The Effect of Congestion on Flight Delays Experienced by Departing Aircraft at Chicago O’Hare International Airport and Illustrative Congestion Fees That Could Alleviate the Problem

by
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June 6, 2005

Senior Thesis for the Mathematical Methods in the Social Sciences Program at Northwestern University

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ACKNOWLEDGMENTS

I would like to thank several people who have been helpful throughout the process of writing this senior thesis. First, I would like to thank my advisor, Ian Savage, whose excitement and interest in the topic in addition to his invaluable insights helped me tremendously throughout these past few months. I would also like to thank our MMSS teaching assistant, Ambarish Chandra, for helping me devise the complex Stata code necessary to complete this project.

Thank you to Lacey Langguth for being my sounding board. Her willingness to let me babble about departing aircraft and taxi-out times, regardless of the hour of day, will forever be appreciated. Lastly, thank you to Bonnie Johnson, my mother, for proofreading this thesis or, rather, all of my papers from elementary school to now.
ABSTRACT

This paper models congestion experienced by departing aircraft at Chicago O’Hare International Airport and determines illustrative congestion pricing schemes that could help alleviate the congestion problem and reduce delays. First, using a static model, congestion functions which relate the taxi-out time to the number of departing aircraft in the queue are estimated from historical departure data for O’Hare. Two pairs of days are analyzed to compare the effects of good and bad weather on congestion and show the difference between weekday and weekend congestion. From the estimated congestion functions, congestion pricing fees for departing aircraft are derived for various traffic levels and tested for sensitivity to varying elasticity estimates. The congestion pricing fees are adjusted relative to an airline’s share of the departure queue so that each airline is charged for the congestion costs it imposes on other departing aircraft that it does not already internalize.
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1. INTRODUCTION

Air travel nationwide is returning to its pre-9/11 levels after a prolonged slump following the terrorist attacks. The commercial air service industry was plagued by major delays in 1999 and 2000, but after the 9/11 terrorist attacks, traffic levels dropped.\(^1\) Increasing delays across the entire aviation system suggest that traffic has once again reached its pre-9/11 levels. Chicago O’Hare International Airport is the second busiest airport in the country in terms of total enplanements and in 2004 had the lowest on-time performance of the 31 major airports in the United States. According to the Bureau of Transportation Statistics, only 72.84% of departures and 70.07% of arrivals at O’Hare in 2004 departed or arrived on-time, which is defined as less than 15 minutes past the scheduled arrival or departure time.\(^2\)

The largest contributor to delays at O’Hare is its busy schedule that often exceeds the airport’s capacity. O’Hare serves as a hub airport for both United Airlines and American Airlines with those airlines accounting for 88% of O’Hare’s flight operations.\(^3\) Since O’Hare is one of the busiest airports and a hub for two major airlines, delays at O’Hare cause delays throughout the entire system. While severe weather is a common cause of delays at airports across the country, even moderately bad weather can cause significant delays at O’Hare because its over-packed schedule prohibits it from enduring or recovering from any stresses to the system.

Between April 2000 and November 2003, United and American increased scheduled operations between 12 and 8 p.m. by 225 and 56 flights, respectively. In the same time period, the net increase in scheduled peak-hour operations by all other airlines was only six flights.\(^4\) Under perfect weather conditions, O’Hare can handle up to 200 arriving and departing flights per hour—roughly 100 landings and 100 takeoffs. After November 2003, the number of flights per hour was

\(^1\) Alan Levin, “Clogs at O’Hare delay passengers everywhere,” *USA Today* 4 Aug. 2004: 1A.
\(^3\) Levin 1A.
near or above that ceiling from 1 to 8 p.m. every weekday. Under previous schedules, the airport had slow periods in between busy periods that allowed air traffic controllers to catch up in response to bad weather. For example, if arriving flights surged to 110 for one hour, they would fall to 70 the next hour, so if some flights were late, they wouldn’t affect the whole day’s schedule. Now without slack in the schedule for the entire afternoon and early evening period, a few late flights in the early afternoon can cause problems for the rest of the day.

Lastly, an increase in the percentage of flights flown by small regional jets is adding to the problem because those flights used to be served by propeller planes that used different runways and flew at different altitudes than jets. Now the regional jets congest the same runways and air routes as large jets, causing more congestion without hauling more passengers. In fact, regional jets accounted for 15% of operations at O’Hare in 2000, but now they account for 44% of operations. Regional jets are attractive to airlines because they are small and fuel efficient; however, the capacity of regional jets is about one-third of a regular airplane.

The Federal Aviation Administration has attempted to seek short-term solutions to the delay problem at O’Hare. Twice in 2004 the FAA negotiated with American and United to reduce their peak-hour operations in an effort to reduce flight delays at O’Hare. From May 1 through October 31, 2004, United and American voluntarily backed off of their proposed schedules by 7.5% under agreements reached with the FAA. However, other airlines thwarted these efforts by increasing operations as much as United and American decreased them.

In a new plan for November 1 through April 30, 2005, United and American reduced their schedules by 5%. Simultaneously, the FAA froze schedules of other airlines including Continental, Delta, Northwest, US Airways, Air Canada, and Independence Air preventing those airlines from

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5 Levin 1A.
6 Ibid. 1A.
8 Bond 48.
shifting their schedules. However, in an effort to maintain competition at the airport, the FAA identified “limited incumbents” as airlines with eight or fewer arrivals during the hours of 7 a.m. and 9 p.m. The provisions for limited incumbents allowed them to increase service up to a total of eight arrivals between 7 a.m. and 9 p.m., but to protect United and American in the afternoon and evening hours when they operate the most flights, only one of a limited incumbent’s or new entrant’s added arrivals may be scheduled between 12 p.m. and 9 p.m.\(^9\)

While the FAA’s actions create some short-term relief for O’Hare, a long-term solution is necessary and not only for O’Hare. Jan Brueckner, a Professor of Economics at the University of Illinois-Urbana/Champaign, highlights three possible long-term solutions for the delay problem.\(^{10}\) First, building new runways at congested airports could help alleviate delays; however, such projects require many years to develop and implement which prolongs relief. Second, improvements in air traffic control could increase both the capacity of the nation’s airspace and busy airports’ abilities to handle more flights. Third, the adoption of congestion pricing could alleviate the delay problem by charging airlines departure and arrival fees that vary with the level of congestion instead of by an aircraft’s weight like the current system of landing fees. Since total operating costs at peak hours would increase considerably due to congestion fees, some flights would shift to off-peak times resulting in a smoother flight schedule throughout the day and a decline in airport congestion and flight delays. Currently, no airport in the United States has implemented congestion pricing despite increasing research and endorsements.

This paper will seek to accomplish two objectives in studying the congestion problem at O’Hare International Airport. First, using the relationship of speed and density in road congestion, a “congestion function” for O’Hare will be derived relating a departing aircraft’s observed

congestion density—the number of departing aircraft in the queue—with its taxi-out time. Using actual historic traffic data from the Bureau of Transportation Statistics and regression analysis, the congestion functions for several days—both good and bad weather—are estimated. This congestion function demonstrates the engineering relationship of congestion and the length of delay that is inherent in the design of O’Hare. For another airport, the congestion function would look different based on the design of runways and the airport’s capacity. The congestion function is only derived for departing aircraft because the congestion function for arrival delays would be more difficult to derive since delays for arriving aircraft are often caused by problems at their origin airports. Moreover, the data used in this study is insufficient for analyzing arrival delays because the data lacks information about arriving aircraft prior to touch-down at O’Hare, which prevents a similar analysis from being performed on arrivals. By focusing only on departing aircraft once they push back from their departure gates, it is possible to focus on O’Hare-related congestion delays rather than other causes of delay such as mechanical problems and weather delays at the destination airport because in those cases of delay, planes usually remain at the gate.

Second, from the congestion function, congestion pricing fees for departing aircraft will be calculated for various levels of departure congestion. Estimates for the private costs incurred by both the airlines and passengers during taxi-out delay are used to transform the congestion function into an average variable cost curve. From the average variable cost curve, the marginal cost curve can be derived. After the formulation of demand curves, illustrative congestion fees for departing aircraft are calculated for various levels of departure congestion. These congestion pricing fees will be weighted according to each airline’s share of the departure queue to force carriers to bear the portion of the external congestion cost that they are not already internalizing.
2. LITERATURE REVIEW

Congestion pricing theory was originally derived for applications to road congestion. However, many transportation researchers have determined that congestion pricing theory can also be applied to airport congestion. Michael E. Levine (1969) and Alan Carlin and R. E. Park (1970) provided some of the first discussions of airport congestion pricing, with Steven A. Morrison and Clifford Winston (1989) providing later discussions. The most technically sophisticated discussion of congestion pricing is provided by Joseph I. Daniel (1995, 2001) which includes a simulation model with stochastic queues, time-varying traffic rates, and endogenous, inter-temporal adjustment of traffic in response to queuing delays and fees. Daniel’s simulations calculate equilibrium traffic patterns, queuing delays, schedule delays, congestion fees, airport revenues, airport capacity, and efficiency gains for Minneapolis-St. Paul International Airport.

The early literature on airport congestion pricing can be criticized by simply extrapolating the results of the road congestion literature and applying them to the airport congestion problem. However, they fail to realize an important difference between the road congestion problem and the airport congestion problem. In the case of road congestion, users are “atomistic” meaning that each user is small relative to the total traffic and does not coordinate its travel schedule with other users. Airlines, on the other hand, are non-atomistic since at most airports there are only a few carriers and they each have a significant share of that airport’s operations with one or two airlines dominating the operations at many airports like United and American at O’Hare. Thus, when United is scheduling flights, it likely takes into account the congestion costs that an additional United flight would impose on all other United flights. Daniel (1995) recognizes the possible internalization of congestion costs by the carriers, and this idea is further developed by Jan K. Brueckner (2002) in a more transparent model than Daniel’s complex model.
Brueckner (2002) concludes that in a Cournot oligopoly situation, an airline internalizes the congestion each flight imposes on the other flights it operates. Thus, each airline would be charged for the congestion costs that it fails to internalize. More specifically, the toll would equal the congestion cost (the difference between the average variable cost and the marginal cost) multiplied by one minus the airline’s flight share. At airports like O’Hare, the internalization conclusion suggests that the perceived over-scheduling of flights during peak times may not be as severe in reality as the atomistic model would predict, but tolls that capture the un-internalized portion of congestion may improve the allocation of traffic. Moreover, Brueckner determines that in the case of a perfectly discriminating monopolist, congestion is fully internalized. The important implication from this analysis is that there might not be a role for congestion pricing in the case of an airport dominated by a single monopolist.

This paper contributes to the current discussion by determining illustrative congestion fees specifically for O’Hare. While Daniel estimated congestion fees for Minneapolis-St. Paul International over a decade ago, similar estimates for O’Hare have not been calculated in congestion pricing literature. Moreover, the description of the derivation of congestion fees through the estimated “congestion function” is a unique contribution of this paper.
3. ARRIVAL AND DEPARTURE DATA FOR O’HARE INTERNATIONAL AIRPORT

Airline on-time data are reported each month to the Department of Transportation, Bureau of Transportation Statistics (BTS) by the 19 U.S. air carriers that each have at least 1% of the total domestic scheduled-service passenger revenues, plus other carriers that report voluntarily. The data cover nonstop scheduled-service flights between points within the United States since January 1995. For every flight by airline and airport, the database includes the carrier, date, flight number, tail number, and destination or origin airport. The on-time statistics cover the following statistics for departures and arrivals:

**Departure data:**
- Scheduled departure time
- Actual departure time—defined as the time a plane actually departed its gate
- Scheduled elapsed time
- Actual elapsed time
- Departure delay
- Wheels-off time
- Taxi-out time

**Arrival data:**
- Scheduled arrival time
- Actual arrival time—defined as the time a plane actually arrived at its gate
- Scheduled elapsed time
- Actual elapsed time
- Arrival delay
- Wheels-on time
- Taxi-in time

Despite being fairly comprehensive, the data set does have a few limitations that are important to note, but the results of the paper are seemingly still worthwhile. First, the data set only includes domestic scheduled-service so it excludes all international service by both domestic and international carriers, flights by cargo carriers, and private or chartered flights. If these flights were assumed to be randomly distributed, their absence from the data would not cause any problems in the results. However, it is unlikely that these flights, especially the international flights, are
randomly distributed because international flights are most likely strategically scheduled at certain times of the day because of the distance and direction of flight.

The second limitation of the data prevents analysis of arrival delay analysis because the data does not include sufficient information about an arriving aircraft’s arrival into its destination airport. The first piece of data recorded for an arriving aircraft is the wheels-on time at the destination airport. Since the most interesting portion of an arriving aircraft’s delay is the possible time that it might have to maintain a holding pattern in the air before it is allowed to land, analysis on the congestion function for arriving aircraft is impossible with the data from the Bureau of Transportation Statistics. Thus, my analysis will focus solely on the delays encountered by departing aircraft.

The third limitation of the data is that it does not detail the reasons for flight delays and cancellations. It is impossible to know whether a plane was delayed or cancelled due to mechanical problems, late arriving aircraft, weather, etc, so it cannot be distinguished if a flight was delayed due to the over-congestion of O’Hare or for some unrelated reason. To minimize this problem, the delay statistic used in the model is the taxi-out time, which is the time it takes between when a plane leaves its gate (actual departure time) to when its wheels lift off the runway (wheels-off time). Since most delays which are not congested-related occur at the gate, such as late crew, mechanical problems, and most ground holds to congested destinations, only analyzing the time it takes a plane to taxi-out narrows in on the O’Hare-related congestion delay for each flight.
4. CONGESTION THEORY

Background of congestion: traffic flow, speed, and density

Traffic flow, speed, and density form the foundation of traffic analysis. From *Principles of Highway Engineering and Traffic Analysis* by Mannering, Kilareski, and Washburn, flow, density and speed are defined as follows:

Traffic flow: \[ q = \frac{n}{t} \]  
where \( q \) = traffic flow in vehicles per unit time,  
\( n \) = number of vehicles passing some designated roadway point during time \( t \), and  
\( t \) = duration of time interval

Traffic speed: \[ u = \frac{l}{t_{average}} \]  
where \( u \) = space-mean speed in unit distance per unit time,  
\( l \) = length of roadway used for travel time measurement of vehicles, and  
\( t_{average} \) = average vehicle travel time

Traffic density: \[ k = \frac{n}{l} \]  
where \( k \) = traffic density in vehicles per unit distance,  
\( n \) = number of vehicles occupying some length of roadway at some specified time, and  
\( l \) = length of roadway

From these definitions a simple identity provides the basic relationship between traffic flow, speed, and density:

\[ q = uk \]  
where \( q \) = flow, typically in units of veh/hr,  
\( u \) = speed (space-mean speed), typically in units of mi/hr, and  
\( k \) = density, typically in units of veh/mi.\(^{11}\)

A generalized traffic model can be created around the relationship between speed and density. Consider a section of highway with only one driver. This driver will be able to travel close to the design speed of the highway, meaning there is some maximum speed determined by the

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degree of turns in the road, etc. In this situation the density is very low, and the speed that this 
driver will be able to travel is called the free-flow speed because the vehicle speed is not inhibited 
by the presence of other vehicles. Adding more and more vehicles to the same section of highway 
will result in higher levels of traffic density, and the average operating speed will decline from the 
free-flow speed as drivers will have to slow to accommodate the maneuvers of others.

**The speed-density relationship of taxi-out time and departure queue length**

The concepts of traffic flow, speed, and density can be applied to the airport congestion of 
departing aircraft as well. For the purposes of this paper, the traffic flow at capacity for an airport is 
the number of flights that can take off in an hour in optimal conditions. The observed traffic flow is 
the actual number of flights that take off in a given hour. The traffic speed can be described by the 
taxi-out time for a departing aircraft. In this case, the distance portion of the speed is the taxiway 
distance which could be assumed to be the same for all departing aircraft. Lastly, the density could 
be calculated by taking a “snapshot” of O’Hare and counting the number of departing aircraft that 
are in front of a given departing plane in the queue. The area portion of density is the fixed size of 
O’Hare’s runways and taxiways.

In this paper the delay experienced by departing aircraft will be modeled relative to only the 
length of the departure queue. It was determined that arriving aircraft, or in particular, the rate of 
arriving aircraft, had little bearing on the taxi-out time of a departing aircraft. For the entire month 
of September 2004, the correlation between arrival rate and taxi-out time was found to be only 0.0390. On September 22, 2004, a day which will be verified in Section 6 as a “good weather day,” 
the correlation between arrival rate and taxi-out time was 0.0946, which while slightly higher than 
the overall September average, is still relatively low. On September 15, 2004, a day which will be 
verified in Section 6 as a “bad weather day,” the correlation between arrival rate and taxi-out time 
was -0.1657, so while the sign has switched to being negative, it is still a small magnitude of
correlation. On a bad weather day, it makes sense that the correlation is negative because the airport is likely to have such minimal operations it is essentially shut down. Thus, if there is a higher arrival rate at a certain time of day, it’s probably because air traffic control is shutting down nearly all departing aircraft in dealing with the limitations the severe weather is placing on the airport, so taxi-out times for departing aircraft would consequently be very low. The main benefit to modeling departure congestion based only on the length of the departure queue is that it will allow for the determination of congestion fees to be calculated for departing aircraft based on the congestion they impose on themselves. Thus, the analysis focused on modeling departing aircrafts’ taxi-out delay relative to the length of the departure queue only.

From the application of traffic flow, speed, and density to airport congestion, an idea develops for what the relationship between speed and density, or taxi-out time and number of departing aircraft in the queue, might look like. For levels of traffic flow that are below O’Hare’s maximum capacity, the taxi-out time is likely constant because there is a fixed amount of time that it will take a plane to push back from its gate, taxi out to the runway, and take off even in the absence of other departing aircraft. However, once the flow is greater than the capacity, taxi-out time will begin to increase as the number of departing aircraft in the queue increases.

Thus, the “congestion function” for the airport is likely a two-piece function, with a flat portion for low levels of departing aircraft in the queue and an increasing portion for higher levels of departing aircraft in the queue. Later in Section 7, this theory of a two-piece function will be confirmed.

The bottleneck model:

The congestion at an airport can be viewed as a bottleneck. In road contexts, a bottleneck refers to a point in the roadway where the capacity of the road decreases causing a queue to develop as vehicles wait for their turn to travel into the bottleneck. Examples of bottlenecks include the
point where two roadways merge or the point at which a lane ends on a roadway. The maximum allowable flow is higher in sections before the bottleneck and lower at the bottleneck and in sections after the bottleneck. Suppose there is a roadway with three lanes traveling in one direction. At Point A, the right lane ends so that after Point A there are now only two lanes. At certain off-peak times of the day, the speed of travel in the different sections of the roadway will be the same because both sections can accommodate the observed flow of traffic. However, at peak times when the flow of traffic on the roadway exceeds the capacity of the roadway at Point A and beyond, a queue will develop prior to A. The speed of traffic before the bottleneck decreases as the density of vehicles increases.

The bottleneck model can be easily applied to describe the departing traffic flow at an airport. The actual bottleneck is the start of the runway because that is the point that determines the speed of traffic since only a certain maximum level of flow can travel through it per hour, and a queue develops immediately prior to it.

For each departing aircraft, when it is sitting at the gate, it is not currently a part of the traffic model. However, as soon as the plane backs from its gate, it has entered the “roadway.” While the plane is taxiing to its assigned runway, it is usually able to travel freely except for possibly having to wait for another plane or vehicle crossing its path. During off-peak times when there is no departure queue, a plane could potentially travel without interruption between its gate to the start of the runway and through the bottleneck without any delay. On the other hand, during congested peak periods, a plane will most likely travel freely while taxiing away from its gate area but soon joins a queue of planes that are waiting to take off and travel through the bottleneck.

Figure 1 illustrates the concept of the bottleneck with its application to airport congestion. The traditional bottleneck is modified to show the effect of arrival traffic. Since departing aircraft often share runways with arriving aircraft, the interaction of the arriving traffic with the departing
traffic is much like that of the intersection of two roads moderated by a stoplight. The stoplight turns red which stops the departing traffic, holding it while some arriving traffic is let through the intersection or, rather, allowed to land on the runway and pass through the bottleneck.

Figure 1.

THE BOTTLENECK MODEL OF AIRPORT CONGESTION

Since departing aircraft usually wait in a single-file line, the bottleneck usually occurs prior to the intersection with the arriving traffic. Essentially, the area of the taxiway holding the queue would then be the actual location of the start of the bottleneck. However, it is possible for air traffic controllers to instruct a plane to bypass the planes already in the queue; thus, the bottleneck is drawn as representing only the runway.
5. CONGESTION PRICING THEORY

Since A.C. Pigou’s writings in the early 1920s, economists have recognized that the principle of marginal-cost pricing applies to road congestion. More recently the concept of congestion pricing has been studied for possible applications to airport congestion. Many of the characteristics of airport congestion are similar to road congestion which allows for the results of road congestion literature to be extrapolated and applied to airport congestion. However, as mentioned previously, Daniel (1995) and Brueckner (2002) made an important distinction that a carrier with market power has already internalized the congestion costs an additional flight imposes on all of its other flights in the queue. Congestion pricing will be explained in the road context with an effort to highlight important differences between airport congestion and road congestion.

To decide when to travel, individual users of the road consider only the congestion costs he or she will experience and not the congestion costs they impose on others by contributing to the congestion. One proposed solution to congestion is the idea of congestion pricing in which users would be charged a toll equal to the amount of costs that they impose on the other users of the congested facility, so users are then faced with the marginal social cost of his or her trip. The toll would equal the difference between the marginal cost and the average variable cost that is already borne by the traveler. Under this scheme, some users, those with little benefit to travel, would no longer find it beneficial to travel during the peak period because of the higher total cost with the toll, so they would shift their use of the congested facility to the off-peak period. Therefore, the volume of traffic would decrease as the users with the least benefit to travel shift to the off-peak period.

Figure 2 graphically shows the determination of the optimal congestion toll. Without congestion pricing, traffic volume would be $V^0$ and the average variable cost is $SRAVC^0$. Since users are not facing the external costs they impose on each other, the traffic volume is greater than
the socially optimal volume of traffic, \( V^1 \), given demand curve \( D \). At any volume \( V \), to force users to bear the external costs they are imposing on others, congestion fees equating to the vertical distance between SRMC and SRAVC must be charged. In particular, for the given demand curve \( D \), the optimal fee is \( \tau \) in the diagram and will induce the socially optimal volume of travel, \( V^1 \). The difference between SRAVC\(^1\) and SRAVC\(^0\) reflects the costs of the non-optimal congestion. The volume of traffic between \( V^1 \) and \( V^0 \) is eliminated because the benefit to travel for those users is not high enough to warrant travel after the imposition of tolls.

Figure 2.

SOCIALLY OPTIMAL TOLLS

Source: Kenneth Small, Urban Transportation Economics.
6. DATES SELECTED FOR ANALYSIS

Historic weather data for O’Hare from WeatherUnderground.com was used to select ideal days for analysis. The visibility, cloud cover, precipitation, and wind speed and direction were used to determine days that were attractive candidates for analysis.

Two pairs of dates from 2004 were chosen to be analyzed—two Wednesdays in September 2004 (September 15 and September 22) and two Saturdays in July 2004 (July 3 and July 24). The historic weather conditions for these four days are shown in Table 1. From these dates the delay variation between weekday and weekend travel can be seen, along with the delay variation caused by good weather and bad weather conditions.

September 22, 2004, was a very typical Wednesday at O’Hare with good weather conditions. The winds were light, averaging about 6 mph, and visibility was good, remaining at 10 miles until the last few hours of the night. Also, there was no precipitation or storm activity with partly to mostly cloudy conditions for most of the day. September 15, 2004, started out in the morning with good weather conditions for air traffic, but around the start of the afternoon and evening peak, the weather turned for the worse. The winds were of moderate speed throughout the day but shifted to coming out of the southwest around 3 p.m. Southwest winds are detrimental to O’Hare because they cause air traffic controllers to have to use a less-efficient set of runways.

<table>
<thead>
<tr>
<th>September</th>
<th>Date</th>
<th>Precipitation</th>
<th>Avg. Wind Speed</th>
<th>Max Wind Speed</th>
<th>Visibility</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good Weather:</td>
<td>Wednesday, September 22, 2004</td>
<td>0.00 in</td>
<td>6 mph (SSW)</td>
<td>12 mph</td>
<td>10 miles</td>
<td>None</td>
</tr>
<tr>
<td>Bad Weather:</td>
<td>Wednesday, September 15, 2004</td>
<td>0.19 in</td>
<td>13 mph (SSW)</td>
<td>26 mph</td>
<td>10 miles</td>
<td>Rain</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>July</th>
<th>Date</th>
<th>Precipitation</th>
<th>Avg. Wind Speed</th>
<th>Max Wind Speed</th>
<th>Visibility</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good Weather:</td>
<td>Saturday, July 24, 2004</td>
<td>0.00 in</td>
<td>8 mph (NE)</td>
<td>15 mph</td>
<td>10 miles</td>
<td>None</td>
</tr>
<tr>
<td>Bad Weather:</td>
<td>Saturday, July 3, 2004</td>
<td>1.32 in</td>
<td>9 mph (ESE)</td>
<td>38 mph</td>
<td>8 miles</td>
<td>Rain, Thunderstorm</td>
</tr>
</tbody>
</table>

Source: www.WeatherUnderground.com
which cuts out a few flights each hour. This can cause delays to exhibit a domino-effect and prolong congestion for many hours. On September 15, light rain in the afternoon and evening accompanied the moderate winds out of the southwest. The weather on September 15 was not severe but rather perfectly demonstrates how even slightly bad weather can wreak havoc on the air traffic at O’Hare. By choosing these two Wednesdays, which are separated by only one week, it is easy to isolate the direct effects of bad weather on delays at O’Hare.

The two Saturdays in July 2004 were also chosen to allow comparison between days that should have exhibited similar traffic patterns and taxi-out times, but because of the variation in weather, actual delays were much longer on the bad weather day. The weather on Saturday, July 24, was fine for air traffic operations with mostly cloudy or overcast conditions without Table 2.

HOURLY WEATHER ON SEPTEMBER 15, 2004

<table>
<thead>
<tr>
<th>Time</th>
<th>Visibility</th>
<th>Wind Direction</th>
<th>Wind Speed MPH</th>
<th>Gust Speed MPH</th>
<th>Precipitation</th>
<th>Events</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>5:56 a.m.</td>
<td>10</td>
<td>South</td>
<td>9.2</td>
<td>-</td>
<td>N/A</td>
<td>Partly Cloudy</td>
<td></td>
</tr>
<tr>
<td>6:56 a.m.</td>
<td>9</td>
<td>South</td>
<td>13.8</td>
<td>19.6</td>
<td>N/A</td>
<td>Partly Cloudy</td>
<td></td>
</tr>
<tr>
<td>7:56 a.m.</td>
<td>10</td>
<td>South</td>
<td>12.7</td>
<td>-</td>
<td>N/A</td>
<td>Partly Cloudy</td>
<td></td>
</tr>
<tr>
<td>8:56 a.m.</td>
<td>10</td>
<td>SSW</td>
<td>13.8</td>
<td>21.9</td>
<td>N/A</td>
<td>Partly Cloudy</td>
<td></td>
</tr>
<tr>
<td>9:56 a.m.</td>
<td>10</td>
<td>South</td>
<td>15</td>
<td>24.2</td>
<td>N/A</td>
<td>Scattered Clouds</td>
<td></td>
</tr>
<tr>
<td>10:56 a.m.</td>
<td>10</td>
<td>South</td>
<td>18.4</td>
<td>26.5</td>
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<td>Partly Cloudy</td>
<td></td>
</tr>
<tr>
<td>11:56 a.m.</td>
<td>10</td>
<td>South</td>
<td>19.6</td>
<td>26.5</td>
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<tr>
<td>12:56 p.m.</td>
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<td>South</td>
<td>16.1</td>
<td>21.9</td>
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</tr>
<tr>
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<td>10</td>
<td>South</td>
<td>26.5</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>2:56 p.m.</td>
<td>10</td>
<td>SW</td>
<td>17.3</td>
<td>27.6</td>
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<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>3:56 p.m.</td>
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<td>WSW</td>
<td>17.3</td>
<td>24.2</td>
<td>0</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>4:56 p.m.</td>
<td>10</td>
<td>SSW</td>
<td>11.5</td>
<td>-</td>
<td>0.02</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>5:56 p.m.</td>
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<td>SW</td>
<td>8.1</td>
<td>-</td>
<td>0</td>
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<td></td>
</tr>
<tr>
<td>6:56 p.m.</td>
<td>10</td>
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<td>9.2</td>
<td>-</td>
<td>0</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>7:56 p.m.</td>
<td>9</td>
<td>SW</td>
<td>8.1</td>
<td>-</td>
<td>0</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>8:56 p.m.</td>
<td>9</td>
<td>SSW</td>
<td>12.7</td>
<td>-</td>
<td>0.04</td>
<td>Rain</td>
<td>Rain</td>
</tr>
<tr>
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<td>10</td>
<td>SSW</td>
<td>11.5</td>
<td>-</td>
<td>0.09</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
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<td>SW</td>
<td>15</td>
<td>21.9</td>
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<td>Rain</td>
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<tr>
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<td>10</td>
<td>SSW</td>
<td>15</td>
<td>-</td>
<td>0.03</td>
<td>Overcast</td>
<td></td>
</tr>
</tbody>
</table>

Source: www.WeatherUnderground.com

12 Levin 1A.
precipitation and only light winds averaging 8 mph out of the northeast. On the other hand, the weather on Saturday, July 3, featured poor conditions for air traffic operations with heavy rain and thunderstorms accompanied by poor visibility in the afternoon and evening and winds gusting to over 40 mph in the late afternoon.

Table 2 and Table 3 show the hourly weather data for July 3 and September 15, which are the bad weather days of each pair. The most important observation from these tables is that the bad weather began in the mid-afternoon on each of the days. Thus, each day theoretically began as a

Table 3.

### HOURLY WEATHER ON JULY 3, 2004

<table>
<thead>
<tr>
<th>Time</th>
<th>Visibility</th>
<th>Wind Direction</th>
<th>Wind Speed MPH</th>
<th>Gust Speed MPH</th>
<th>Precipitation</th>
<th>Events</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>5:56 a.m.</td>
<td>10</td>
<td>ESE</td>
<td>8.1</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>6:56 a.m.</td>
<td>10</td>
<td>SE</td>
<td>10.4</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>7:56 a.m.</td>
<td>10</td>
<td>SE</td>
<td>10.4</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>8:56 a.m.</td>
<td>8</td>
<td>ESE</td>
<td>12.7</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>9:56 a.m.</td>
<td>7</td>
<td>SSE</td>
<td>11.5</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>10:56 a.m.</td>
<td>8</td>
<td>SE</td>
<td>11.5</td>
<td>-</td>
<td>N/A</td>
<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>11:56 a.m.</td>
<td>8</td>
<td>ESE</td>
<td>12.7</td>
<td>-</td>
<td>N/A</td>
<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>12:56 p.m.</td>
<td>7</td>
<td>East</td>
<td>13.8</td>
<td>-</td>
<td>N/A</td>
<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>1:56 p.m.</td>
<td>8</td>
<td>East</td>
<td>10.4</td>
<td>-</td>
<td>0</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
<tr>
<td>2:56 p.m.</td>
<td>10</td>
<td>East</td>
<td>12.7</td>
<td>20.7</td>
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<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>3:56 p.m.</td>
<td>3</td>
<td>SSE</td>
<td>38</td>
<td>49.5</td>
<td>0.2</td>
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<td>Thunderstorms and Rain</td>
</tr>
<tr>
<td>4:04 p.m.</td>
<td>3</td>
<td>SSW</td>
<td>16.1</td>
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<td>0.28</td>
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<td>Thunderstorms and Rain</td>
</tr>
<tr>
<td>4:10 p.m.</td>
<td>6</td>
<td>SSW</td>
<td>10.4</td>
<td>25.3</td>
<td>0.3</td>
<td>Rain-Thunderstorm</td>
<td>Light Thunderstorms and Rain</td>
</tr>
<tr>
<td>4:24 p.m.</td>
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<td>South</td>
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<td>-</td>
<td>0.3</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>4:56 p.m.</td>
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<td>SSE</td>
<td>5.8</td>
<td>-</td>
<td>0.16</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>5:56 p.m.</td>
<td>10</td>
<td>SSE</td>
<td>3.5</td>
<td>-</td>
<td>0</td>
<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>6:56 p.m.</td>
<td>10</td>
<td>ENE</td>
<td>8.1</td>
<td>-</td>
<td>0</td>
<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>7:44 p.m.</td>
<td>3</td>
<td>NE</td>
<td>8.1</td>
<td>-</td>
<td>0.32</td>
<td>Rain</td>
<td>Heavy Rain</td>
</tr>
<tr>
<td>7:56 p.m.</td>
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<td>NE</td>
<td>6.9</td>
<td>-</td>
<td>0.42</td>
<td>Rain-Thunderstorm</td>
<td>Heavy Thunderstorms and Rain</td>
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<td>8:06 p.m.</td>
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<td>ENE</td>
<td>6.9</td>
<td>-</td>
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<td>Thunderstorms and Rain</td>
</tr>
<tr>
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<td>North</td>
<td>5.8</td>
<td>-</td>
<td>0.5</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>8:56 p.m.</td>
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<td>SW</td>
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<td>-</td>
<td>0.54</td>
<td>Rain</td>
<td>Light Rain</td>
</tr>
<tr>
<td>9:14 p.m.</td>
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<td>5.8</td>
<td>-</td>
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<td></td>
</tr>
<tr>
<td>9:31 p.m.</td>
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<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>9:56 p.m.</td>
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<td>Calm</td>
<td>Calm</td>
<td>-</td>
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<td>Overcast</td>
<td></td>
</tr>
<tr>
<td>10:56 p.m.</td>
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<td>Calm</td>
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<td></td>
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<tr>
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<td></td>
</tr>
<tr>
<td>11:56 p.m.</td>
<td>10</td>
<td>SSE</td>
<td>6.9</td>
<td>-</td>
<td>N/A</td>
<td>Mostly Cloudy</td>
<td></td>
</tr>
</tbody>
</table>

Source: www.WeatherUnderground.com
“good day” meaning it should be able to be compared to its “good day” partner for the morning hours at least. The information in Table 2 and Table 3 will be useful when evaluating the graphs shown in the next section.
Determination of density observed by each departing aircraft

To analyze the data using the speed-density approach, a metric for measuring the density was derived. Density is defined as the number of objects per given area. In this case, O’Hare’s taxiways and runways serve as the given area. The number of objects must be calculated. For a given departing aircraft, the density it observes is the number of other departing aircraft that contribute to its observed congestion, or rather the number of departing aircraft that are in front of it in the departure queue. A hypothetical flight is useful in explaining the methodology used to calculate every departing aircraft’s observed density. Suppose that American Airlines Flight 100 is scheduled to leave its gate at 8:00 a.m. and actually backs away at 8:05 a.m. After taxiing and waiting for aircraft which are ahead in the queue, Flight 100 has a wheels-off time of 8:20 a.m. During the 15 minutes that it took for Flight 100 to take off, it could have experienced congestion by waiting in the queue while other planes took off in front of it, and it could have even experienced congestion while traveling from its gate to the queue if, for instance, another plane was backing out of its gate and blocking the taxiway.

For the purposes of this paper, each departing aircraft’s observed density level will be calculated at the time it backs away from its gate. Thus, for Flight 100, the density level would be calculated at 8:05 a.m. Departing aircraft will be counted in Flight 100’s observed density if they have left their gate at or prior to 8:05 a.m. but have not yet experienced wheels-off. Thus, in general, for each departing aircraft at the time it actually leaves its gate, the number of departing aircraft in the queue is determined by counting the number of planes who have left their gate at the same time as or before the aircraft in question. By counting the density in this manner, a hypothetical departure queue is created. While the data does not allow the determination of the actual historical order of the queue, the above-mentioned data manipulation creates a hypothetical
model of the departure queue at the time each departing aircraft backed away from its gate. It’s
important to clarify that planes are counted into the congestion on the end points of a departing
plane’s taxi-out time because the various times are only specified to the minute, so it’s impossible to
know which plane might have actually taken off earlier or later within a given minute. Also, a
departing aircraft is counted in its own observed queue length. It does not really matter whether or
not a plane is counted in its own observed queue length since it essentially just increases or
decreases each departing flight’s density by one, but it was included for the sake of later analysis to
avoid queue lengths of zero aircraft which could cause mathematical issues.

By observing density as a snapshot of the airfield at the time Flight 100 backs away from its
gate, it is assumed that all other departing aircraft that have previously left their gates but have not
yet taken off are in front of Flight 100 in the departure queue; however, this is not necessarily the
case. In reality, sometimes one departing aircraft can take off before another plane that actually
departed its gate earlier than the one that is taking off. In this case, it’s possible that the planes took
off from different runways with different queue lengths or that one of the planes departed from a
gate that was closer to its assigned runway than the other plane. In fact, many different scenarios
are possible, but the data does not explain what actually happened. By assuming that departing
planes take off in the order in which they leave their gates, it is therefore assumed that incidences of
planes overtaking the queue are random, which is a plausible assumption.

**Observed traffic patterns from September 15, 2004, and September 22, 2004**

With the density statistic—the number of departing aircraft in the queue—calculated for all
of the departing flights on September 15 and September 22, the traffic patterns were graphed to gain
an initial understanding of the speed-density relationship at O’Hare. The expectation is that as the
number of departing aircraft in the queue increases, the taxi-out time will increase. Also, it seems
as though there would be some fixed amount of taxi-out time that will always be experienced even
in the absence of congestion. This fixed amount of taxi-out time might vary based on a plane’s
gate, whether it’s close to or far away from the assigned runway. And the expectation is also that as
long as the flow is below the airport’s capacity for arrivals and departures, for small values of the
number of departing aircraft in the queue, the observed taxi-out times should be relatively constant.
Once flow is greater than O’Hare’s capacity, the observed taxi-out time should increase for
increasing levels of departing aircraft in the queue.

In Chart 1 the observed taxi-out times for all of the departing aircraft on September 22 are
plotted against the congestion, or the number of departing aircraft in the queue, that each departing
plane experienced. As anticipated, there is a relatively flat portion of the graph at low levels of
Chart 1.

![Observed Taxi-out Times for Departing Aircraft on September 22, 2004](image)

departing aircraft in the queue with the taxi-out time in minutes beginning to increase at about 25
departing aircraft in the queue. The taxi-out times at low levels of departing aircraft in the queue
range from a little above 5 minutes to about 25 minutes, which is a pretty sizable range. The appearance of the graph seems to verify the conclusion that September 22, 2004, was a good weather day for air travel at O’Hare. The observations follow a fairly regular pattern with few outliers, of which the magnitude of their variation is slight compared to levels observed on bad weather days. The outliers that have higher taxi-out times (around 35 minutes) despite experiencing only 10 departing aircraft in the queue could have higher taxi-out times due to non-O’Hare congestion problems such as ground holds for air traffic into certain destinations.

Next, the number of departing aircraft in the queue and the taxi-out time in minutes were plotted against the actual departure time of each flight in minutes. Based on Chart 2, departures began a little under 400 minutes, which is approximately 6 a.m. Departures continued throughout Chart 2.
the day until about 1400 minutes or about 11 p.m. The peaks in the data represent departure banks. Because of American Airlines’ and United Airlines’ hub and spoke system at O’Hare, there are many departure and arrival banks throughout the day. Daniel (1995), in his study of Minneapolis-St. Paul International Airport, concluded that arrival rates peak less severely than departure rates because arrival queues are more costly than departure queues. Thus, if the same chart was graphed for arrivals, the peaks would likely be less noticeable. It is also important to point out that it appears there are more observations of taxi-out time than number of departing aircraft in the queue because flights that left at the same time experienced the same observed departure queue lengths but most likely had different taxi-out times. Thus, for each data point for number of departing aircraft in the queue, there is likely more than one flight observation with that value of number of departing aircraft.

The afternoon peaks are significantly taller than the morning peaks. The first afternoon peak occurs at about 1:30 p.m. followed by peaks at 4 p.m., 6 p.m., and 8 p.m. The taxi-out times increase concurrently with the number of departing aircraft in the queue during the peak and concurrently recede following the peak. Again, the data for September 22 shows regular traffic patterns stemming from the large amount of hub and spoke activity at O’Hare. Because the traffic patterns appear regular, this is also an indication of a good weather day.

By plotting the same graphs for September 15, 2004, the effects of the bad weather are easily observed. Chart 3 shows maximum taxi-out times which are more than twice as long as the maximum taxi-out times on September 22. On September 15 the maximum taxi-out time exceeds two hours; whereas, on September 22 the maximum taxi-out time was about 45 minutes. Similarly, the maximum number of departing aircraft in the queue reaches levels significantly higher than those on September 22. On September 15 the maximum number departing aircraft in
the queue reaches about 70 aircraft compared to about 45 departing aircraft in the queue on September 22.

Chart 3.

In Chart 3, there seem to be two sub-groups in the data with high levels of number of departing aircraft in the queue. There are some flights that had relatively low taxi-out times of only 20 minutes despite encountering over 60 departing aircraft in the queue, while there are also some flights that encountered over 60 departing aircraft in the queue yet waited for over two hours during taxi-out time. One theory to explain this phenomenon is that the planes which experienced relatively short taxi-out times yet observed long departure queue lengths were possibly able to bypass the queue as instructed by air traffic control and took off quickly. This could happen because that flight had already been significantly delayed at its gate due to a variety of reasons, so
perhaps it was given higher priority for take-off. However, the flights with longer taxi-out times most likely were forced to wait the length of the queue, explaining their long waits.

Chart 4 shows the relationship of number of departing aircraft in the queue and observed taxi-out times by actual departure time in minutes across the day for September 15. The end points are roughly the same as they were for September 22, with departures beginning roughly around 6 a.m. and ending around 11 p.m. For the first half of the day, traffic appears to be following a pattern similar to the traffic on September 22.

While things look relatively similar up until about 950 minutes (roughly 3:45 p.m.), the regular peak pattern observed during the afternoon and evening rush on September 22 is lost on September 15. According to Table 2, at 2:56 p.m. on September 15, winds shifted to coming out of the southwest and gusted to nearly 30 mph. It is no surprise that the erratic pattern begins shortly
after the change in the weather since southwest winds are detrimental to O’Hare and force air traffic controllers to use a less efficient set of runways. For the rest of the evening rush, the traffic lost its regular peaking pattern and doesn’t recover until very late in the evening.

**Observed traffic patterns from July 3, 2004, and July 24, 2004**

The same graphs used for the September days were also created for both July 3, 2004, and July 24, 2004. The comparison between the July pair with the September pair illuminates differences between a weekday and a weekend day, both in good and bad weather. Overall on the good weather days, comparing July 24 and September 22, there were 934 departing flights on July 24 and 1,021 departing flights on September 22, so there is less traffic on the weekends as

![Observed Taxi-out Times for Departing Aircraft on July 24, 2004](chart)
expected. Moreover, July is a busier travel month than September; in 2004, domestic enplanements at O’Hare in July totaled about 2.94 million in comparison to only about 2.56 million domestic enplanements in September.\textsuperscript{13} Thus, comparing a July weekend day with a September weekend day would most likely yield the July day as the busier day for O’Hare.

Chart 5 plots the observed taxi-out times for departing aircraft on July 24, and it shows many similarities to Chart 1 which plotted the same information for September 22. There is a flat portion of the graph for low values of departing aircraft in the queue; the taxi-out time ranges between about 10 minutes and about 25 minutes until there are about 15 departing aircraft in the queue and then after that point taxi-out times begin to increase. The maximum taxi-out time reaches levels similar to those of September 22. However, the maximum number of departing aircraft

\textsuperscript{13} Bureau of Transportation Statistics, www.bts.gov.
aircraft in the queue is a bit smaller on July 24 than on September 22, which coincides with expectations for a weekend day.

Chart 6 shows the traffic patterns for July 24, and just like September 22, it exhibits significant peaks of departure banks. Since it is a weekend, the peaks and their timing in Chart 6 vary from those of Chart 2 as would be expected. Traffic seems to be somewhat more evenly spread across the day. As the distinct departure banks resulting from hub and spoke activity indicated that September 22 was a good weather day, the case remains the same here. The peaks occur at regular intervals with the majority of the data following the pattern. Eyeballing the data seems to confirm that July 24, 2004, was a good day for flying weather-wise.

The observed taxi-out times on July 3, 2004, are shown in Chart 7. Similar to the September bad weather day, much higher levels of departing aircraft in the queue and taxi-out times are

Chart 7.
observed than on the respective good day; however, on July 3 the maximum levels of departing aircraft in the queue reaches nearly 80 departing aircraft and maximum taxi-out times top four hours, which is significantly worse than the levels observed on the bad weather day in September.

There are a few more outliers in Chart 7 than in some of the other charts, such as some of the observations with relatively low levels of departing aircraft in the queue (slightly under 40) but high taxi-out times of about three hours. These anomalies could have experienced non-O’Hare related congestion such as a ground hold for arrivals into their destinations or mechanical problems. Again, there seem to be two subsets of flights at high levels of departing aircraft in the queue like on September 15. Again the hypothesis is that some planes were allowed to bypass long queues while others were not, leading to the disparity seen in the data. The points on the graph where the taxi-out times reached four hours were spot-checked to confirm they were legitimately delayed because of O’Hare congestion. Those extreme observations are linked to flights that all departed their gates at the same time and were departing for many different destinations scattered across the country. Thus, it’s concluded that the observations at the extreme for July 3 are legitimate cases of O’Hare congestion.

The traffic pattern for July 3 begins in a similar manner as that of July 24 with peaks representing the morning departure banks as shown in Chart 8. However, at about 800 minutes (or about 1:30 p.m.), the traffic pattern becomes erratic just like that of September 15. From Table 3, it is confirmed that weather took a turn for the worse at that point in the day. At 2:56 p.m., wind gusts and light rain were reported, and with the previous report occurring at 1:56 p.m., the wind gusts and rain could have begun anytime during the 2 p.m. hour. While on September 15 it appeared the airport was able to recover by mid to late evening, the delays and longer taxi-out times appear to have lasted well into the evening on July 3, especially since thunderstorm activity was reported as late as 8:06 p.m.
8. SPEED-DENSITY RESULTS OF REGRESSION ANALYSIS

The regression tactics needed to create the congestion functions representing the speed-density relationship of taxi-out time at O’Hare are fairly simple. The number of departing aircraft in the queue is the only explanatory variable. Again, the taxi-out time was found to not be very correlated with the arrival rate, so the taxi-out delay experienced by departing aircraft will be estimated solely based on the length of the departure queue.

With the number of departing aircraft in the queue (D) as the foundation for regression analysis, several OLS regressions of different non-linear functional forms were run for September 22, 2004. The most difficult part of the regression analysis was determining the functional form that best represented the data. In addition to using the adjusted R-squared value to compare the merit of various functional forms, graphs of the predicted values from all functional forms were compared to determine which one best fit the observed shape of the data. The flat portion of taxi-out time observed in Charts 1, 3, 5, and 7 is the most difficult portion of the graph to model. Finding a model that truly “best fits” the data would require splitting the data into two sections—the flat section and the increasing section. However, doing so would require “guessing” the point at which taxi-out times start to increase, and Charts 1, 3, 5, and 7 prove that this would be difficult to do so accurately.

The adjusted R-squared values for all of the regressions of different functional forms were relatively low, as would be expected. The data has a rather large number of observations with significant variation in taxi-out time spread over relatively few levels of number of departing aircraft in the queue. Thus, because there is such variation in the data, the adjusted R-squared value will be low regardless of the functional form. Comparisons between adjusted R-squared values were made to determine the best of the attempts, but none of them produced “high” R-squared values because of the variation in the data.
The functional form of $\ln(T) = \alpha + \beta D^2$ seems to best represent the data where $T$ is the taxi-out time in minutes, $D$ is the number of departing aircraft in the queue, and $\alpha$ and $\beta$ are constants. Actual regression results of the functional form $\ln(T) = \alpha + \beta D^2$ can be found in Table 4. Charts 9-12 plot the actual and predicted taxi-out times for each of the four days.

Chart 9 shows the actual and predicted taxi-out times on September 22. The functional form appears to fit the flat portion of the data relatively well to about 15 other aircraft. The functional form also appears to match the relationship observed at higher levels of departing aircraft and taxi-out time. The actual and predicted taxi-out times for September 15 are shown on Chart 10, and the functional form also fits the flat portion of the data to about 15 departing aircraft in the queue. Moreover, the functional form continues to fit the data on September 15 well in high levels of
departing aircraft in the queue because it appears to pass approximately through the middle of the data. Table 4 on page 38 lists the actual regression output for each of the four days.

Chart 10.

As seen in Chart 13, which compares the different congestion functions for each of the days, the difference between the predicted values on September 15 and September 22 is rather small except for at high levels of departing aircraft in the queue where they significantly diverge. Thus, in essence, it can be interpreted that the taxi-out time and number of other aircraft observations more or less move along a similar curve on September 15 as opposed to following a different pattern. The main difference between a good day and a bad day is that on a bad day O’Hare experiences portions of the curve not normally encountered on a good weather day. However it does seem that for all low levels of departing aircraft in the queue (up to about 40 planes in the queue), the predicted taxi-out time on September 15 is higher than that on September 22. Thus, for levels of
departing aircraft which were experienced on both the bad weather day and the good weather day, the predicted taxi-out time for the bad weather day is higher at every level of departing aircraft in the queue than the predicted taxi-out time for the good weather day. This makes sense because if the air traffic controllers have to use a less-efficient set of runways due to the southwest winds experienced on that day, the predicted taxi-out times should be slightly higher on average for each level of departing aircraft in the queue.

Charts 11 and 12 plot the actual and predicted values for July 24 and July 3, respectively. The congestion function for July 24 does not seem to have as clear of a division between the flat portion of the graph and the increasing portion; however the raw data exhibits this same observation, so it seems as though the estimated congestion function fits the data relatively well.

Chart 11.

Actual vs. Predicted Taxi-out Times for July 24, 2004
From Chart 13, it appears that the congestion function for July 24 is similar to the congestion function for September 22, so that the good weather days follow the same pattern. This makes sense that without other causes for delay, such as weather, that the inherent relationship between the number of departing aircraft in the queue and taxi-out time should be the same no matter if it is on a weekend or not.

Chart 12 shows the predicted taxi-out times for July 3, 2004. The functional form of \( \ln(T) = \alpha + \beta D^2 \) seems to fit the data very well. It again achieves the flat portion of the graph for low levels of number of departing aircraft in the queue. Then at high levels of number of departing aircraft in the queue, it nicely goes through the middle of the data.

Chart 12.
Just like as experienced for the September pair, the predicted taxi-out times on July 3, the bad weather day, are higher than those for July 24, the good weather day, up to about 50 departing aircraft in the queue, and such levels of departing aircraft in the queue were never achieved on July 3. Thus, for levels of departing aircraft in the queue experienced on both days, the predicted taxi-out times were higher for every level of number of departing aircraft in the queue on July 3 than on July 24. Again, this makes intuitive sense since on the bad weather day, the air traffic controllers have to use a less-efficient set of runways so that taxi-out times will be higher because they cannot accommodate as much traffic as quickly. Overall, the congestion functions for the July pair are even more similar than the congestion functions of the September pair over the whole range in Chart 13, which again shows that a bad weather day follows roughly the same pattern as a good weather day. Table 4 explicitly shows that the congestion functions for the July pair are more similar than those for the September pair because the variation in the coefficient on the explanatory variable and the constant between the two days is smaller for the July pair than the September pair. For instance, the difference in the coefficient on the explanatory variable between the two Saturdays in July is 0.00012; whereas, for the two Wednesdays in September, the difference in the coefficient on the explanatory variable is twice as high, 0.00024.

In summary, both pairs resulted in an interesting conclusion that the congestion function is very similar on the good weather day as on the bad weather day. The main difference is that on the bad weather day the extreme ends of the curve for high levels of departing aircraft in the queue are experienced; whereas, on the good weather day, O’Hare never reaches the extremely high levels of departing aircraft in the queue as seen in bad weather. Moreover for levels of departing aircraft in the queue shared by both the good and bad weather day of the pair, the bad weather day congestion function predicted higher taxi-out times, which makes sense since air traffic controllers are using a less efficient set of runways on the bad weather day.
A closer investigation of Table 4 shows that the bad weather day of each pair had a higher adjusted R-squared value. Perhaps this is due to roughly the same number of observations being spread more thinly over a larger range of number of departing aircraft in the queue, so regression analysis can by default explain more of the variation of the taxi-out time because at each level of departing aircraft in the queue there is probably less variation in taxi-out time.

Table 4.

<table>
<thead>
<tr>
<th>Date:</th>
<th>3-Jul</th>
<th>24-Jul</th>
<th>15-Sep</th>
<th>22-Sep</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_departing_sq</td>
<td>0.00034</td>
<td>0.00046</td>
<td>0.00027</td>
<td>0.00051</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.00001</td>
<td>0.00004</td>
<td>0.00001</td>
<td>0.00003</td>
</tr>
<tr>
<td>Constant</td>
<td>2.89889</td>
<td>2.61264</td>
<td>2.90684</td>
<td>2.49827</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.03421</td>
<td>0.02239</td>
<td>0.02374</td>
<td>0.01771</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.3489</td>
<td>0.1073</td>
<td>0.2779</td>
<td>0.2233</td>
</tr>
<tr>
<td>Observations</td>
<td>856</td>
<td>935</td>
<td>990</td>
<td>1021</td>
</tr>
</tbody>
</table>

Chart 13.

Predicted Taxi-out Times Using Functional Form \( \ln(T)=\alpha+\beta D^2 \)
9. CONGESTION PRICING RESULTS

As described in Section 3, the relationship between speed and density, or rather, taxi-out time and number of departing aircraft in the queue, can be used as the foundation of the average variable cost curve which is necessary for determining congestion pricing fees to be charged to departing aircraft for the congestion they impose on other departing aircraft. September 22 with its good weather and well-fitting taxi-out time curve is an ideal candidate for congestion pricing. September 22 represents a moderate weekday with typical levels of congestion that are normally seen at O’Hare. It is important to emphasize that the derived congestion pricing results are those for a static model and are intended for illustration purposes only. This model does not determine the dynamic movement of fees as airlines and passengers shift their demand from peak periods to off-peak periods, nor does it determine how airlines and passengers will react to congestion pricing at O’Hare.

A linear transformation of the congestion function from Table 4 for September 22 derives the average variable cost (AVC) curve which will be used to determine congestion pricing for a good weather day at O’Hare. To transform the taxi-out time to cost in dollars, the total cost per minute of taxi-out time must be approximated. The costs incurred while taxiing out are airplane operating costs—fuel, crew, and airplane utilization—and passenger time costs since congestion causes it to take longer for passengers to reach their desired location. From a report by the FAA, critical values for the value of passenger time per hour and aircraft total operating cost per hour were used. The FAA’s report estimates the value of passenger time for all travel purposes at $26.70 per hour and the aircraft total operating costs including fixed and variable costs at $3,285 per hour, both in 2002 dollars. These values were adjusted for inflation to 2004 dollars using inflation rates from the Minneapolis Federal Reserve Bank for 2002-2003 and 2003-2004 of 2.3% and 2.7%

14 Federal Aviation Administration, http://www.api.faa.gov/economic/EXECSUMM.PDF.
respectively. Also, the average number of passengers per plane was calculated using values from the Bureau of Transportation Statistics for total September 2004 enplanements and total departing flights to achieve an average of about 86 passengers per plane. From these values, the total cost per minute of taxi-out time is $97.84 per minute.

Functions for the demand of travel at several levels of departing aircraft in the queue (5, 10, 30, 40, and the overall September 22, 2004, average of 20.7 departing aircraft in the queue) were derived using levels of varying levels of elasticity: -1.5, -1.25, and -1.0. Brons, et al. (2002) compared various studies of passenger price elasticity in the aviation sector and determined an overall mean price elasticity of -1.146. It’s important to note that the mean elasticity of -1.146 resulting from Brons, et al. was used only as a guide in selecting levels of elasticity to be used in sensitivity testing because the elasticity estimates studied by Brons, et al. are not exactly the same estimates as those necessary for the demand calculations. The elasticity estimates studied by Brons, et al. were for price elasticity estimates for passenger demand. The demand of interest in the calculation of congestion pricing fees is the demand for aircraft departures relative to the generalized costs of travel, including passenger time costs and aircraft operating costs. There is likely a proportional relationship between passenger demand and the demand for aircraft departures, which justifies using the Brons, et al. results as a guide. Lastly, it needs to be emphasized that the varying levels of elasticity used in determining congestion pricing schemes are not meant to be taken as reliable values. The congestion fees derived are simply an illustration of the use of congestion fees. Chart 14 shows the AVC and MC curves for September 22, 2004, along with the demand curves using an elasticity of -1.25.

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As described in Section 4, the congestion fee is calculated as the vertical difference between the MC curve at the point it intersects the demand curve to the corresponding value on the AVC curve, which represents the external costs that an additional departing aircraft is imposing on all others when it joins the queue. The derived congestion fees are shown in Table 5. For each level of departing aircraft in the queue, a corresponding time of day is included. For example, while the level of 30 other aircraft occurs at several points of the day, the time of 6:00 p.m. was selected for illustration purposes.

Chart 14.

![Chart 14. Average and Marginal Cost for September 22, 2004](image)

In Table 5, the column entitled “Atomistic model congestion fee” shows the total external cost that an additional departing plane imposes on the other departing aircraft by adding itself to the queue. Brueckner (2002) clarifies an interesting and important distinction between congestion pricing for airports compared to road congestion. In road congestion, Brueckner emphasizes that

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users are “atomistic” because they are small relative to the total traffic volume and they do not coordinate their travel decisions. However, in the scenario of an airport, the airplanes are non-atomistic because even the busiest airports are only served by a few dozen carriers with many being dominated by one or two airlines. For example, at O’Hare, United and American each comprise nearly one-half of the traffic so the airport essentially is a duopoly. In contrast to the road model where one driver would not consider the congestion costs he or she is imposing on others, it is likely that United considers the congestion costs an additional United flight would cause on all other United flights.

Thus, Brueckner shows how the results of the road-pricing literature should be modified for applications to an airport where the economic agents causing congestion have market power. Brueckner’s analysis shows that when an airport is dominated by a monopolist, congestion is fully internalized, which indicates there is no role for congestion pricing in a monopoly situation. However, in a Cournot oligopoly situation, carriers are shown to only internalize the congestion their flights impose on their other flights and not the flights of other airlines. Therefore, Brueckner asserts that a congestion toll charging for the un-internalized portion of congestion costs could improve the distribution of flights and alleviate congestion.

To find the un-internalized portion of congestion costs for each airline, it was necessary to determine each airline’s share of the departure queue at the times of day that correspond with the studied levels of departure queue length. Therefore, for 6:00 p.m., the number of planes in the departure queue was counted by airline (including regional carriers as flights of their contracted major airline, such as counting a Skywest flight as a United flight). Thus, exact departure queue shares were determined for 5:55 a.m., 6:50 a.m., 10:30 a.m., 6:00 p.m., and 8:00 p.m. instead of just taking an overall daily average.
When an airline is non-atomistic, it is not considering the congestion it imposes on others. Thus, Airline X should be charged a congestion fee such that $fe_{x} = (1 - share_{x}) \times \text{atomistic congestion fee}$. The airline has already taken into account the external cost ($share_{x} \times \text{atomistic congestion fee}$) when determining its schedule because that is the external cost that an additional Airline X flight would cause on the other flights of Airline X. Northwest Airlines’ and United Airlines’ share of the departure queue at each studied time of day are shown in Table 5. Comparing Northwest to United is interesting because Northwest represents a carrier with moderate operation at O’Hare compared to United which controls nearly 50% of O’Hare operations. At the times of day included in the table, Northwest Airlines never had more than two planes in the departure queue at one time, and this was characteristic of other major carriers like Delta and Continental. A smaller

Table 5.

**CONGESTION FEES FOR VARIOUS DEMAND ELASTICITY ESTIMATES**

<table>
<thead>
<tr>
<th>Number of departing aircraft in queue</th>
<th>Exemplary time of day</th>
<th>Elasticity of demand estimate</th>
<th>Slope of demand curve</th>
<th>Atomistic model (Alaska Airlines) congestion fee ($\tau$)</th>
<th>Northwest Airlines' share of relevant departure queue</th>
<th>Northwest Airlines' congestion fee</th>
<th>United Airlines' share of relevant departure queue</th>
<th>United Airlines' congestion fee</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>5:55 a.m.</td>
<td>-1.5</td>
<td>-47.65</td>
<td>$25.06$</td>
<td>$20.05$</td>
<td>$20.05$</td>
<td>$20.05$</td>
<td>$20.05$</td>
</tr>
<tr>
<td>10</td>
<td>6:50 a.m.</td>
<td>-1.5</td>
<td>-47.65</td>
<td>$90.13$</td>
<td>$81.94$</td>
<td>$72.77$</td>
<td>$24.58$</td>
<td>$371.81$</td>
</tr>
<tr>
<td>30</td>
<td>6:00 p.m.</td>
<td>-1.5</td>
<td>-47.65</td>
<td>$743.62$</td>
<td>$694.04$</td>
<td>$50.00$</td>
<td>$317.11$</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>8:00 p.m.</td>
<td>-1.5</td>
<td>-47.65</td>
<td>$1,452.09$</td>
<td>$1,415.79$</td>
<td>$50.00$</td>
<td>$726.04$</td>
<td></td>
</tr>
<tr>
<td><strong>Average (20.7)</strong></td>
<td>10:30 a.m.</td>
<td>-1.5</td>
<td>-47.65</td>
<td>$350.32$</td>
<td>$329.72$</td>
<td>$35.35$</td>
<td>$226.68$</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>5:55 a.m.</td>
<td>-1.25</td>
<td>-57.18</td>
<td>$25.73$</td>
<td>$20.59$</td>
<td>$20.00$</td>
<td>$20.00$</td>
<td>$20.00$</td>
</tr>
<tr>
<td>10</td>
<td>6:50 a.m.</td>
<td>-1.25</td>
<td>-57.18</td>
<td>$93.70$</td>
<td>$85.18$</td>
<td>$72.77$</td>
<td>$25.55$</td>
<td>$390.28$</td>
</tr>
<tr>
<td>30</td>
<td>6:00 p.m.</td>
<td>-1.25</td>
<td>-57.18</td>
<td>$780.56$</td>
<td>$728.52$</td>
<td>$50.00$</td>
<td>$378.40$</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>8:00 p.m.</td>
<td>-1.25</td>
<td>-57.18</td>
<td>$1,516.81$</td>
<td>$1,478.89$</td>
<td>$50.00$</td>
<td>$758.40$</td>
<td></td>
</tr>
<tr>
<td><strong>Average (20.7)</strong></td>
<td>10:30 a.m.</td>
<td>-1.25</td>
<td>-57.18</td>
<td>$367.45$</td>
<td>$345.83$</td>
<td>$35.35$</td>
<td>$237.76$</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>5:55 a.m.</td>
<td>-1</td>
<td>-71.47</td>
<td>$26.53$</td>
<td>$21.23$</td>
<td>$20.00$</td>
<td>$20.00$</td>
<td>$20.00$</td>
</tr>
<tr>
<td>10</td>
<td>6:50 a.m.</td>
<td>-1</td>
<td>-71.47</td>
<td>$98.03$</td>
<td>$89.12$</td>
<td>$72.77$</td>
<td>$26.73$</td>
<td>$414.92$</td>
</tr>
<tr>
<td>30</td>
<td>6:00 p.m.</td>
<td>-1</td>
<td>-71.47</td>
<td>$829.83$</td>
<td>$774.51$</td>
<td>$50.00$</td>
<td>$414.92$</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>8:00 p.m.</td>
<td>-1</td>
<td>-71.47</td>
<td>$1,605.89$</td>
<td>$1,565.74$</td>
<td>$50.00$</td>
<td>$802.94$</td>
<td></td>
</tr>
<tr>
<td><strong>Average (20.7)</strong></td>
<td>10:30 a.m.</td>
<td>-1</td>
<td>-71.47</td>
<td>$389.89$</td>
<td>$366.96$</td>
<td>$35.35$</td>
<td>$252.28$</td>
<td></td>
</tr>
</tbody>
</table>

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airline, like Alaska Airlines or America West, that has very few operations at O’Hare, would essentially have to pay the full atomistic congestion fee since their share of the departure queue is usually zero at the selected times of day. The results of congestion pricing yield some interesting conclusions. At demand elasticity of -1.25, the atomistic congestion fees range from $25.73 with five departing aircraft in the queue to $1516.81 with 40 departing aircraft in the queue. Moreover, it’s interesting that the congestion fees do not vary much for varying levels of elasticity. For elasticity estimates of -1.0 and -1.5, the congestion fee varies by only $1.47 with five departing aircraft in the queue and varies by $153.80 with 70 departing aircraft in the queue, which is a percentage difference of only 5.9% and 10.6% respectively.

These fees do not represent the exact fee that would be charged to an airline for its use of O’Hare. Currently there are, of course, landing fees that are intended to cover the operating costs of the airport. Airports currently charge only a landing fee, but that fee covers the costs related to both landing and taking off from that airport, so the charges are just lumped together for convenience sake. The congestion fees discussed could potentially replace or partially replace landing fees, which at U.S. airports are currently assigned by a plane’s weight. However, a similar analysis would have to be performed for arrivals to determine the congestion costs that arriving aircraft impose on other arriving aircraft and the appropriate congestion fees to alleviate arrival congestion and reduce arrival delays. If the collected congestion fees surpass the revenue necessary to operate the airport, the congestion fees could be reinvested into airport renovations like the O’Hare Expansion Plan. Using congestion fees to finance airport renovations might reach a social optimum rather than using taxation to fund airport projects. Furthermore, it’s important to note that the O’Hare Expansion Plan will eventually lead to a decrease in congestion and a subsequent decrease in congestion fees, which highlights that the congestion fees will forever be changing and subject to current congestion levels.
To compare the congestion fees that have been calculated in this paper with the current landing fees, signatory carriers, which are carriers that have signed contracts related to gates, etc., with O’Hare, paid $2.591 per 1,000 lbs of landing weight in 2004. For example, a Boeing 757-200 has a maximum design landing weight of about 200,000 lbs. Thus, if United Airlines was landing a Boeing 757-200, its landing fee would be no more than $518.20. In comparison, a Canadair CRJ200 has a maximum design landing weight of about 47,000 lbs. Canadair CRJ200s are commonly used by the regional contract carriers like Skywest, which is a regional carrier of United. The maximum landing fee for the Canadair CRJ200 would be only $121.78. While a Canadair jet would impose the same congestion costs on other aircraft as the Boeing jet, the Canadair jet currently pays a landing fee that is less than one-fourth the fee of the Boeing jet. Moreover, the Canadair jet holds significantly fewer passengers than the Boeing jet. Thus, it is likely that if congestion fees were implemented, the aircraft mix would change resulting in larger aircraft being more prevalent at peak times of day and smaller aircraft shifting towards the off-peak.

Assuming the airlines would pass the burden of a congestion fee on to passengers in the form of higher airfares, dividing the highest observed departure congestion fee, $1,605.89 at 40 departing aircraft in the queue and elasticity of -1.0, by the average number of passengers per plane (86) would equate to roughly an $18.67 average fare increase on the portion of a round-trip originating at O’Hare. However, in reality, the average fare increase would most likely be less because the aircraft size is likely to be larger at peak times along with a higher average load ratio and hence the average number of passengers is likely to be higher as well. Thus, the same departure congestion fee of $1,605.89 would most likely be spread over more people generating a lower per passenger charge.

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Another debatable aspect of the congestion fees derived for United Airlines and Northwest Airlines in Table 5 is that those fees assume that airlines internalize their own passengers’ time costs. This assumption depends on an equilibrium model as Brueckner (2002) specified, but perhaps this model is not in equilibrium. If airlines do not internalize its passengers’ time costs, the congestion fees would need to be higher because in effect the average variable cost curve would be lower and airlines would have to be charged for the external cost of passenger time.
10. CONCLUSION

This paper has analyzed the effect of congestion on flight delays experienced by departing aircraft at Chicago O’Hare International Airport through estimating a congestion function and determining illustrative departure congestion fees that could alleviate the problem. The congestion tolls offer a more long-term solution than the micro-management techniques employed by the FAA to manage O’Hare congestion. At the same time, the congestion tolls are much easier and cheaper to implement than the construction of a new airport or rebuilding of O’Hare, which are alternative solutions to the congestion problem.

In analyzing the two pairs of days—September 15, 2004, and September 22, 2004, and July 3, 2004, and July 24, 2004—congestion functions were estimated to demonstrate the relationship between the number of departing aircraft in the queue and the taxi-out time for a departing flight. For the two days chosen in September, the good weather day, September 22, and the bad weather day, September 15, the selected functional form of $\ln(T) = \alpha + \beta D^2$ seems to fit the data very well, and in fact, the two days seem to follow a similar curve. The two Saturdays in July exhibited this same similarity for the functional form of $\ln(T) = \alpha + \beta D^2$, and in fact, as demonstrated by the smaller difference between the coefficient on the explanatory variable and the smaller difference in the constant between the good and bad weather days, the July pair seems to follow the same congestion function even more closely than the September pair. Furthermore, the congestion functions for July 24 and September 22, the good weather days, were similar which makes sense that there should be no difference between a weekend day and a weekday with the absence of bad weather. The functional form of $\ln(T) = \alpha + \beta D^2$ was the best choice for the data because it achieved the highest R-squared value compared to the other alternatives, and it achieved the flat portion of the curve for low levels of departing aircraft in the queue.
From the congestion function for September 22, 2004, an average variable cost curve and a marginal cost curve for the taxi-out time for departing aircraft were derived. Then, demand curves for flight operations were approximated using various levels of elasticity. The resulting congestion pricing fees varied only slightly for the varying elasticity levels, which is an interesting finding. Thus, it can be concluded that even without an accurate estimation of the elasticity for the demand for flight operations, calculated congestion fees would likely be relatively close to the socially optimal fees. Acknowledging Brueckner’s conclusion that airlines already internalize the congestion an additional flight imposes on the other flights it operates, departure congestion fees were illustrated for United Airlines and Northwest Airlines. Since Northwest had a lower flight share of the departure queue, its congestion tolls are much higher than United, who has internalized much of the congestion already since it represents about half of the operations in the departure queue.

The imposition of congestion pricing would improve the congestion problem at O’Hare by inducing some flights to shift to the off-peak period. Congestion pricing would also cause airplane size and load ratios to increase since airlines would find it more optimal to use larger and fuller planes during peak times because of the higher total cost of landing and taking off due to the congestion toll. While this model is limited by its static nature, this paper provides an illustration of the effect of congestion on flight delays at O’Hare and calculates congestion pricing fees that could help alleviate the problem. To make the results more reliable, more days would have to be analyzed so that congestion pricing fees could be derived using an average of many good weather days so that any anomalies would be moderated. Also, the critical values for passenger values of time and aircraft operating costs would need to be verified, while the demand curve for aircraft operations should be verified as well by obtaining more reliable demand elasticity estimates.
Another key portion of analysis that this paper could not complete is the determination of congestion pricing fees for arriving aircraft based on the congestion that arriving aircraft impose on other arriving aircraft. Since the data from the Bureau of Transportation Statistics does not contain information on an arriving aircraft prior to its arrival at its destination, specifically the time it might spend in a holding pattern in the air waiting for its turn to land, the analysis on arriving aircraft cannot be completed. Thus, the analysis completed here has determined illustrative congestion fees for departing aircraft, and a similar analysis would have to be completed for arriving aircraft to determine arrival congestion fees.

In summary, delays at Chicago O’Hare International Airport are not only annoying to travelers at O’Hare, but they are crippling the national aviation system. Even moderately bad weather conditions can wreak havoc on O’Hare because its overstressed schedule cannot sustain any anomaly. Thus, since O’Hare is one of the busiest airports in the country and the hub for two major airlines, delays at O’Hare have repercussions throughout the entire system. Solutions need to be sought, and congestion pricing offers an option to the congestion problem that can be easily and cheaply implemented compared to more costly and time-consuming options like the building of new airports or improvements in air traffic control technology.
11. REFERENCES


Levin, Alan. “Clogs at O’Hare delay passengers everywhere.” USA Today 4 Aug. 2004: 1A.


