.0017	0.0381 **	0.0010	0.0017
Last Flight of Day	-0.0610 **	0.0087	-0.0026	-0.0641 **	0.0088	-0.0027	-0.0764 **	0.0090	-0.0032
Time01	0.0307	0.0166	0.0014	0.0338 *	0.0166	0.0015	0.0476 **	0.0168	0.0021
Short Flight (< 400 miles)	-0.0039	0.0134	-0.0002	-0.0048	0.0134	-0.0002	-0.0211	0.0139	-0.0009
Middle Distance (400 to 800 miles)	-0.0099	0.0146	-0.0004	-0.0104	0.0145	-0.0005	-0.0236	0.0145	-0.0010
Labor Unrest	0.3166 **	0.0154	0.0189	0.3167 **	0.0154	0.0189	0.3165 **	0.0153	0.0189
Weather Variables									
Minimum Temperature Origination	-0.0003	0.0004	0.0000	-0.0003	0.0004	0.0000	-0.0002	0.0004	0.0000
Minimum Temperature Destination	-0.0032 **	0.0004	-0.0001	-0.0031 **	0.0004	-0.0001	-0.0031 **	0.0004	-0.0001
Rain Origination	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001
Rain Destination	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001
Frozen Precipitation Origination	0.0121 **	0.0006	0.0005	0.0121 **	0.0006	0.0005	0.0121 **	0.0006	0.0005
Frozen Precipitation Destination	0.0105 **	0.0006	0.0005	0.0105 **	0.0006	0.0005	0.0105 **	0.0006	0.0005
Constant	-1.1702 **	0.0430		-1.1544 **	0.0439		-1.1038 **	0.0451	
Log Likelihood		-154,843			-154,840			-154,796	
Pseudo R-squared		0.088			0.088			0.088	
Number of Observations		1,447,095			1,447,095			1,447,095	

Note: Bootstrapped standard errors are reported. Regressions include carrier, day of week, month, and year dummy variables.
Marginal effects are defined as the effect on the probability that the average flight is cancelled. * and ** indicate significance at the 5% and 1% levels.

Table 4: Probit Estimations of Flight Cancellations - The Effect of Route Competition, contd.

Dependent Variable: Flight Cancellations for Major U.S. Carriers, January 1995 - August 2001.

Model	(4)			(5)			(6)		
	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.
Route Competition Variables									
Monopoly	0.0536 **	0.0102	0.0024				0.0674 **	0.0157	0.0030
Market Share				0.0552 **	0.0195	0.0025			
Large Duopoly Carrier							0.0117	0.0161	0.0005
Small Duopoly Carrier							0.0395 *	0.0174	0.0018
Airport Competition Variables									
Airline Hub Origination	-0.1292 **	0.0127	-0.0056	-0.1311 **	0.0128	-0.0057	-0.1287 **	0.0127	-0.0056
Airline Hub Destination	-0.1330 **	0.0136	-0.0059	-0.1248 **	0.0136	-0.0055	-0.1375 **	0.0136	-0.0060
Airport Concentration Origination	0.0343	0.0336	0.0015	0.0335	0.0335	0.0015	0.0334	0.0336	0.0015
Airport Concentration Destination	0.0284	0.0315	0.0013	0.0289	0.0315	0.0013	0.0286	0.0315	0.0013
Economic Variables									
Average Revenue (in $10,000s)	-0.0180	0.0410	-0.0008	-0.0155	0.0409	-0.0007	-0.0131	0.0408	-0.0006
Load Capacity (Monthly Average)	-1.3815 **	0.0384	-0.0614	-1.3716 **	0.0386	-0.0611	-1.3740 **	0.0396	-0.0611
Logistical Variables									
Daily Total Airport Operations Orig.	0.0035 **	0.0012	0.0002	0.0030 *	0.0014	0.0001	0.0032 **	0.0013	0.0001
Daily Total Airport Operations Dest	0.0087 **	0.0011	0.0004	0.0076 **	0.0012	0.0003	0.0086 **	0.0012	0.0004
Daily Scheduled Flights	0.0377 **	0.0010	0.0017	0.0377 **	0.0011	0.0017	0.0380 **	0.0011	0.0017
Last Flight of Day	-0.0737 **	0.0091	-0.0031	-0.0684 **	0.0090	-0.0029	-0.0726 **	0.0092	-0.0031
Time01	0.0441 **	0.0166	0.0020	0.0379 *	0.0166	0.0017	0.0439 **	0.0167	0.0020
Short Flight (< 400 miles)	-0.0150	0.0135	-0.0007	-0.0085	0.0136	-0.0004	-0.0163	0.0138	-0.0007
Middle Distance (400 to 800 miles)	-0.0124	0.0145	-0.0005	-0.0127	0.0147	-0.0006	-0.0146	0.0144	-0.0006
Labor Unrest	0.3163 **	0.0152	0.0189	0.3166 **	0.0154	0.0189	0.3163 **	0.0152	0.0189
Weather Variables									
Minimum Temperature Origination	-0.0001	0.0004	0.0000	-0.0003	0.0004	0.0000	-0.0002	0.0004	0.0000
Minimum Temperature Destination	-0.0031 **	0.0004	-0.0001	-0.0031 **	0.0004	-0.0001	-0.0030 **	0.0004	-0.0001
Rain Origination	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001
Rain Destination	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001	0.0022 **	0.0001	0.0001
Frozen Precipitation Origination	0.0121 **	0.0006	0.0005	0.0121 **	0.0006	0.0005	0.0121 **	0.0006	0.0005
Frozen Precipitation Destination	0.0105 **	0.0006	0.0005	0.0105 **	0.0006	0.0005	0.0105 **	0.0006	0.0005
Constant	-1.2020 **	0.0431		-1.2112 **	0.0447		-1.2213 **	0.0452	
Log Likelihood		-154,809			-154,834			-154,802	
Pseudo R-squared		0.088			0.088			0.088	
Number of Observations		1,447,095			1,447,095			1,447,095	

Note: Bootstrapped standard errors are reported. Regressions include carrier, day of week, month, and year dummy variables.
Marginal effects are defined as the effect on the probability that the average flight is cancelled. * and ** indicate significance at the 5% and 1% levels.

Table 5: Probit Estimations of Flight Cancellations - The Effect of Airport Competition

Dependent Variable: Flight Cancellations for Major U.S. Carriers, January 1995 - August 2001.

Model	(7)				(8)			
	Coeff		Std. Error	Marg. Eff.	Coeff		Std. Error	Marg. Eff.
Route Competition Variable								
Monopoly	0.0955	**	0.0111	0.0042	0.0630	**	0.0106	0.0028
Airport Competition Variables								
Airline Hub Origination					-0.0928	**	0.0124	-0.0040
Large Airline Hub Origination	-0.2443	**	0.0185	-0.0092				
Medium Airline Hub Origination	-0.2204	**	0.0187	-0.0083				
Small Airline Hub Origination	-0.0674	**	0.0146	-0.0028				
Airline Hub Destination					-0.0958	**	0.0133	-0.0042
Large Airline Hub Destination	-0.2554	**	0.0206	-0.0096				
Medium Airline Hub Destination	-0.1920	**	0.0152	-0.0076				
Small Airline Hub Destination	-0.1565	**	0.0189	-0.0060				
Slot Origination					0.1137	**	0.0153	0.0056
Slot Destination					0.1314	**	0.0157	0.0064
Airport Concentration Origination	0.0429		0.0339	0.0019	0.0406		0.0336	0.0018
Airport Concentration Destination	0.0325		0.0315	0.0014	0.0347		0.0317	0.0015
Economic Variables								
Average Revenue (in $10,000s)	-0.0680		0.0408	-0.0030	-0.0981	**	0.0395	-0.0044
Load Capacity (Monthly Average)	-1.3683	**	0.0382	-0.0606	-1.2560	**	0.0407	-0.0558
Logistical Variables								
Daily Total Airport Operations Orig.	0.0093	**	0.0014	0.0004	0.0014		0.0013	0.0001
Daily Total Airport Operations Dest	0.0143	**	0.0013	0.0006	0.0029	*	0.0013	0.0001
Daily Scheduled Flights	0.0381	**	0.0010	0.0017	0.0347	**	0.0010	0.0015
Last Flight of Day	-0.0753	**	0.0090	-0.0032	-0.0822	**	0.0091	-0.0035
Time01	0.0484	**	0.0165	0.0021	0.0488	**	0.0167	0.0022
Short Flight (< 400 miles)	-0.0012		0.0137	-0.0001	-0.0182		0.0131	-0.0008
Middle Distance (400 to 800 miles)	0.0000		0.0148	0.0000	-0.0515	**	0.0146	-0.0022
Labor Unrest	0.3145	**	0.0152	0.0187	0.3193	**	0.0153	0.0191
Weather Variables								
Minimum Temperature Origination	-0.0006		0.0004	0.0000	-0.0002		0.0004	0.0000
Minimum Temperature Destination	-0.0028	**	0.0004	-0.0001	-0.0025	**	0.0004	-0.0001
Rain Origination	0.0022	**	0.0001	0.0001	0.0022	**	0.0001	0.0001
Rain Destination	0.0022	**	0.0001	0.0001	0.0021	**	0.0001	0.0001
Frozen Precipitation Origination	0.0121	**	0.0006	0.0005	0.0121	**	0.0006	0.0005
Frozen Precipitation Destination	0.0105	**	0.0006	0.0005	0.0105	**	0.0006	0.0005
Constant	-1.2453	**	0.0470		-1.3081	**	0.0460	
Log Likelihood			-154,695				-154,623	
Pseudo R-squared			0.089				0.089	
Number of Observations			1,447,095				1,447,095	

Note: Bootstrapped standard errors are reported. Regressions include carrier, day of week, month, and year dummy variables. Marginal effects are defined as the effect on the probability that the average flight is cancelled. * and ** indicate 5% and 1% significance levels, respectively.

Table 6: Probit Estimations of Flight Cancellations & Delays - The Effect of Aircraft Characteristics

Flight Cancellations and Departure Delays[1] for Major U.S. Carriers, January 1995 - August 2001.

Dependent Variable:	Flight Cancellation			Departure Delay		
Model	(9)			(10)		
	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.
Route Competition Variable						
Monopoly	0.0722 **	0.0205	0.0000	0.0579 **	0.0080	0.0148
Airport Competition Variables						
Airline Hub Origination	-0.1044 **	0.0230	0.0000	0.0009	0.0073	0.0002
Airline Hub Destination	-0.0803 **	0.0252	0.0000	-0.1026 **	0.0079	-0.0261
Airport Concentration Origination	0.0587	0.0657	0.0000	-0.0059	0.0175	-0.0015
Airport Concentration Destination	0.0235	0.0614	0.0000	-0.0131	0.0210	-0.0033
Economic Variables						
Average Revenue (in $10,000s)	0.0756	0.1238	0.0000	0.1310 **	0.0218	0.0335
Load Capacity (Monthly Average)	-1.1930 **	0.0634	-0.0002	0.1874 **	0.0255	0.0480
Aircraft Characteristics						
Aircraft Age	0.0047 **	0.0012	0.0000			
Airbus	0.0227	0.0326	0.0000			
McDonnell-Douglas	-0.0251	0.0168	0.0000			
Seating capacity of aircraft	-0.0009 **	0.0002	0.0000			
Logistical Variables						
Daily Total Airport Operations Orig.	0.0105 **	0.0029	0.0000	0.0121 **	0.0009	0.0031
Daily Total Airport Operations Dest	0.0120 **	0.0028	0.0000	0.0107 **	0.0009	0.0027
Daily Scheduled Flights	0.0296 **	0.0029	0.0000	0.0053 **	0.0008	0.0014
Last Flight of Day	-0.0297	0.0174	0.0000	-0.0787 **	0.0060	-0.0197
Time01	-0.0031	0.0330	0.0000	1.1934 **	0.0123	0.3055
Short Flight (< 400 miles)	-0.0817 **	0.0297	0.0000	-0.0163	0.0108	-0.0042
Middle Distance (400 to 800 miles)	-0.0869 **	0.0253	0.0000	0.0481 **	0.0096	0.0124
Labor Unrest	0.1886 **	0.0317	0.0001	0.2415 **	0.0131	0.0679
Weather Variables						
Minimum Temperature Origination	-0.0034 **	0.0006	0.0000	-0.0006 **	0.0003	-0.0002
Minimum Temperature Destination	-0.0013	0.0007	0.0000	-0.0013 **	0.0002	-0.0003
Rain Origination	0.0023 **	0.0002	0.0000	0.0036 **	0.0001	0.0009
Rain Destination	0.0018 **	0.0002	0.0000	0.0025 **	0.0001	0.0006
Frozen Precipitation Origination	0.0132 **	0.0009	0.0000	0.0111 **	0.0004	0.0028
Frozen Precipitation Destination	0.0099 **	0.0010	0.0000	0.0078 **	0.0004	0.0020
Constant	-7.7066 **	0.3522		-2.0296 **	0.0320	
Log Likelihood		-29,116			-654,970	
Pseudo R-squared		0.218			0.060	
Number of Observations		749,467			1,447,095	

Note: Bootstrapped standard errors are reported. Regressions include carrier, day of week, month, and year dummy variables. Marginal effects are defined as the effect on the probability that the average flight is cancelled. * and ** indicate 5% and 1% significance levels, respectively.

[1]Departure delay equals 1 if the flight leaves the gate more than 15 minutes after its scheduled departure time.

Table 7: Probit Estimations of Flight Cancellations - The Effect of Revenue

Dependent Variable: Flight Cancellations for Major U.S. Carriers, January 1995 - August 2001.

Model	(11)				(12)			
	Coeff		Std. Error	Marg. Eff.	Coeff		Std. Error	Marg. Eff.
Route Competition Variables								
Monopoly	0.0536	**	0.0102	0.0024	0.0499	**	0.0102	0.0023
Airport Competition Variables								
Airline Hub Origination	-0.1289	**	0.0130	-0.0056	-0.1244	**	0.0125	-0.0055
Airline Hub Destination	-0.1329	**	0.0138	-0.0058	-0.1306	**	0.0129	-0.0059
Airport Concentration Origination	0.0343		0.0336	0.0015	0.0290		0.0321	0.0013
Airport Concentration Destination	0.0284		0.0315	0.0013	0.0290		0.0306	0.0013
Economic Variables								
Potential Revenue (in $10,000s)	-0.0134		0.0301	-0.0006				
Load Capacity (Monthly Average)	-1.3871	**	0.0359	-0.0617	-1.3807	**	0.0382	-0.0629
Yield (dollars per mile)					0.0519	**	0.0125	0.0024
Logistical Variables								
Daily Total Airport Operations Orig.	0.0035	**	0.0013	0.0002	0.0068	**	0.0012	0.0003
Daily Total Airport Operations Dest	0.0087	**	0.0011	0.0004	0.0117	**	0.0011	0.0005
Daily Scheduled Flights	0.0377	**	0.0010	0.0017	0.0349	**	0.0010	0.0016
Last Flight of Day	-0.0737	**	0.0091	-0.0031	-0.0690	**	0.0089	-0.0030
Time01	0.0441	**	0.0166	0.0020	0.0284		0.0165	0.0013
Short Flight (< 400 miles)	-0.0154		0.0137	-0.0007	-0.0331	**	0.0126	-0.0015
Middle Distance (400 to 800 miles)	-0.0126		0.0143	-0.0006	0.0019		0.0142	0.0001
Labor Unrest	0.3162	**	0.0153	0.0189	0.3059	**	0.0149	0.0185
Weather Variables								
Minimum Temperature Origination	-0.0001		0.0004	0.0000	-0.0003		0.0004	0.0000
Minimum Temperature Destination	-0.0031	**	0.0004	-0.0001	-0.0033	**	0.0003	-0.0002
Rain Origination	0.0022	**	0.0001	0.0001	0.0022	**	0.0001	0.0001
Rain Destination	0.0022	**	0.0001	0.0001	0.0022	**	0.0001	0.0001
Frozen Precipitation Origination	0.0121	**	0.0006	0.0005	0.0120	**	0.0006	0.0005
Frozen Precipitation Destination	0.0105	**	0.0006	0.0005	0.0107	**	0.0006	0.0005
Constant	-1.1975	**	0.0442		-1.1929	**	0.0430	
Log Likelihood			-154,809				-167,920	
Pseudo R-squared			0.088				0.086	
Number of Observations			1,447,095				1,544,653	

Note: Bootstrapped standard errors are reported. Regressions include carrier, day of week, month, and year dummy variables. Marginal effects are defined as the effect on the probability that the average flight is cancelled.
 * and ** indicate significance at the 5% and 1% levels.

Table 8: Probit Estimations of Flight Cancellations - The Effect of Airport Size

Dependent Variable: Flight Cancellations for Major U.S. Carriers, January 1995 - August 2001.

Model	(13)			(14)			(15)		
Sample	Large Airports			Medium Airports			Small Airports		
	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.
Route Competition Variables									
Monopoly	0.0813 **	0.0110	0.0039	-0.0938 **	0.0208	-0.0032	0.0077	0.0638	0.0004
Airport Competition Variables									
Airline Hub Origination	-0.1660 **	0.0198	-0.0080	-0.1186 **	0.0283	-0.0036			
Airline Hub Destination	-0.1696 **	0.0203	-0.0077	-0.1166 **	0.0274	-0.0038	-0.0170	0.0570	-0.0009
Airport Concentration Origination	0.0004	0.0378	0.0000	0.0380	0.0782	0.0012	0.1554	0.0871	0.0079
Airport Concentration Destination	0.0356	0.0437	0.0017	-0.0492	0.0710	-0.0016	0.0501	0.0681	0.0025
Economic Variables									
Average Revenue (in $10,000s)	0.0232	0.0483	0.0011	-0.3016 **	0.0766	-0.0098	-0.6180 **	0.2231	-0.0314
Load Capacity (Monthly Average)	-1.6527 **	0.0438	-0.0784	-1.0925 **	0.0844	-0.0355	-0.8254 **	0.0893	-0.0420
Logistical Variables									
Daily Total Airport Operations Orig.	0.0127 **	0.0019	0.0006	-0.0193	0.0125	-0.0006	0.0020	0.0455	0.0001
Daily Total Airport Operations Dest	0.0117 **	0.0016	0.0006	0.0039	0.0033	0.0001	-0.0071	0.0044	-0.0004
Daily Scheduled Flights	0.0427 **	0.0013	0.0020	0.0494 **	0.0027	0.0016	0.0305 **	0.0066	0.0015
Last Flight of Day	-0.1097 **	0.0117	-0.0048	-0.0677 **	0.0195	-0.0021	-0.0636 **	0.0238	-0.0032
Time01	0.0450 *	0.0217	0.0021	0.0163	0.0392	0.0005	0.2924 **	0.0540	0.0149
Short Flight (< 400 miles)	-0.0960 **	0.0186	-0.0044	-0.2227 **	0.0389	-0.0071	0.2158 *	0.0980	0.0096
Middle Distance (400 to 800 miles)	-0.0888 **	0.0176	-0.0041	-0.1120 **	0.0325	-0.0035	0.0144	0.0932	0.0007
Labor Unrest	0.3055 **	0.0193	0.0191	0.4041 **	0.0368	0.0199	0.2460 **	0.0429	0.0157
Weather Variables									
Minimum Temperature Origination	-0.0003	0.0005	0.0000	0.0010	0.0008	0.0000	0.0026 *	0.0012	0.0001
Minimum Temperature Destination	-0.0033 **	0.0005	-0.0002	-0.0019 *	0.0009	-0.0001	-0.0069 **	0.0011	-0.0004
Rain Origination	0.0026 **	0.0001	0.0001	0.0014 **	0.0002	0.0000	0.0020 **	0.0002	0.0001
Rain Destination	0.0022 **	0.0001	0.0001	0.0021 **	0.0002	0.0001	0.0021 **	0.0002	0.0001
Frozen Precipitation Origination	0.0129 **	0.0007	0.0006	0.0108 **	0.0011	0.0004	0.0108 **	0.0009	0.0005
Frozen Precipitation Destination	0.0106 **	0.0007	0.0005	0.0109 **	0.0009	0.0004	0.0092 **	0.0010	0.0005
Constant	-1.0875 **	0.0525		-1.3290 **	0.1064		-1.5807 **	0.1867	
Log Likelihood		-106,184			-29,046			-18,879	
Pseudo R-squared		0.096			0.077			0.065	
Number of Observations		926,627			357,362			164,781	

Note: Bootstrapped standard errors are reported. Regressions include carrier, day of week, month, and year dummy variables.
Marginal effects are defined as the effect on the probability that the average flight is cancelled. * and ** indicate significance at the 5% and 1% levels.

Appendix Table 1: Dummy Variables from Flight Cancellation Models (4, 5, & 6)

	(4)			(5)			(6)		
Carrier	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.	Coeff	Std. Error	Marg. Eff.
Alaska	-0.0406	0.0371	-0.0017	-0.0638	0.0373	-0.0027	-0.0331	0.0373	-0.0014
Aloha	-0.4426 **	0.0708	-0.0126	-0.4291 **	0.0714	-0.0124	-0.4492 **	0.0716	-0.0127
American Eagle	0.4188 **	0.0326	0.0285	0.4228 **	0.0325	0.0290	0.4237 **	0.0327	0.0290
America West	0.1425 **	0.0237	0.0073	0.1472 **	0.0239	0.0076	0.1419 **	0.0237	0.0073
Continental	0.0081	0.0174	0.0004	0.0137	0.0174	0.0006	0.0131	0.0175	0.0006
Delta	0.0240	0.0146	0.0011	0.0357 **	0.0147	0.0016	0.0249	0.0146	0.0011
Northwest	0.1884 **	0.0167	0.0099	0.1956 **	0.0166	0.0103	0.1904 **	0.0166	0.0100
Southwest	-0.3792 **	0.0221	-0.0127	-0.3699 **	0.0219	-0.0125	-0.3800 **	0.0220	-0.0127
TWA	0.0811 **	0.0256	0.0039	0.0943 **	0.0252	0.0046	0.0849 **	0.0255	0.0041
United	0.1315 **	0.0140	0.0064	0.1332 **	0.0140	0.0065	0.1346 **	0.0144	0.0066
US Airways	0.1255 **	0.0153	0.0062	0.1352 **	0.0153	0.0067	0.1244 **	0.0152	0.0061
Month									
jan	-0.1454 **	0.0224	-0.0057	-0.1497 **	0.0225	-0.0059	-0.1432 **	0.0225	-0.0056
feb	-0.1938 **	0.0235	-0.0073	-0.1976 **	0.0235	-0.0074	-0.1919 **	0.0235	-0.0072
mar	-0.2184 **	0.0209	-0.0081	-0.2225 **	0.0210	-0.0082	-0.2173 **	0.0210	-0.0080
apr	-0.2225 **	0.0203	-0.0081	-0.2252 **	0.0202	-0.0082	-0.2216 **	0.0204	-0.0081
may	-0.1175 **	0.0162	-0.0047	-0.1191 **	0.0163	-0.0048	-0.1168 **	0.0162	-0.0047
jun	0.0224	0.0168	0.0010	0.0218	0.0169	0.0010	0.0223	0.0168	0.0010
aug	-0.0335 *	0.0161	-0.0014	-0.0333 *	0.0162	-0.0014	-0.0333 *	0.0161	-0.0014
sep	-0.1675 **	0.0195	-0.0064	-0.1678 **	0.0196	-0.0064	-0.1665 **	0.0194	-0.0064
oct	-0.2361 **	0.0199	-0.0085	-0.2384 **	0.0199	-0.0086	-0.2353 **	0.0199	-0.0085
nov	-0.3441 **	0.0198	-0.0112	-0.3479 **	0.0198	-0.0113	-0.3429 **	0.0199	-0.0112
dec	-0.2520 **	0.0210	-0.0090	-0.2573 **	0.0209	-0.0091	-0.2504 **	0.0209	-0.0089
Year									
1996	-0.0183	0.0160	-0.0008	-0.0176	0.0160	-0.0008	-0.0176	0.0160	-0.0008
1997	-0.1204 **	0.0170	-0.0049	-0.1200 **	0.0171	-0.0049	-0.1202 **	0.0170	-0.0049
1998	0.0036	0.0155	0.0002	0.0031	0.0156	0.0001	0.0037	0.0155	0.0002
1999	0.0569 **	0.0148	0.0026	0.0560 **	0.0149	0.0026	0.0563 **	0.0148	0.0026
2000	0.1418 **	0.0138	0.0069	0.1417 **	0.0139	0.0069	0.1411 **	0.0138	0.0069
Day of the Week									
mon	0.0011	0.0085	0.0000	0.0010	0.0085	0.0000	0.0011	0.0085	0.0000
tue	0.0064	0.0095	0.0003	0.0064	0.0095	0.0003	0.0064	0.0095	0.0003
thu	-0.0224 **	0.0088	-0.0010	-0.0224 **	0.0088	-0.0010	-0.0223 **	0.0088	-0.0010
fri	-0.0398 **	0.0104	-0.0017	-0.0399 **	0.0104	-0.0017	-0.0398 **	0.0104	-0.0017
sat	-0.0107	0.0107	-0.0005	-0.0121	0.0107	-0.0005	-0.0104	0.0108	-0.0005
sun	-0.1378 **	0.0095	-0.0055	-0.1383 **	0.0095	-0.0056	-0.1375 **	0.0095	-0.0055