Service Competition in the Airline Industry: Schedule Robustness and Market Structure

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Abstract

Robustness of aircraft schedules is essential for an airline to improve on-time performance and accomplish high levels of consumer satisfaction. This paper addresses the question how airlines adjust their schedule robustness when market structure changes. To answer this question, the paper first recreates each flight's ground buffer time using historical flight schedules and uses it as a measure for schedule robustness. Examining the relationship between ground buffers and market structure shows that there exists service quality competition in the airline market. Empirical estimations reveal that carriers adopt more robust flight schedules when airport concentration at the origin airport decreases, or when route competition increases. However, such an effect is slightly reduced for hub originating flights, as competitors trade off robust schedules for shorter layover times at the hubs when competition heats up.

Key word: Flight Delays; Service Competition; Airline Industry
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1 Introduction

Starting from as early as 1987, air traffic delays and their impact on consumers have become a significant issue in the airline industry. Over the past 20 years, on-time arrival performance (percentage of flights arriving at the destination gate within 15 min of scheduled arrival) has fluctuated between 65% and 90% on a seasonal basis.[1] The successful implementation of solutions to flight delays depends on understanding the airline's scheduling decisions, given the impact of these decisions on delays. While a large literature studies the factors that affect airlines' scheduling decisions, little attention has been paid to the relationship between market structure and airlines' schedule robustness (how well can a schedule cope with a delay to a particular aircraft). To remedy this issue, the present paper attempts to answer the question of how airline decisions on schedule robustness are affected by market structure. The contribution of this paper is to measure a flight's "ground buffer", which equals the excess turnaround time over the minimum possible time, and to relate it to measures of competition. The results show how competition affects the "tightness" of airline scheduling, and thus the schedule's robustness to disruptions. More generally, this paper provides evidence on product-quality competition in the airline industry, asking whether carriers improve the robustness of their schedules when markets become more competitive.

High costs arise from delays for airlines and passengers. For airlines, delays increase the costs of staffing, fuel, maintenance and potential rebooking (Peterson et al. 2013). Besides these direct costs, delays also have a impact on airlines' revenue, as inferior on-time performance may lead passengers to switch to airlines with better on-time performance (Cook, Tanner, and Lawes 2012). For passengers, delays cause unanticipated additional travel time, hence creating opportunity costs both for leisure and business activities (Baumgarten et al., 2014). In addition, delays also

[1]The terrorist attack of 9-11 and the subsequent crisis of SARS alleviated the flight delay concerns for a short period after 2001, but the issue returned in 2005.

induce a welfare loss incurred by passengers who avoid air travel. Using econometric and simulation models, Ball et al. (2010) estimate the costs of delays borne by airlines in 2007 due to above factors to be \$8.3 billion, and the total costs of delay borne by passengers to be \$18.9 billion. Moreover, travel delays are also estimated to reduce gross domestic product (GDP) by a further \$4 billion.

To identify the cause of delays, airlines are required by DOT to report the causes of flight delays using the following five tracking codes: 1) carrier delays: airline-specific factors including mechanical failures, limited labor resources, gate/ramp congestion, etc. 2) extreme weather 3) National Airspace System (NAS): delays and cancellations attributable to the national aviation system arising from a broad set of conditions, such as non-extreme weather conditions, airport operations, heavy traffic volume, and air traffic control 4) security: delays caused by bomb threats, weapon issues and excessive lines at security screening area, etc. 5) late arriving aircraft. It should be noted that airport congestion caused by limited airport capacity is one of the major contributors to NAS delays (i.e. aircraft queuing for runways).

Figure 1 summarizes the total number of delay minutes associated with each cause in the period Aug 2004 - May 2005. It shows that carrier-related delays cause 28% of overall flight delays, and NAS related delays are responsible for around 31% of delays. It should be noted that the most important source of delays is aircraft late arrivals, which account for 34% of total delays. Moreover, as Figure 2 shows, this percentage has been increasing over the years. Since the year 2004, late arriving aircraft delays have become the #1 cause of delays. Taking a closer look at the cause of delays through a single day, Figure 3 shows that late aircraft delays snowball through the day as the follow-on impact of carrier, weather and airspace delays is felt on future flight departures using the impacted aircraft (Jenkins et al. 2012).

Airport congestion is a major cause of NAS delays and may be the original cause of late arriving aircraft delays (i.e. aircraft encountered runway congestion

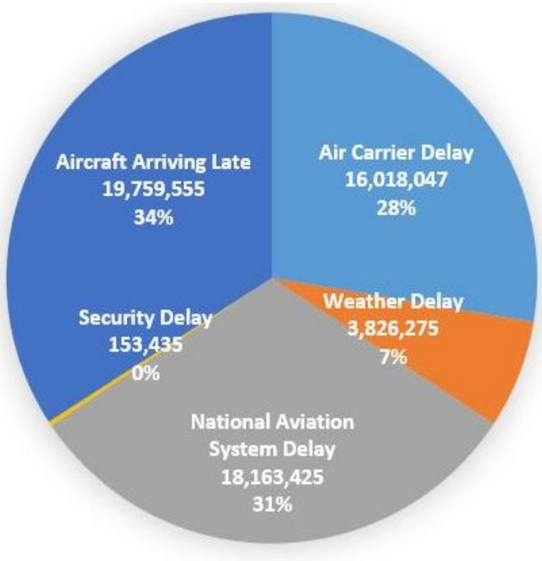

Figure 1: Minutes of flight delays and percentage of total delays for different causes of delay. Aug 2004-May 2005

during their previous flight segment), and a large literature focuses on mitigating such congestion, mainly through investigating the relationships between on-time performance, airlines' bank structure, airport hubbing, and airports' competitive structure (Mazzeo and Michael, 2003; Rupp et al. 2006). Among these studies, the existence of internalization of airport congestion has been shown to have important public policy implications for the magnitude of airport congestion tolls. Internalization by airlines (where carriers take account of self-imposed congestion) implies that flight operations in airports where one airline operates most of the flights will be organized to generate less congestion on the runways and gates than in airports where multiple airlines operate and each airline operates a small share of the flights, limiting the extent of internalization (Brueckner, 2002; Brueckner and Pels, 2005; Pels and Verhoef, 2004; Zhang and Zhang, 2006; Basso and Zhang, 2007; Brueckner, 2009).

Mixed results are found by the empirical literature on whether internalization actually occurs. While Brueckner (2002) and Mayer and Sinai (2003) offer some empirical support for internalization, Rupp (2009), Daniel (1995) and Daniel & Harback (2008) find no support for internalizing behavior. Trying to solve the puz-

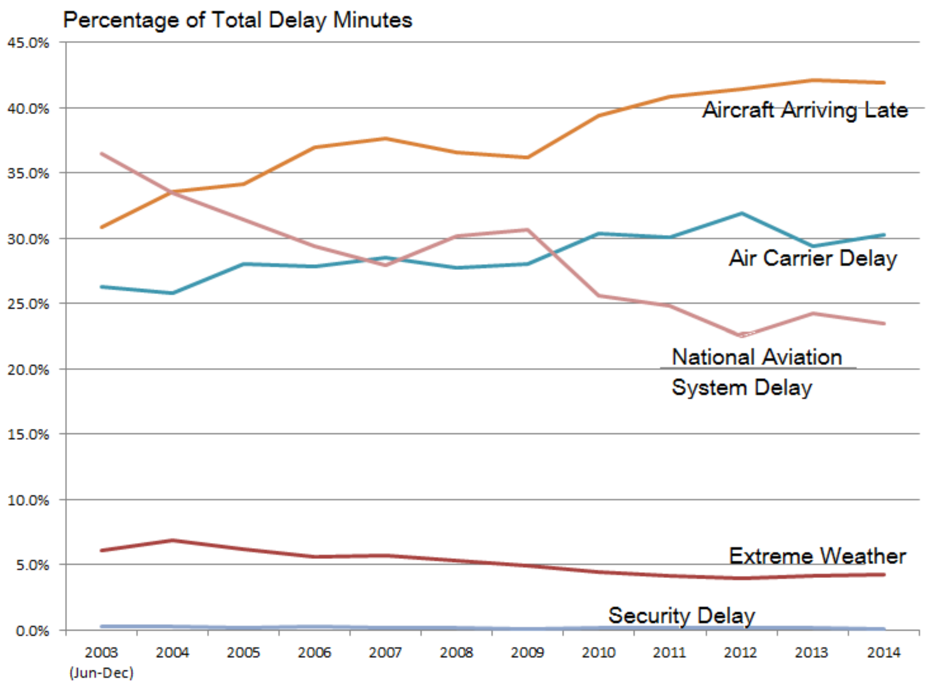

Figure 2: Percentage of total delay minutes by cause, from 2003 to 2014.
SOURCE: Bureau of Transportation Statistics

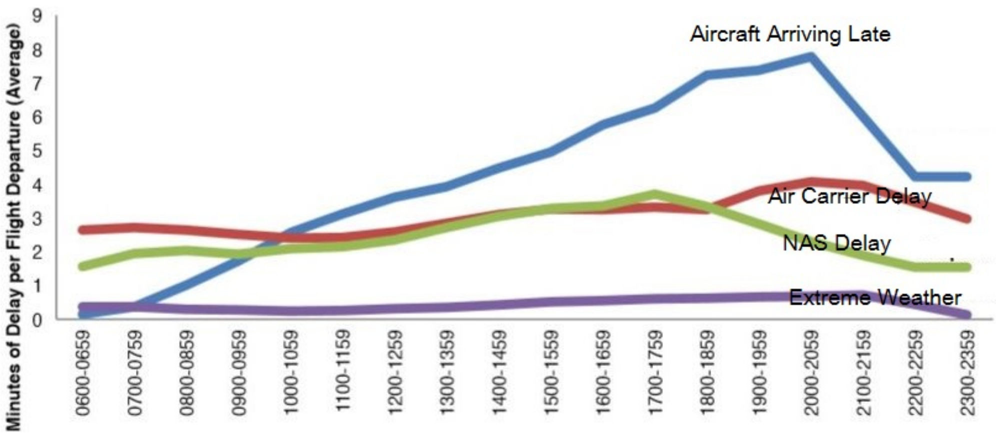

Figure 3: Average delay per scheduled flight, by cause and hour of day.
SOURCE: "The State of US Aviation: Comprehensive Analysis of Airline Schedules and Airport Delays" by Jenkins et al. 2012, *American Aviation Institute*

zle, further discussion has delved deeper into understanding the interaction between competition and airlines' scheduling decisions and their impact on the congestion. Ater (2012) studies the relationship between bank length, airport concentration and delays, and finds that banks are stretched longer maybe for better on-time performance when less competition is present in hub airports, providing some evidence consistent with internalizing behavior.

However, one should also realize that, besides reducing airport congestion and increasing airport capacity, on-time performance can also be improved through mitigating the "snowball effect" of late aircraft delays by loosening aircraft rotation schedules, allowing more "buffer" time between flights. Therefore, it is crucial to understand how such scheduling decisions are made and how they depend on the competitive structure of the market.

Combining elements of previous approaches, this paper explores this issue, offering an innovative addition to the theoretical and empirical literature on the cause of delays and the effect of market structure on delays. While empirical literature on the subject mainly focuses on the relationship between market structure and airport congestion-related delays (Daniel (1995) and Ater (2012)), this paper explores how market structure affects airlines' scheduling-related delays. In particular, this paper hypothesizes airlines would respond to competition by adjusting the operational robustness of their schedules, which is captured by the buffer time built into an aircraft's turnaround time. This buffer time equals the extra time beyond the minimum time required for loading and unloading that is incorporated in the turnaround interval. The connection is explored by relating the length of buffer time (in minutes) to the extent of route competition (measured by the number of carriers serving the same route) and airport concentration (measured by the Herfindahl-Hirschman index (HHI), which is computed from airline flight shares at the airport).

Theoretically, buffer time should be added until the resulting marginal cost equals the marginal benefit from fewer flight delays caused by foreseeable factors. However, such marginal costs and marginal benefits are also subject to change under a different competitive environment. Following this intuition and to motivate the empirical analysis, section 2 provides a simple theoretical model with price and service-level competition (each firm simultaneously chooses a service level and a price level). Such "attraction models" (Bernstein and Fedegruen (2004)) are commonly used in the marketing and operations research literature. For example, Calton (1989) and Calton and Perloff (1999) argue that demand functions should be specified as a function of prices and customer service levels, which they quantify by the customer's waiting time. Banker et al. (1998) and Tsay and Agrawal (2000) characterize the equilibrium behavior of oligopolies with a fixed number of firms competing simultaneously with their price and a "quality" or service instrument. Similar models are also used to explain flight frequency in the airline industry (Brueckner and Flores-Fillol (2006), Brueckner and Zhang (2010), Brueckner (2010), and Brueckner and Luo (2012)).

The model points out that airlines face a trade-off between benefits arising from increased operational robustness through adding buffers into flight schedules and the costs due to a decrease in fleet utilization. Moreover, the model yields an unique Nash equilibrium and provide comparative-static properties of the equilibrium. A large empirical literature studies such a choice of product quality using structural models (Berry (1994), Berry, Levinsohn and Pakes (1995)), yielding estimates of taste and cost parameters, which are then used to simulate the effects of mergers on product quality or variety. By contrast, the goal of this paper is to measure the direction and strength of market-structure effects on airline scheduling decisions instead of identifying the underlying parameters of the utility and production parameters.

Guided by the theoretical model in section 2, the first step of the empirical analysis is to use a Tobit model to verify that an increase in the length of the ground buffer indeed reduces departure and arrival delays (the negative empirical relationship is shown in Figure 4) after controlling for other factors that may contribute to delays (including schedule-related factors like airport congestion and non-schedule related factors like weather). The measure of ground buffer is derived using flight schedules, following a detailed procedure described in section 3.2. The estimation reveals that around 0.35 minutes of departure delay can be eliminated by 1 extra minute of buffer, while the effect of buffers on arrival delays is around 0.23 minutes.

The second step of the empirical analysis examines how buffer length is affected by market structure, which is quantified at the route and airport level using the airport concentration level and route competition. While route competition is used to account for the direct effects of competition driven by the non-stop passengers on the route, it should be noted that airlines operating hub-and-spoke networks will inevitably compete on one-stop routes that originate at the airport, flying passengers to the same destinations via different hubs. Hence effects of competition at such a level is captured by the airport concentration at the origin airport, as the concentration levels reflect the choice sets of airlines for the originating passengers.

Controlling for route-specific effects, the baseline estimations reveal a significant positive effect of competition on buffer time, so that decreasing the market concentration at the origin airport, or increasing the number of competitors serving a route, increases the operational robustness of flight schedules, improving on-time performance. As an extension of the baseline estimations, the paper also explores whether this positive relationship between competition and buffer time is heterogeneous across routes playing different roles in a hub-and-spoke network. In such a network, a longer buffer time at hub airports not only improves the operational robustness of the schedule, but it also serves as a tool to synchronize the arrival and departure banks (waves of flights departing or arriving at the hubs). Moreover, longer buffer time at the hubs also prolongs the layover time for connecting passengers. With this additional trade-off between achieving economies of density and lower demand (due to the longer layovers), the effect of market structure on buffer decisions for hub originating flights is expected to differ from non-hub originating flights. Interacting the market structure measures with an indicator of an airline-hub originating flight, extended estimation in section 4 reveals that the effect of competition on operational robustness is weaker for the hub originating flights.

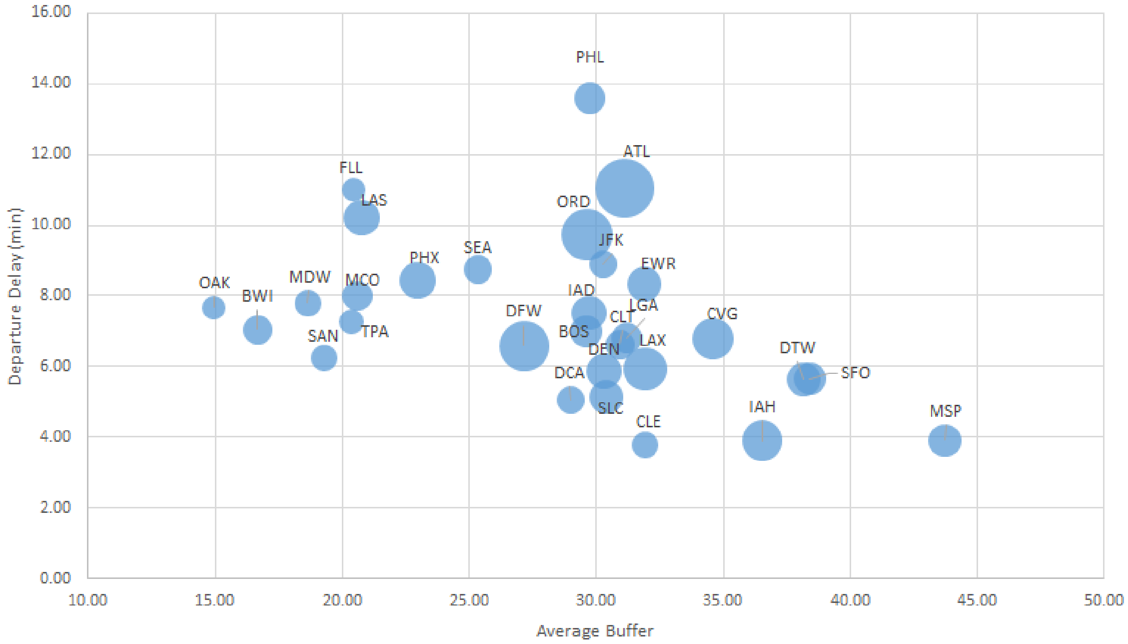

Figure 4: The relationship between ground buffer time and departure delay for airports with at least 1 percent of flights, calculated from flights departed during Aug 2004 - May 2005. This figure displays a negative empirical relationship between ground buffer length and departure delay experienced by flights.The bubble size denotes the percentage of total flights handled by the airport.

The remainder of the paper is organized as follows. Section 2 describes the theoretical model that guides the empirical estimation. Section 3 presents the sources of data and the construction of variables used in the estimation. Section 4 discusses the empirical model and presents the estimation results. Section 5 concludes the paper.

2 Theoretical Framework

2.1 Turnaround time and buffer

Before the theoretical model is presented, it is important to clarify the concepts of turnaround time and buffer, as well as the relationships between them and delay. Before an airplane can make another trip, it must remain at the gate to allow passengers to disembark, have cargo and baggage unloaded, have the airplane serviced, have cargo and baggage loaded, and to allow passengers to board for the next trip. According to Geodeking (2010), the time span from touching the gate ("on blocks") until pushing back from the gate again ("off blocks") is called turnaround time, or TAT, of an aircraft.

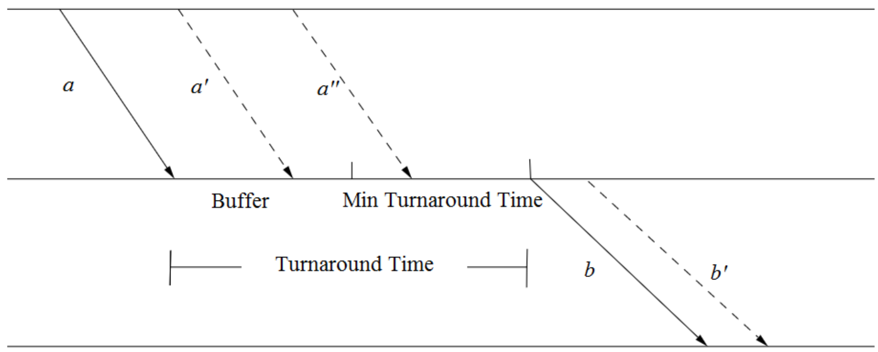

Figure 5: The relationships between turnaround time, buffer and departure delay. The solid arrows represent the scheduled arrival time and the scheduled departure times of flights a and b. The dotted arrows represent the actual departure and arrival times of flights a and b. The scheduled turnaround time (TAT) is the time in between flight a's scheduled arrival and flight b's scheduled departure. The TAT must be larger than the minimum turnaround time (minTAT) required for turning the aircraft, and the additional time in TAT in excess of minTAT is the (ground) buffer.

Because each aircraft routing is a sequence of flight segments flown by a single aircraft, and arrival delay will result in a departure delay if not enough TAT is scheduled between the two consecutive flight segments in that routing. This "delay propagation" often results in delays for downstream flight segments. Building buffers into ground times[2] helps reduce departure delays, as shown in Figure 5. The solid arrows in Figure 5 represent the original schedule for two flight segments a and b, performed by one aircraft. The dotted arrows represent the actual departures and arrivals of these flight segments. As illustrated in the figure, the scheduled TAT consists of two components: the minimum turnaround time (minTAT) which is the minimum time required to turn the plane around, and the buffer built into the TAT

[2]Adding buffers to "airtime" was found ineffective in reducing delays by the airlines, as these buffers were reabsorbed probably due to down-prioritization when approaching a congested airport and to less favorable taxiing routes or gate allocation (Geodeking, 2012, p.69).

to reduce the vulnerability of the schedule structure to delays. Hence, buffer is the additional time in TAT in excess of minTAT:

$$\text{Buffer}_{ab} = \text{TAT}_{ab} - \text{minTAT} \tag{1}$$

If the arrival delay of flight a is shorter than the buffer built into the turnaround time (i.e., the actual departure and arrival time follows a'), then the arrival delay can be absorbed by the buffer and the aircraft can depart on time for its next flight segment b. However, if the actual arrival delay of flight a is longer than the buffer built into the turnaround time between flight a and b (i.e., the actual departure and arrival time follows a''), then some portion of the arrival delay cannot be absorbed and is propagated to flight b, causing the actual departure and arrival time at b to be postponed to b'.

2.2 Theoretical model

Consider a travel market connecting two cities. Passengers in the market have mass M, and the market is served by n identical competing airlines. First consider the demand side of the model, where consumers value consumption and travel, and travel valuation depends on the airline used to make the trip. Assume a random utility model in which consumers make a discrete choice among the n airlines in the market, selecting the alternative yielding the greatest utility (Ben-Akiva and Lerman, 1985; McFadden, 1974). In the model, indirect utility for consumer i traveling by airline j is given by $y - p_j + travel\ benefit - flight\ delay\ cost_j + \epsilon_{ij}$, where y is income, and p_j is airline j's fare, so that $y - p_j$ is consumption of other goods if the price of the other goods is normalized to 1. The term ϵ_{ij} represents an individual-specific component of utility that is uncorrelated with price, p_j.

Flight delay measures the difference between the scheduled departure and the actual departure times. As was previously discussed, shorter turnaround time for a flight means a higher expected departure delay, implying an negative correlation between turnaround time T_j and expected departure delay. For determinate results, assume that the expression for expected departure delay takes the following specific form: $D + \frac{\omega}{T_j}$, where $\omega > 0$ indicates the magnitude of reduction in departure delay from adding turnaround time (or adding buffer time, since turnaround time T_j equals the minimum turnaround time plus buffer time). When the turnaround time is set to a value that is sufficiently large (so that $\frac{\omega}{T_j}$ is sufficiently small), departure delay can still happen due to other factors such as weather; hence the expected departure delay given enough turnaround time is denoted by D. Flight delay cost is given by a disutility parameter $\psi > 0$ times the above expression, thus equaling $\psi(D + \frac{\omega}{T_j}) \equiv F + \frac{\phi}{T_j}$, for $j = 1, 2...n$ where $F = \psi D$ and $\phi = \psi\omega$.

Given the expression for the flight delay cost, the indirect utility function for consumer i flying on airline j is $y - p_j + b - F - \frac{\phi}{T_j} + \epsilon_{ij}$, where b denotes the travel benefit, assumed to be constant for all airlines and consumers. Hence, the only quality difference among different airlines is on-time performance. Let $B = b - F$, so the indirect utility function can be simplified to $y - p_j + B - \frac{\phi}{T_j} + \epsilon_{ij}$.

If the ϵ_{ij}'s are independently and identically distributed according to the Type I extreme value distribution, the choice probability, or the aggregate market share of airline j, has the familiar multinomial logit form:

$$\Pi_j = \frac{exp(y - p_j + B - \frac{\phi}{T_j})}{\sum_{k=1}^{n} exp(y - p_k + B - \frac{\phi}{T_k})} \tag{2}$$

Recalling that the total consumer population is M, the quantity of passengers for airline j is simply

$$q_j = M\Pi_j \tag{3}$$

On the cost side, following Brueckner(2004), but changing the specification of cost per flight to cost per hour, the cost of operating a flight per hour is given by $\theta + \tau s$, where s equals the number of seats on the flight. Each operation hour thus entails a fixed cost θ, and also a marginal cost per seat τ. Under such a specification, cost per seat (given by $\frac{\theta}{s} + \tau$) realistically falls with the total number of seat flown per hour. Multiplying the expression by total air time e gives the total air-time cost $e(\theta + \tau s)$.

In addition to the cost incurred while an aircraft is in the air, the fixed cost per hour (θ) is also incurred when an aircraft is not generating passenger miles (when the aircraft is on the ground). Recalling that the turnaround time (TAT) scheduled for a flight before take-off is T, the total cost of operating a flight is $c(T) = e(\theta+\tau s)+\theta T$, or $c(T) = e\tau s + (e + T)\theta$, where the first term denotes the variable cost per flight, and the second term is the fixed cost per flight. Under this specification, total cost per flight rises with the number of seats on an aircraft and rises if more operation time is required by a flight (if $e + T$ increases).

To account for aircraft utilization in the model, let H denote the total number of hours that an aircraft is "available" in a given period (i.e. a year)[3]. Hence, dividing aircraft availability H by the operation time of a flight $(e + T)$ gives the maximum number of flights an aircraft can complete in a given period. Moreover, the total number of flights provided by an airline is the product of the number of aircraft it operates and the maximum number of flights that can be provided by each aircraft, or $\frac{fH}{e+T}$, where f represents the number of aircraft operated by the airline. Using this information, the airline's total cost is assumed to be given by

$$c(T) = (e\tau s + (e + T)\theta)\left(\frac{fH}{e+T}\right)^{\alpha} \tag{4}$$

where α is the economies of scale parameter. For example, when $\alpha = 1$, the average cost per flight does not rise with the total number of flights operated (the total cost is linear in $\frac{fH}{e+T}$). However, when $\alpha > (<)1$, the average cost per flight increases (decreases) when the total number of flights operated increases.

A final assumption in the model is that all aircraft seats are filled, with the

[3]In the airline industry, H is usually called the aircraft availability (Mirza, 2008).

load factor equal to 100 percent. Under this assumption, total seats provided by the airline must be sufficient to accommodate its passenger volume, requiring

$$\frac{sfH}{(e+T)} = q \tag{5}$$

Combing the above elements, airline j's profit-maximization problem can be stated. Given that an airline can adjust its flight schedule fairly easily, it may be reasonable to assume that in maximizing profit to the constraint in (5), the airline chooses the fare and the length of turnaround time simultaneously, taking the choices of its competitors as given in Nash fashion. Thus, the problem is

$$\max_{\{p_j, T_j\}} \quad \pi_j = p_j q_j - (e\tau s + (e+T_j)\theta)\left(\frac{fH}{e+T_j}\right)^{\alpha} \tag{6}$$

$$= p_j q_j - (e\tau s + (e+T_j)\theta)\left(\frac{q_j}{s}\right)^{\alpha} \tag{7}$$

$$= p_j M\Pi_j - (e\tau s + (e+T_j)\theta)\left(\frac{M\Pi_j}{s}\right)^{\alpha} \tag{8}$$

where the second equality is derived using (5) and the third equality is derived using (3).

With the model specification now clear, the first-order conditions are

$$\frac{\partial \pi_j}{\partial p_j} = M\Pi_j + Mp_j\frac{\partial \Pi_j}{\partial p_j} - \left(\frac{1}{s}\right)^{\alpha}(e\tau s + (e+T_j)\theta)\alpha M(M\Pi_j)^{\alpha-1}\frac{\partial \Pi_j}{\partial p_j} = 0 \tag{9}$$

$$\frac{\partial \pi_j}{\partial T_j} = p_j M\frac{\partial \Pi_j}{\partial T_j} - \left(\frac{1}{s}\right)^{\alpha}\left[\theta\,(M\Pi_j)^{\alpha} + (e\tau s + (e+T_j)\theta)\alpha M(M\Pi_j)^{\alpha-1}\frac{\partial \Pi_j}{\partial T_j}\right] = 0 \tag{10}$$

The second-order conditions $\partial^2\pi_j/\partial p_j^2$, $\partial^2\pi_j/\partial T_j^2 < 0$ are satisfied if $\alpha > 1$ and the remaining positivity condition on the Hessian determinant is assumed to hold. Consider the choice of T_j holding p fixed. The first-order condition for T says that the increase in revenue after increasing turnaround time should equal the increase in costs, which consist of the increase in cost per flight and the increase in the total number of flights operated to accommodate the increased number of passengers. While the optimality rule embodied in (10) is unsurprising, its usefulness lies in formalizing the trade-off between better on-time performance and higher operation costs.

It is easily verified that, the price sensitivity of each firm's market share with respect to its own price is given by $\frac{\partial \Pi_j}{\partial p_j} = -\Pi_j(1-\Pi_j)$. Similarly, it can be proven that $\frac{\partial \pi_j}{\partial T_j} = \frac{\phi}{T_j^2}\Pi_j(1-\Pi_j)$. Moreover, with firm symmetry, the symmetric equilibrium is the natural focus. This equilibrium can be found by setting $p_j = p_k, T_j = T_k, \forall j \neq k$ and $\Pi_j = \frac{1}{n}, \forall j$ in (9) and (10) and solving for these values. Substituting (8) into (9), the T_j and p_j solution satisfies

$$p_j = (\frac{1}{s})^{\alpha}(e\tau s + (e + T_j)\theta)\alpha(\frac{M}{n})^{\alpha-1} + \frac{n}{n-1} \tag{11}$$

$$T_j = \sqrt{\frac{s^{\alpha}\phi n^{\alpha-1}}{\theta M^{\alpha-1}}} \tag{12}$$

The optimal T is increasing in the number of seats (s) and the efficiency of turnaround time ϕ, while decreasing in the amount of fixed cost (θ). These results also capture the trade-off between improving service quality (higher T) and the increased cost from the increased cost per flights (longer $(e+T)$) and the requirement of a larger fleet (higher f).

Moreover, the effect of the number of competitors on turnaround time depends on the parameter α. When the cost function exhibits diseconomies of scale ($\alpha - 1 > 0$), an increase in the number of competitors (n) increases turnaround time (T). However, there has been an ongoing debate over the existence of economies of scale in the airline industry. Caves et al. (1984) show that there is little evidence of economies of scale in the airline industry. However, that paper and others focus on evaluating the economies of scale on the network level instead of the route level. Hence, given the current empirical literature, the magnitude of α and thus the effect of market competition on T is hard to infer. Given this lack of generality, the current analysis should be viewed as only providing an example of how optimal turnaround time can be derived in a full theoretical model, a demonstration that helps to motivate the ensuing empirical work.

A final point is that, the model only considers the decision on the turnaround time at the route level, and the role of network structures and banking behaviors in the choice of buffer time is overlooked. For instance, prolonging buffers for aircraft at a hub airport allows the hub originating flights to "collect" connecting passengers from more arrival flights, which lowers the average cost per seat for the airlines by increasing load factors of the airline-hub originating flights. However, prolonging the buffer time of such flights also induces longer layovers for connecting passengers, hence presenting a new trade-off for the airlines on their decisions on buffer length at hubs. Such issues are explored further in the empirical models.

3 Data and variable construction

3.1 Dataset

The most important data source for this study is the On-Time Performance Database from Bureau of Transportation Statistics (BTS), which includes data on all non-stop domestic flights operated by airlines carrying more than 1% of US domestic passengers. The 19 reporting carriers during the sample period, Aug 2004-May 2005 were American, Alaska, JetBlue, Continental, Independence, Delta, ExpressJet, Frontier, AirTran, Hawaiian, America West, Envoy, Northwest, Comair, Skywest, ATA, United, US Airways and Southwest. For each flight, the dataset provides the scheduled and actual departure and arrival times, the departure and arrival delays, flight origin and destination, distance, and tail number of the aircraft that flew the flight. A majority of the variables used in the empirical estimation are constructed from the original dataset of 5 million flights during the sample period. For example, the tail numbers are used to reproduce historical aircraft rotations (routes and schedules of a specific aircraft), which is then used to derive the scheduled and actual Turnaround Time (TAT) before each flight, as well as the scheduled buffer time before each flight in the dataset. Due to computational constraints presented by such a large dataset, a 10% sample from the original dataset is randomly selected after all the variables are constructed, reducing the sample size to around 0.5 million.

The On-Time Performance Database has limits that prevent this study from fully reproducing the historical schedule. First, international flights are not included. This is an issue because some airports analyzed in the study are also important international hubs. Thus, the study is missing a proportion of the airlines' scheduled operations as international departures and arrivals at not accounted for. Hence, in this study, buffer time and on-time performance for international flights cannot be observed and no formal conclusion on how international flights are handled in airline scheduling can be drawn. The second limitation of the On-Time database is that it does not include all flights flown domestically, as many small affiliate airlines are not required to report their on-time statistics. Without these affiliate airline flights, market structures including route competition and airport concentration, operation rates and flight frequencies at the origin and destination airports cannot be accurately calculated.

Using the aircraft tail number, the characteristics of the aircraft are known including type of the aircraft and seat capacity.[4] The number of runways of each airport in the dataset is tabulated using the FAA's airport data (from the National Flight Data Center (NFDC)).[5] Finally, daily weather data at both origination and destination airports are collected from the U.S. National Oceanic & Atmospheric

[4]Since some of the tail numbers in the On-Time dataset are actually fleet numbers (or registration numbers), two websites (rzjet and avitop) are used to recreate the tail numbers of the aircraft (available at http://rzjets.net/aircraft and http://www.avitop.com). Then, the "Landings" database (available at http://www.landings.com) and the FAA aircraft registration database (available at http://registry.faa.gov/aircraftinquiry) are used to find the type of aircraft for each tail number.

[5]Available at http://nfdc.faa.gov/xwiki/bin/view/BFDC/Airport+Data

Administration (NOAA).[6]

3.2 Measuring Turnaround Time and Buffer

The BTS on-time performance data includes reported scheduled gate departure and arrival times, the actual gate departure and arrival times, and the tail number of each flight as a unique identifier for the aircraft. This information is used to construct each aircraft's daily itinerary and to derive the scheduled and actual turnaround times by calculating the elapsed time between the arrival and departure of consecutive flight segments. The same method is employed by Robingson et al. (2011) using Airline Service Quality Performance (ASPQ) data. For example, Table 1 shows the BTS flight records from October 28, 2004 for Delta Airlines (DL) tail number N326DL. This aircraft was scheduled to arrive at ORD at 7:48am and to depart ORD to return to ATL at 9:05am, leaving 77 minutes to "turn" the aircraft. Using a similar method, the scheduled and actual TATs are calculated for all flights in the sample period. If the scheduled TAT is greater than 200 minutes,[7] then it is most likely that the previous flight segment of the aircraft happened on the previous day, or that the aircraft was on a flight with international endpoint and hence the record is incomplete, resulting in large TATs. Such TATs were considered invalid and the observations were deleted.

Table 1: October 28, 2004 aircraft rotation for Delta Airline Tail Number N326DL

Origin	Destination	Scheduled			Actual		
		Depart Time	Arrive Time	Turn Time	Depart Time	Arrive Time	Turn Time
ATL	ORD	6:50	7:48	N/A	6:59	7:50	N/A
ORD	ATL	9:05	12:06	77	9:31	12:18	99
ATL	MKE	12:49	13:49	43	12:55	14:03	36
MKE	ATL	14:55	17:57	66	14:56	18:21	53
ATL	RIC	18:47	20:23	50	19:39	21:15	78

[6] Available at http://www.ncdc.noaa.gov/cdo-web

[7] The maximum turnaround time for a large aircraft type such as the Boeing 747, DC-8 or MD-11 is 180 minutes according to Schaefer and Tene (2003). Allowing for some slack, 200 minutes is used as the cutoff point.

Figure 6 shows the distribution of all turnaround times under 200 minutes. The distribution is skewed to the right, with the mean TAT equal to 53.9 minutes and 99% of flights having a TAT greater than 16 min (the 1st percentile of the distribution is thus 16 minutes).

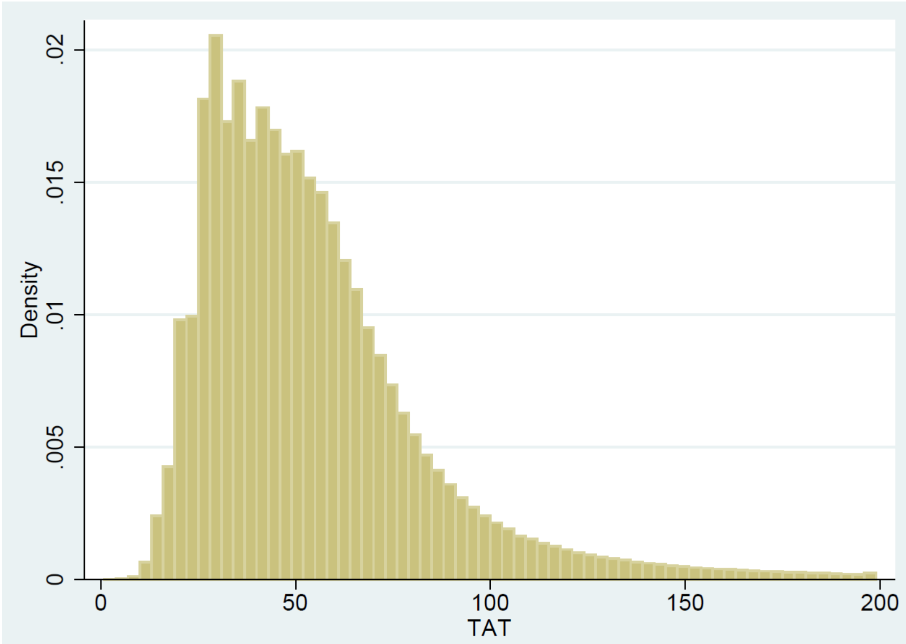

Figure 6: Distribution of turnaround times that are under 200 min

Note that the TAT of a flight depends upon the aircraft type, the airline operating the aircraft and the airport at which the turn occurs. The same logic applies to the minimum TAT. Without official data on airport, airline and aircraft specific-minimum TATs, the BTS dataset is exploited to measure the minimum TAT for each airport-airline-aircraft configuration. The minimum TAT is set equal to the 1st percentile[8] of all the valid actual TATs in a specific airport-airline-aircraft configuration. For example, among all Delta operated Boeing 757-232s (with a passenger capacity of 240) that departed from Atlanta (ATL), 1% of them departed with an TAT of less than or equal to 42 minutes. Thus the minimum TAT for the configuration ATL-DL-Boeing 757-232 is 42 min. Similarly, for a smaller aircraft like the Boeing 737-2H4 (with a passenger capacity of 130) operated by Southwest departing

[8]Buffers can also be derived using the a minimum TAT set equal to the 5th percentile. However, the estimation results are qualitatively unchanged. These results are available upon request.

from Houston (IAH), the minimum TAT is 10 minutes. Finally, applying equation (1), the scheduled ground buffer time of a flight was then calculated by subtracting the minimum TAT from the scheduled TAT.

3.3 Airport concentration and route competition

To examine the effect of competition on schedule robustness, airport concentration (the HHI based on the share of flights by the various airlines that serve the airport each day) and route competition (the number of airport-pair competitors) are constructed. The role of affiliate airlines in the airline scheduling process is also considered when constructing the two measures since affiliate airlines can make up a large portion of total operations at hub airports.

Affiliate airlines developed in response to the creation of the hub-and-spoke network (Gillen 2005). Since major airlines do not have enough aircraft to serve all the endpoints in their hub-and-spoke networks, they seek arrangements with smaller airlines operating regional aircraft, with these "feeder" airlines "feeding" passengers from smaller origins/destinations to/from the hubs. To identify partnerships, the regional carrier assignment information provided by Pai (2007) and the annual 10K reports filed each year with the Securities and Exchange Commission for all the carriers are analyzed, and the carriers are regrouped using the assignments in Table 2.

In all, the sample includes 4475 routes and 486 airports. Route competition and airport concentration variables are then constructed using the adjusted carrier identifications. Slightly more than 50% of flights serve monopoly routes, and one third of the flights are on duopoly routes while the rest of the flights are serving routes with more than two carriers. Table 3 identifies the major carriers and reports airport concentration, average buffer time and average departure delay for all airports with at least 1 percent of the total flights during the sample period.

Note that the two competition measures capture the effects of competition on

Table 2: Affiliated Airlines Assignment, Aug 2004 May 2005

Major Carrier	Feeder Airline
United(UA)	Skywest[a]
	Independence Air
American(AA)	Envoy*
Delta(DL)	Independence Air
	Skywest[b]
	Comair*
Continental(CO)	ExpressJet
	Skywest[c]
Southwest(WN)	ATA*

Note : Flights of Independence Air are assigned based on hub identities. Asterisks indicate that the feeder airline is owned by the major carrier.

[a] Including routes involving Portland, OR (PDX), Seatle/Tacomo, WA (SEA), Los Angeles, CA (LAX), Denver, CO (DEN), Chicago, IL (ORD).

[b] Only routes involving Dallas, TX (DFW) for flights in 2004, and routes involving Salt Lake City, UT (SLC) for flights in 2005.

[c] Only routes involving Houston, TX(IAH).

service quality from different sources. Route competition captures the direct effect under which non-stop passengers on this route may switch to another airline if their flight is frequently delayed. However, in current hub-and-spoke networks, a large proportion of the passengers are transported from the origin to the destination through connecting flights at the airline's hub. Hence, airlines can compete in the same origin and destination market without operating the same route. As such, competition cannot be captured by the route-competition measure alone, being partially measured by airport concentration.

Airport concentration at the origin affects the available airline choices for all originating passengers. For example, if an airport is served by only one airline (having an airport concentration of 1), then all the passengers in the catchment area of this airport can only travel on this particular airline, regardless of their destination. With other airlines present, passengers unhappy with the on-time performance of a given flight could switch to a connecting (rather than nonstop) flight to their destination. In this way, lower airport concentration can raise competition on a route even while route-level competition itself remains fixed. Another source of competition captured by origin-airport concentration is competition for frequent fliers in the catchment area (Bilotkach & Lakew, 2014), as airlines at less concentrated airports are expected to compete more aggressively for frequent fliers residing in the airport's catchment area.

3.4 Other control variables

To isolate the effect of market structure on schedule robustness, it is necessary to control for factors that also affect the choice of buffers. One such variable is a bank departure indicator, which equals one if the flight departs during a bank period. As was mentioned in section 2, operational stability and hubbing activities are also interdependent, and flights that depart in a bank at the airline's hub airport may have longer buffers to synchronize the arrival banks and the departure banks. Because of the irregularity in the spacing and length of banks, heuristic procedures for identifying bank flights are developed for this study. The appendix contains a detailed description of the bank identification procedure. In all, around 30% of the flights in the sample were identified as departing their airline's hub (from which the airline serves more than 26 destinations) during a bank. Among all the flights that depart from their airline's hub, more than 70% depart during a bank period.

Congestion at the origin and sometimes the destination airport is also included as a control variable. Congestion is measured by the operation rate per hour, which divides the airport's daily operations (takes-offs at the origin airport and landings at the destination airport) by the number of runways at the airport. As runway congestion reduces the efficiency of the buffer (with on-time departures becoming less efficient in reducing arrival delays), shorter buffers may be assigned to flights departing or landing during peak hours. In addition, a longer buffer can be crucial for an aircraft departing later in a day as these aircraft are more likely to experience an arrival delay on their previous flight segment. Moreover, for an aircraft flying a longer route (i.e., from the East coast to the West coast), a longer buffer may be required as it takes a longer time to prepare these flights for take-off. For aircraft scheduled to fly "ping-pong" schedules (a daily routing with multiple short-haul flight segments between the hub and non-hub airports), shorter buffers are natural because of the need to operate many segments per day. Hence, the departure hour (measured on a 24-hour clock), flight distance, and flight segments per day (to capture the "ping-pong" effect) are also included as control variables.

4 Empirical estimation

4.1 Delays and buffer

Before exploring the relationship between market structure and scheduled robustness, it is important to confirm that improving schedule robustness through adding buffers into the schedule can actually reduce delays. Departure and arrival delays happen when the time a flight is ready to take off or land is later than the scheduled time of departure or arrival. In most cases, a flight would choose to depart or arrive on time even if it is ready to depart or arrive before schedule, so that the dependent variables of departure and arrival delays are truncated at zero. Hence, a Tobit model is used to estimate the impact of buffers on delays, aiming at establishing a link between ground buffers and better on-time performance. The empirical Tobit model for the estimation of the impact of buffers on departure or

Table 3: Buffer and concentration for airports with at least 1 percent of flights during Aug 2004-May 2005

Airports	% of Total Flights	Average Buffer (min)	Airport Concentration[a] (flights')	Dominant Carrier	Departure Delay (min)
Atlanta(ATL)	5.95	31.11	0.37	Delta	11.04
Chicago O'Hare (ORD)	4.8	29.62	0.37	American+[b]United	9.73
Dallas-Fort Worth (DFW)	4.51	27.15	0.58	American	6.59
Los Angeles (LAX)	3.26	31.92	0.21	United+Delta	5.94
Houston (IAH)	2.91	36.54	0.52	Continental	3.91
Cincinnati (CVG)	2.9	34.59	0.55	Delta	6.79
Phoenix (PHX)	2.39	22.95	0.26	Southwest	8.45
Las Vegas (LAS)	2.28	20.76	0.22	Southwest	10.21
Denver (DEN)	2.19	30.29	0.38	United	5.88
Newark (EWR)	2.16	31.90	0.44	Continental	8.34
Salt Lake City (SLC)	2.08	30.38	0.26	Skywest	5.13
Washington Dulles (IAD)	2.06	29.72	0.48	United	7.53
Detroit (DTW)	1.99	38.14	0.40	Northwest	5.65
Minneapolis-St.Paul (MSP)	1.97	43.71	0.42	Northwest	3.91
Philadelphi (PHL)	1.83	29.75	0.26	US Airways	13.60
Boston (BOS)	1.83	29.59	0.13	American+Delta	7.01
San Fransisco (SFO)	1.77	38.40	0.29	United	5.65
LaGuadia (LGA)	1.74	31.18	0.16	American+Delta	6.82
Orlando(MCO)	1.61	20.59	0.10	Southwest	7.99
Charlotte (CLT)	1.59	30.92	0.36	US Airways	6.63
Baltimore (BWI)	1.49	16.67	0.22	Southwest	7.05
Seattle (SEA)	1.47	25.35	0.16	Alaska	8.75
Washinton National(DCA)	1.39	29.01	0.21	US Airways	5.04
New York International (JFK)	1.37	30.29	0.11	JetBlue+ExpressJet	3.80
Chicago Mideway (MDW)	1.25	18.63	0.45	Southwest	7.81
San Diego (SAN)	1.22	19.27	0.13	Southwest	6.23
Tempa (TPA)	1.09	20.37	0.08	Southwest	7.27
Oakland (OAK)	0.99	14.95	0.21	Southwest	7.67
Fort Lauderdale (FLL)	0.98	20.42	0.14	Southwest	11.00

[a] Note: The measurement of market concentration is affiliation adjusted so that feeder carriers and its major carrier are considered the same carrier and their total operation at one airport is used to calculate the market share and the market concentration.

[b] Note: "+" here denotes that the airlines have similar shares of total operation at the airport.

arrival delays of flight i flying from airport j to airport k at time t is:

$$
\begin{aligned}
delay_{ijkt} = \beta_0 &+ \beta_1 Buffer_{ijkt} + \beta_2 Prev\_delay_{ijkt} \\
&+ \beta_3 Orig\_hub_{jt} + \beta_4 Dest\_hub_{kt} \\
&+ \beta_5 Operation\_rate_{jt} + \beta_6 Operation\_rate_{kt} \\
&+ \beta_7 SeatCapacity_{+} \beta_8 Distance_i + \beta_9 Dep\_time \\
&+ \sum_w \omega_w Weather_t + \sum_l \delta_l Carrier_l + \sum_w \sigma_w Day\_of\_week_w \\
&+ \sum_m \sigma_m Month_m + \sum_n \gamma_n Quarter_n + \epsilon_{ijkt} \qquad (13)
\end{aligned}
$$

The control variables include *prev_delay*, which is the arrival delay of the previous flight segment. In addition, delays may also depend on whether an airport is a hub, since hub airports may experience greater delays due to the banking activities by the hub airline (i.e., waiting for connecting passengers). Mayer and Sinai's (2003a) definition for hub airport is used, with airports that serve more than 26 destinations considered hubs. In addition to these control variables, the two congestion measures mentioned above are also included in the regressions. A high operation rate at the origin may produce departure delays, and a high operation rate at the destination may have the same effect, with aircraft subject to origin "ground holds" when the destination is congested.

Important logistical factors such as seat capacity of the aircraft, distance of the flight and departure time are also included as control variables. The control variable $Weather$ is a vector covering the daily weather conditions at both origin and destination airports, including daily precipitation, minimum and maximum temperature, average wind speed and snow depth. To address carrier-specific characteristics and weekly and seasonal demand fluctuations, all estimations include $Carrier_l$, $Day\_of\_Week_w$, $Month_m$ and $Quarter_n$, which are carrier, day of week, month and quarter fixed effects, respectively. Dummy variables for each origin and destination airport are included in some of the regressions to control for unobserved airport-specific effects that may affect delays, such as runway layout, equipment and maintenance facilities. Note that the hub indicators for the origin and destination airports are dropped in such regressions, as there is not enough variation in hub status over time to identify the airport hub effects. Descriptive statistics for the variables are presented in Table 5.

The Tobit results are shown in Table 4.[9] The first two columns of the table give the effect of buffers on departure delays, and columns 3 and 4 give the effect of buffers on arrival delays. Origin and destination airport fixed effects are included in the even columns. All the regressions reveal that a longer ground buffer before the scheduled departure time of a flight reduces departure and arrival delays. In all the regressions, the buffer coefficients are negative with an absolute value smaller than 1 minute, implying that departure or arrival delays decrease by less than 1 minute with a 1 minute increase in the buffer. More specifically, according to the Tobit estimations, a buffer increase of 1 minute is associated with a 0.35 minute reduction in departure delay. The effect of buffers on arrival delay is slightly smaller, implying that, although buffering ground time is useful when preventing the propagated delay from spreading to an aircraft's other flight segments, on-time departure alone does not guarantee on-time arrival of a flight, as other factors like weather and airport congestion occurring after take-off also contribute to arrival delay.

The coefficients on the arrival delay from the previous flight segment are positive and significant, as expected. Increasing the arrival delay of the previous flight segment by 1 minute increases the departure delay of the next flight operated by the same aircraft by as much as 0.9 minutes, which indicates that delay propagation is a

[9]Estimations for the subset of non-slot constrained airports are also conducted and the results are provided in the Appendix, Table A.1. The four airports during the sample period that operated under the FAA's High Density Traffic Airports Rule (HDR) established in 1969 are ORD (Chicago O'Hare), LGA (Laguadia New York), JFK (New York), and DCA (Washington Reagan), this rule requires that each carrier obtain a "slot" for each take-off and landing during a specific 60 minute period, which may affect the delays experience by flights related to such airport. The results show that excluding the slot controlled airports slightly increases the effect of buffers in reducing departure and arrival delays.

Table 4: Tobit estimation of the effect of ground buffers on departure and arrival delay, 10% sample of U.S. domestic flights, Aug 2004 May 2005

Dependent Variable: Minutes of:	Departure Delay				Arrival Delay			
	(1)		(2)		(3)		(4)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error	Coef	Std Error
Ground buffer (min)	-0.35***	(0.01)	-0.35***	(0.01)	-0.24***	(0.01)	-0.23***	(0.01)
Previous delay (min)	0.99***	(0.01)	0.98***	(0.01)	0.90***	(0.01)	0.89***	(0.01)
Hub airport at origination	3.27***	(0.34)			2.43***	(0.41)		
Hub airport at destination	0.00	(0.98)			1.11***	(0.29)		
Operation rate at origination	0.23***	(0.04)	0.33***	(0.04)	0.21***	(0.03)	0.53***	(0.05)
Operation rate at destination	0.06***	(0.01)	0.04**	(0.02)	-0.15	(0.18)	0.06***	(0.02)
Distance (100 miles)	0.29***	(2.58)	0.25***	(2.58)	0.24***	(0.03)	0.32***	(0.03)
Seat Capacity	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)
Scheduled departure time	0.57***	(0.03)	0.58***	(0.03)	0.32***	(0.03)	0.40***	(0.03)
Weather	Yes		Yes		Yes		Yes	
Carrier FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes		Yes	
Airport FE	No		Yes		No		Yes	
R square	0.12		0.13		0.08		0.09	
Observations	432,918		432,918		432,918		432,918	

Note: Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Hubs are defined as airports that serve more than 26 markets. Operation rate is calculated by dividing the total number of flights per day by the number of runways at the orgin or destination airport. Scheduled departure time are measured by a 24 hour clock. Airport fixed effects are included in even columns, and hub airport indicators are dropped in even columns as there is little variation through out time for these variables.

* Significant at the 10% level

** Idem. 5% level

*** Idem. 1% level

Table 5: Descriptive Statistics

Variables	Description	Mean	Std
Dep_delay	Difference between the actual departure time and the scheduled departure time	9.274	27.386
Arr_delay	Difference between the actual arrival time and the scheduled arrival time	10.892	28.612
Buffer	The excess turnaround time over the minium possible time	26.097	22.978
Prev_delay	Arrival delay of the previous flight in an aircraft rotation (not applicable to the first flight in an aircraft rotation)	9.524	24.873
Bank_flight	Dummy variables=1 if the flight depart from a bank of its airline's hub	0.315	0.463
Airp_conc_orig	Airport concentration (HHI) at the origin airport of flight	0.337	0.177
Route_competition	Number of competitors on the route of flight	1.696	0.842
Orig_hub	Dummy variable=1 if the origin airport is a hub	0.744	0.493
Dest_hub	Dummy variable=1 if the destination airport is a hub	0.744	0.493
Operation_rate_orig	The origin airport's hourly operations divided by the number of runways at the scheduled departure time of flight	5.925	4.233
Operation_rate_dest	The destination airport's hourly operations divided by the number of runways at the scheduled arrival time of flight	8.271	9.956
Distance	Length of flight in miles	7.144	5.687
Dep_time	Scheduled time of departure of the flight	13.130	4.647
Segment	Total number of flight segments scheduled in the day for the aircraft used by flight	5.568	2.159
Orig	Dummy variables indicating the origin airport of flight	NA	NA
Dest	Dummy variables indicating the destination airport of flight	NA	NA
Carrier	Dummy variables indicating the airline that flew flight (adjusted for affiliated airline)	NA	NA
Month	Month of flight	NA	NA
Day_of_week	Dummy variables indicating the day of the week of flight	NA	NA
Quarter	Dummy variables indicating the quarter of flight	NA	NA
Prcp_orig	Precipitation level at the origin airport on the day of flight (tenths of mm)	25.170	81.878
Snow_orig	Snow level at the origin airport on the day of flight (tenths of mm)	1.820	13.128
Tmax_orig	Maximum temperature at the origin airport on the day of flight	149.016	616.170
Tmin_orig	Minimum temperature at the origin airport on the day of flight	84.557	90.494
Awnd_orig	Average wind speed at the origin airport on the day of flight(tenths of meters per second)	36.968	16.564
Prcp_dest	Precipitation level at the destination airport on the day of flight	25.263	82.430
Snow_dest	Snow level at the destination airport on the day of flight (tenths	1.794	12.907
Tmax_dest	Maximum temperature at the destination airport on the day of flight	185.488	96.584
Tmin_dest	Minimum temperature at the destination airport on the day of flight	84.478	90.611
Awnd_dest	Average wind speed at the origin airport on the day of flight (tenths of meters per second)	36.977	16.605

major factor in departure delays. Hubbing at the origin airports also contributes to departure and arrival delays, as flights with a hub-airport origin experience 3 more minutes of departure delay. The coefficients for the operation rate at the origin airport is positive and significant: adding one flight per runway can increase the departure delay and arrival delay of flights by around 0.2-0.5 minutes, while the effect of runway congestion at the destination is much smaller. Such results imply that runway congestion, especially runway congestion at the origin airport, has a strong impact on the length of delays. The coefficients for distance are positive, so that longer flights are more likely to be delayed (increasing the distance of a flight by 100 miles increases the departure delay by 0.3 minutes). The coefficients on the scheduled departure hour are positive, implying that both departure delays and arrival delays increase as a day progresses onward, so that flights departing later during a day experience more delays than flights departing early in the morning.

4.2 Market structure and buffers

With the results in the previous section confirming that schedule robustness can effectively improve on-time performance, this section explores the main focus of this study: the effect of airport concentration and route competition on schedule robustness, as measured by buffers. The central question then is: all else equal, will competition increase or decrease the length of buffers and thus schedule robustness? An underlying assumption is that airlines, operating flights on a daily basis, can learn first hand how many flights other airlines operate and when. Using information on the amount of traffic, market structure at the origination and destination airports, competition at route level, departure time, day of the flight, and the type of aircraft, the hub carrier can adjust the length of the buffer of each flight.

4.2.1 Empirical model

a. Baseline estimation

To estimate how the length of buffers of flight i departing from airport j to airport k at time t varies with the market structure, variations of the following baseline equation are estimated:

$$\begin{aligned} Buffer_{ijkt} = \beta_0 &+ \beta_1 Airp\_Conc_{jt} + \beta_2 Route\_Compet_{jkt} \\ &+ \beta_3 Bank\_flight_{jt} + \beta_4 Operation\_rate_{jt} \\ &+ \beta_5 Aircraft\_char + \beta_6 Route\_char \\ &+ \sum_c \sigma_c Carrier_c + \sum_m \sigma_m Month_m + \sum_n \gamma_n Quarter_n \\ &+ \sum_j \phi_j Origin_j + \sum_k \phi_k Dest_k + \epsilon_{ijkt} \end{aligned} \tag{14}$$

As described in section 3, in addition to market structure measures, variables that could affect carriers' decisions on buffer times are included. These factors include the bank-departing flight indicator, the operation rates at the origin airport, as well as aircraft characteristics variables (seat capacity and the type of engine) and route characteristics, including scheduled departure time, flight distance, and the total number flight segments each day scheduled for the aircraft used by flight i. Again, all estimations include carrier, day-of-week, month and quarter fixed effects. As buffer choices are likely to be clustered due to unobserved influences like carrier experience or previous weather conditions, standard errors are clustered into the following groups: carrier $\times$ month $\times$ year (i.e., Delta August 2004). Basic descriptive statistics of all the variables are also presented in Table 5.

In this set of regressions, airport fixed effects are also added to control for unobserved airport-specific effects that may affect buffer choices, such as equipment, airport facility and the airport's position in the carrier's network. Since these variables eliminate any time-invariant airport specific effects, identification of the coefficients is driven by the variation in variables within, not across, airports and routes. For instance, the coefficient on airport concentration reveals how buffers respond to changes in concentration at the endpoint airports of a route over time, not how buffers respond to differences across airports. Note that as the market structure measures are constructed daily and the panel is sufficiently long, within-route variation in the key market structure measures is enough for identification of market-structure effects.

b. Hub vs. non-hub originating flights

According to Mirza (2008), buffer (and turnaround time) for flights departing a hub may be longer to allow for synchronization between the feeder network and trunk routes. However, longer turnaround times at the hub airport usually mean a longer connecting time for passengers (Geodeking 2010) as aircraft will have to wait longer on the ground, shifting the departure bank away from the previous arrival bank and prolonging bank length. This relationship between buffers for hub departure flights and bank length (reflecting average layover times of the passengers) at hubs is depicted empirically in figure 7, where bank length is calculated heuristically using the method described in the appendix. As these longer layovers may generate disutility for the passengers, buffer decisions for flights leaving a hub also take into consideration the trade-off between bank synchronization (lower cost through economies of density) and longer layovers (less demand). With such considerations, the sources of service competition is different for flights flying different routes: while passengers on a flight originating from the airline's hub airport care about both layover time and on-time performance, passengers on a flight originating from a non-hub airport are mostly local passengers who only care about on-time performance. Consequentially, the market-structure/schedule-robustness relationship may be different between flights originating from the airline's hub airport and flights originating from a non-hub airport.

In order to test the above prediction and better understand the effect of market structure on buffers at the network level, the main sample is supplemented by a sub-sample including flights destined for non-hub airports. As passengers on such flights are terminating, not connecting at the destination, possible hubbing activities are not considered by airlines when making the buffer choice for these flights. Moreover, in regressions using the sub-sample, interaction terms between an airline-hub-originating indicator variable (equal to 1 if the flight originates from the airline's hub) and the market-structure variables are added to the baseline estimation, so that the difference in market structure's effect on schedule robustness between airline-hub originating flights and non-hub originating flights can be captured.

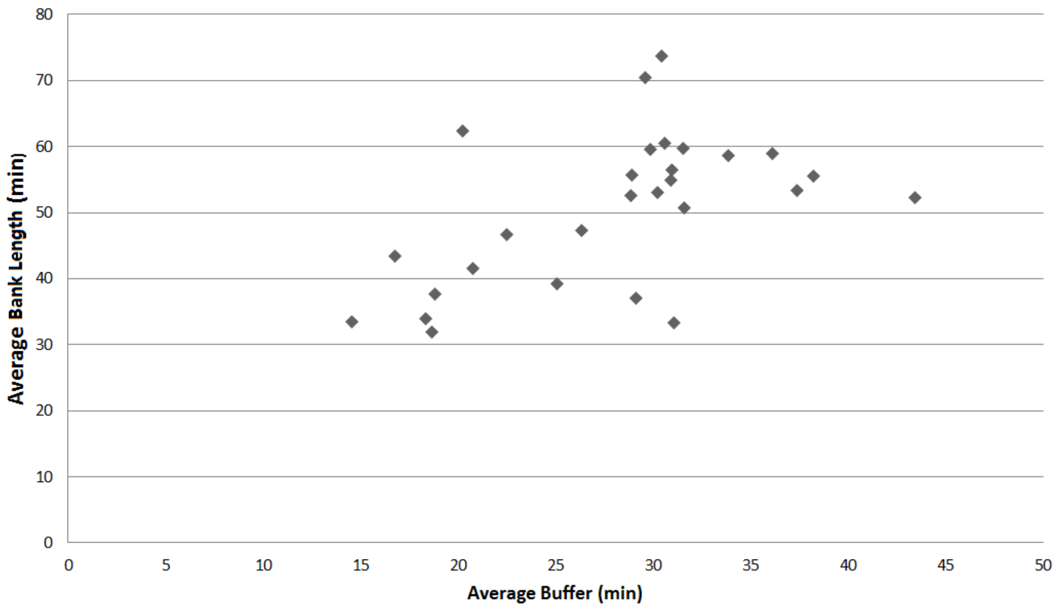

Figure 7: The relationship between airport average buffer time and average bank length for the 30 biggest airport in the US. This figure displays a strong positive relationship between the buffer times of flights departing these airports and bank length. Bank length is derived using a peak and trough identification algorithm described in the appendix A.1

4.2.2 Results

a. Baseline estimation

Results for the baseline estimations are shown in Table 6.[10] While column 1 and 2 only include one of the two market-structure measures, column 3 includes both measures in the estimation. The most noteworthy finding from Table 6 is that,

[10]Estimations for the subset of non-slot constrained airports are also conducted. However, the results are qualitatively unchanged. These results are available upon request.

when market structure becomes more competitive (airport concentration decreases or route competition increases), longer buffers are chosen. Numerically, when market concentration at the origin airport decreases by 0.1, buffer time increases by around 1.3 minutes. Moreover, an increase of one competitor on a route would cause the carriers to increase the buffer of the flights on this route by around 0.4 minutes. The results thus show evidence of service competition in the airline industry, as competition drives the carriers to improve the robustness of their schedules and thus on-time performance. Moreover, recall that, in the theoretical model presented in section 2, buffer increases with the number of competitors on a route when $\alpha > 1$ is satisfied. Therefore, the empirical positive effect of competition on the buffer is consistent with decreasing returns of scale in the number of flights on a route.

There are no surprises present in the coefficients for control variables. The regression reveals that flights departing in a bank period at the airline's hub experience around 2.7 minutes of additional buffer time, confirming the argument that flights are waiting longer at the hub airport to synchronize the arrival and departure banks, "collecting" passengers and thus increasing load factors. Increasing the operation rate at the origin airport shortens buffers, as congestion on the origin runways reduces the efficiency of buffers in limiting departure delays. Aircraft configurations also affect the choice of buffer length. Larger aircraft are given less buffer time, probably because the long minimum turnaround time assigned for these larger aircraft makes buffers less important. Turboprops are scheduled longer buffers probably because such aircraft are sometimes not assigned a gate after they land, so that longer buffers are needed to control for such an uncertainty. Other control variables all show the expected signs. Flights that depart later in a day, or flights flying a longer distance are given longer buffers, and aircraft flying more segments per day are given shorter buffers, probably due to their demanding schedules. Although not shown in the tables, the signs of the carrier fixed effects also show expected signs and magnitudes, with the hub-and-spoke carriers like United, American, Delta, Continental

Table 6: The effect of market structure on ground buffer, 10% sample of U.S. domestic flights, Aug 2004- May 2005

	Dependent Variable: Minutes of Ground Buffer					
	(1)		(2)		(3)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Market Structure						
Airport concentration at origin	-13.67***	(2.54)			-13.11***	(2.54)
Route competition			0.48***	(0.13)	0.40***	(0.12)
Banking and Congestion						
Depart in a bank	2.70***	(0.30)	2.79***	(0.31)	2.77***	(0.30)
Operation rate at origin	-0.15***	(0.06)	-0.15**	(0.06)	-0.15***	(0.06)
Aircraft Charateristics						
Seat capacity	-0.01***	(0.00)	-0.01***	(0.00)	-0.01***	(0.00)
Turboprop	6.90***	(0.72)	7.06***	(0.72)	7.00***	(0.71)
Route Characteristics						
Scheduled departure hour	0.45***	(0.03)	0.45***	(0.03)	0.45***	(0.03)
Distance	0.18***	(0.02)	0.19***	(0.02)	0.19***	(0.02)
Segment	-1.95***	(0.13)	-1.97***	(0.13)	-1.95***	(0.13)
Fixed Effect						
Carrier FE	Yes		Yes		Yes	
Day of Week FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Airport FE	Yes		Yes		Yes	
Observations	432,918		432,918		432,918	
R-squared	0.18		0.18		0.18	

Note:Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Operation rate is calculated by dividing the total number of flights per hour by the number of runways at the orgin or destination airport. Segment is the total number of flight segment served by an aircraft per day.

* Significant at the 10% level
** Idem. 5% level
*** Idem. 1% level

and Northwest scheduling longer buffers, and low cost carriers like Southwest and Jetblue scheduling shorter buffers.

b. Hub vs. non-hub estimations

Taking into consideration the network effect on schedule decisions, Table 7 give the results after sub-sampling flights heading toward a non-hub airport and including interaction terms between the origin airline-hub indicator and the market structure variables from the baseline model. Several stylized facts appear from the tables. First, similar to the results obtained in the baseline model, lower market concentration and higher route competition are associated with longer buffers for flights destined for non-hub airports. Numerically, a flight between two non-hub airports experience an additional 2.3-2.6 minutes additional buffer, when the origin airport market concentration falls by 0.1. Moreover, a flight between two non-hub airports with one more competitor serving the same route is given around 0.8-1 minutes more buffer. Note that the market structure effects in this sub-sample almost double the effect estimated in the baseline model. Therefore, it appears that the results for the full sample estimation are mainly driven by flights with passengers terminating at the destination.[11] While passengers care most about the on-time arrival performance at their final destination (arriving late at a hub for connecting trips may not generate disutilities for the passengers, as long as the delays do not lead to missed connections), it is expected that service competition is the fiercest on routes where most of the passengers are terminating at the destination.

Second, as predicted in section 4.2.1, the association between buffers and competition is slightly weakened for flights departing from an airline's hub airport, as the signs of the coefficients on the interaction terms are the opposite of those on the market structure variables, reducing the effects. According to column 3 in Table 7,

[11]Regressions using flights destined for the airline-hub airport shows that origin airport concentration has little effect on buffer choices. These results are available upon request.

hub originating flights are scheduled around 2.2 more minutes[12] of additional buffer time when the origin airport market concentration falls by 0.1. Similarly, the effect of an extra route competitor reduces to around 0.4 minutes for hub originating flights. Although the individual coefficients on the interaction terms in column 1 and column 2 are insignificant, an F-test also finds joint significance of sum the market structure coefficient (airport concentration or route competition) and the interaction term coefficient for each regression. The above results provide some evidence that airlines are less motivated to compete via on-time performance on routes originating from the airline's hub, since longer buffers for such flights improve on-time performance, at the expense of prolonging layover time, which reduces the utility of connecting passengers.

[12]The effect of market concentration on buffer for flights originating from the airline-hub airport is calculated as follows: $(-26.09 + 5.85) * 0.1 = 2.24$ minutes.

Table 7: Sub-sample estimation of the effect of market structure on buffer with interaction terms

	Dependent Variable: Minutes of Ground Buffer					
	(1)		(2)		(3)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error
Market Structure and Interaction Terms						
Airport concentration at origin	-23.45***	(3.68)			-26.09***	(3.85)
Route competition			0.81***	(0.21)	0.99***	(0.25)
Airport concentration at origin * airline hub at origin	2.00	(1.72)			5.85***	(2.03)
Route competition * airline hub at origin			-0.06	(0.26)	-0.55*	(0.31)
Congestion						
Depart in a bank	1.77***	(0.38)	2.02***	(0.38)	1.86***	(0.38)
Operation rate at origin	0.00	(0.06)	0.01	(0.06)	0.00	(0.06)
Aircraft Charateristics						
Seat capacity	-0.03***	(0.00)	-0.03***	(0.00)	-0.03***	(0.00)
Turboprop	10.81***	(0.91)	11.10***	(0.91)	11.02***	(0.91)
Route Characteristics						
Scheduled departure hour	0.44***	(0.03)	0.44***	(0.03)	0.44***	(0.03)
Distance	0.13***	(0.03)	0.14***	(0.03)	0.14***	(0.03)
Segment	-2.38***	(0.18)	-2.41***	(0.18)	-2.37***	(0.18)
Fixed Effect						
Carrier FE	Yes		Yes		Yes	
Day of Week FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Airport FE	Yes		Yes		Yes	
Observations	328,364		328,364		328,364	
R-squared	0.13		0.13		0.13	

Note:Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Airline hubs is defined as dummy variable that equal to one if the carrier serves more than 26 destinations at the airport. Operation rate is calculated by dividing the total number of flights per hour by the number of runways at the airport. Segment is the total number of flight segment served by an aircraft per day.

* Significant at the 10% level

** Idem. 5% level

*** Idem. 1% level

5 Conclusion

This paper differs from most papers examining on-time performance in the airline industry in one important way. Instead of looking at how market structure directly affects on-time performance at the route level, this study asks how carriers adjust their schedule robustness when market structure changes, recognizing that schedule robustness is an important factor affecting the flight on-time performance.

To answer this question, the paper first recreates each flight's ground buffer time from historical flight schedules, using it as a measure of schedule robustness. Examining the relationship between on-time performance and buffers of flights confirms that lack of schedule robustness is a major culprit in producing delays.

Further examining the relationship between buffers and market structure shows that there exists service-quality competition in the airline market, with carriers adopting more robust flight schedules when competition heats up. Furthermore, examining the association between competition and schedule robustness using interaction terms shows that market structure's effect on buffer choices is slightly attenuated for hub-originating flights.

Such results shed new light on the debate in the internalization literature, where some empirical evidence fails to support the basic prediction that more-concentrated airports should have better on-time performance. While congestion externalities can be internalized when an airport is dominated by one carrier, this study shows that airport domination may also induce worse on-time performance as the dominant carriers reduce their schedule robustness, hence offsetting the probable improved on-time performance brought about by internalization.

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A Appendix

A.1 Bank structure measurements construction

Because of the irregularity in the spacing and length of banks, heuristic procedures for identifying bank characteristics are developed for this study.

For each hub airport, and each major carrier in the hub airport, the total number of departure and arrival flights for each 5 minutes is derived using the BTS dataset. Then, as depicted by Figure (A.1), a 1-hour moving average (MA) is calculated to smooth out the flight frequency time series. The smoother MA is then compared with the daily mean of flight frequency per 5 minutes. A peak occurs when the MA is higher than the daily mean of the departure frequency (the constant threshold) while trough occurs when the MA is lower than the daily mean. The algorithm then locates the point with the minimum MA level for each trough period, and these minimum points are identified as the "cutoff points" between banks, and the length of time between the cutoff points is derived and considered the length of a bank. However, without further constraint, it is possible that two cutoff points are extremely close to each other if the MA process exhibit a volatile fluctuation, as in the cases illustrated by the black circles in the upper panel of Figure (A.1). Hence, to eliminate such cases, the second cutoff point is deleted if the time gap between two points is within 1 hour.

In all, around 30% of the flights in the sample were identified to be departing their airline's hub (an airport serving more than 26 destinations for the airline) during a bank. The average departure bank length is around 110 minutes (less than 2 hours), so that on average, a hub would operate around 10 banks per day (assuming it operates from 6am to 11pm).

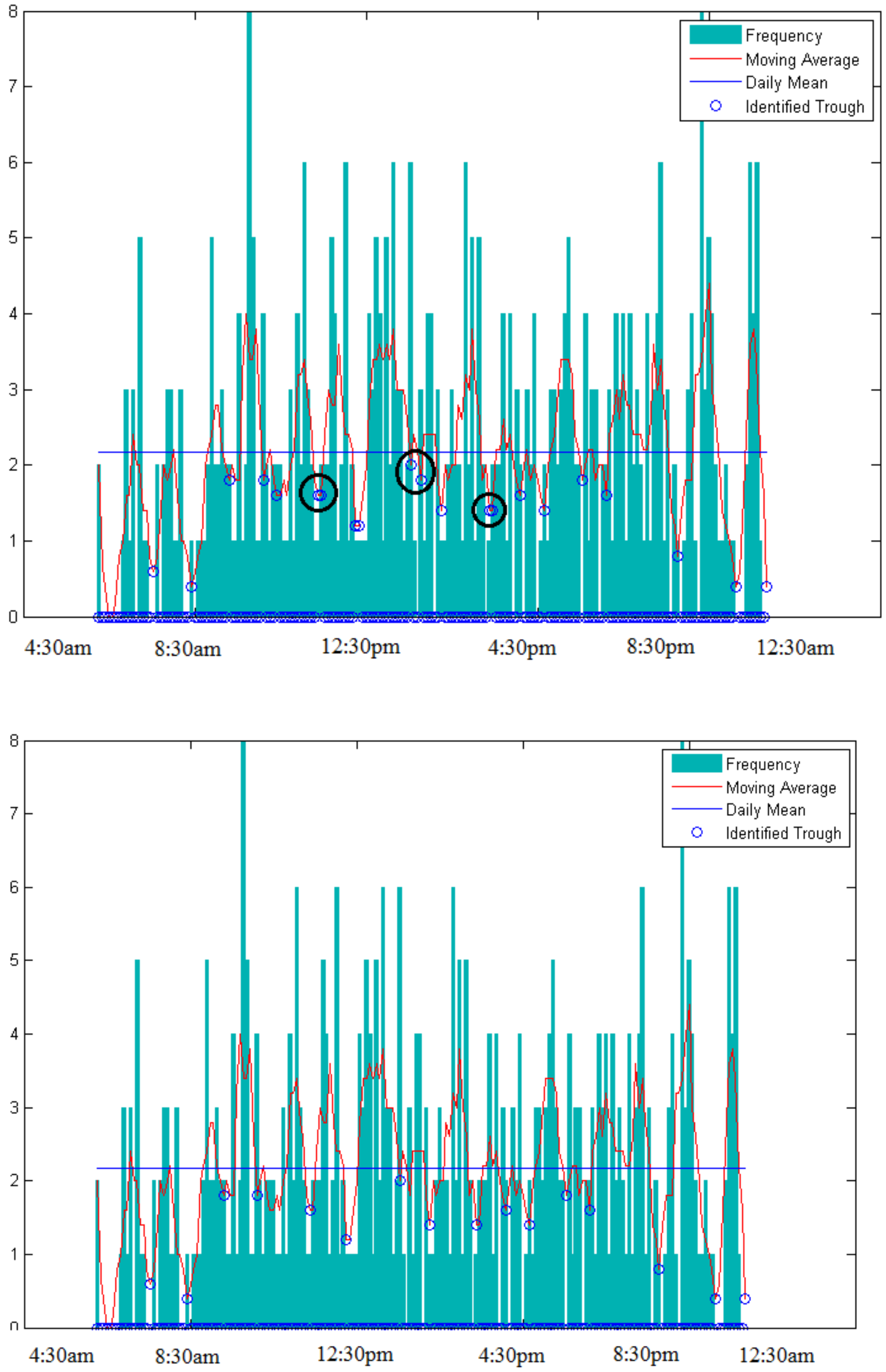

Figure A.1: Departure Bank of AA at DFW on 08/01/2004. The figure illustrates the algorithm used to identify banks in DFW, where AA operates as a hub-carrier. The smooth line depicts the 1 hour moving average based on the hub-carrier number of departing flights.

Table A.1: Tobit estimation of the effect of ground buffers on departure and arrival delay, 10% sample of U.S. domestic flights excluding slot controlled airports, Aug 2004- May 2005

Dependent Variable: Minutes of:	Departure Delay				Arrival Delay			
	(1)		(2)		(3)		(4)	
	Coef	Std Error	Coef	Std Error	Coef	Std Error	Coef	Std Error
Ground buffer (min)	-0.46***	(0.01)	-0.47***	(0.01)	-0.33***	(0.01)	-0.33***	(0.01)
Previous delay (min)	0.95***	(0.01)	0.94***	(0.01)	0.85***	(0.01)	0.84***	(0.01)
Hub airport at origination	3.62***	(0.36)			3.37***	(0.36)		
Hub airport at destination	-0.91***	(0.30)			-0.84***	(0.32)		
Operation rate at origination	0.37***	(0.05)	0.29***	(0.05)	0.28***	(0.05)	0.41***	(0.06)
Operation rate at destination	0.24***	(0.04)	-0.08*	(0.04)	0.47***	(0.04)	0.36***	(0.05)
Distance (100 miles)	0.28***	(0.03)	0.28***	(0.02)	0.21***	(0.04)	0.19***	(0.04)
Seat Capacity	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)	0.01***	(0.00)
Scheduled departure time	0.62***	(0.04)	0.58***	(0.04)	0.41***	(0.04)	0.41***	(0.03)
Weather	Yes		Yes		Yes		Yes	
Carrier FE	Yes		Yes		Yes		Yes	
Month FE	Yes		Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes		Yes	
Airport FE	No		Yes		No		Yes	
R square	0.12		0.13		0.08		0.09	
Observations	331,328		330,822		331,328		330,822	

Note: Standard errors are clustered by carrier, month and year (i.e Delta August 2004). Hubs are defined as airports that serve more than 26 markets. Operation rate is calculated by dividing the total number of flights per day by the number of runways at the orgin or destination airport. Scheduled departure time are measured by a 24 hour clock. Airport fixed effects are included in even columns, and hub airport indicators are dropped in even columns as there is little variation through out time for these variables.

* Significant at the 10% level

** Idem. 5% level

*** Idem. 1% level