Internalization of Congestion at U.S. Hub Airports*

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April 26, 2009

Abstract

Congestion externalities arise when airlines do not consider that scheduling another flight may result in flight delays for other airlines. Open questions are whether and how carriers take into account the delays a flight inflicts on other flights operated by the same carrier. This paper addresses these questions by studying congestion during high-volume time periods, used by hub-carriers to reduce the layover time of connecting passengers (also known as flight banks). To facilitate the empirical application, I employ individual flight time data, as well as airport, aircraft and weather information and explicitly identify the characteristics of banks, such as their time length and the number of flights offered by each carrier. The empirical analysis proceeds in two main steps: First, I show that banks dominated by one airline are longer and are characterized by lower flight density. Second, I find that longer banks are associated with shorter flight delays. These findings imply that hub-carriers internalize congestion by scheduling longer banks. Furthermore, these findings may suggest that congestion management solutions implemented at hub airports dominated by one airline could have a limited impact on congestion itself.

*This paper is a revised version of the second chapter of my Ph.D. dissertation. I received valuable comments from Ran Abramitzky, Amitay Alter, Tim Bresnahan, Ron Borzekowski, Assaf Eilat, Liran Einav, Shachar Frank, Mark Hansen, Oren Rigbi, Peter Reiss and Frank Wolak as well as from participants at the 2007 ATRS meeting, Berkeley-Nextor seminar, the 2007 Aspen Wye Conference on Congestion, Tel Aviv University. Special thanks to Assaf Ater for help with coding. I thank the NET Institute www.NETinst.org for financial support. All remaining errors are mine. email: ater@post.tau.ac.il

JEL classification: L50; L93; R41;

Keywords: Congestion; Air Transportation; Air Delays;

1 Introduction

Delays and congestion in the airline industry are a major concern[1] and policy makers are considering solutions such as congestion pricing or restricting the number of flights during high-demand periods to reduce congestion.[2] The early theoretical literature on congestion pricing showed that the scarcity of public infrastructure results in congestion and delays since commuters ignore the impact of their scheduling decisions on other commuters' travel time. More recent theoretical papers illustrated that the incentive to reduce congestion by taking into account the impact of an additional flight on other flights' performance increases as the share of flights operated by one airline increases. Indeed, the optimal implementation of the proposed solutions to congestion depends on how airlines schedule their flights without regulatory intervention, and specifically on whether airlines internalize the impact of scheduling an additional flight on other flights operated by the same airline.

Looking for evidence for internalizing behavior, empirical research explored whether more concentrated airports, as a measure of the incentive to internalize congestion,[3] exhibit shorter flight delays, as a measure of congestion. These papers did not distinguish between

[1] In the U.S. the total estimated costs of air transportation delays are $9.4 billion annually. Between 2002-2004 more than $4.5 billion annually was spent to reduce flight delays; See www.fightgridlocknow.gov/docs/conginitoverview070301.htm. The cost of air delays in 1999 in Europe is estimated between EUR 6.6 - 11.5 billions; see www.eurocontrol.int/prc/gallery/content/public/Docs/stu2.pdf. During the first five months of 2007, U.S. Airlines' on-time performance, measured as the share of flights arriving less than 15 minutes after their schedule time, was 73.5% the lowest in seven years. "Passengers Scowl as Airlines Smile", *NY Times*, August 4, 2007.

[2] In the U.S., the Federal Aviation Administration adopted new rules and procedures regulating flight landings and departures. These changes effectively allow U.S. airports to implement congestion pricing, where high landing fees will be charged during peak hours and lower landing fees will be charged during off-peak periods. Currently, in most U.S. airports the order of flights arrivals and departures is based on a first-come first-served process. Landing charges are based on aircraft weight, rather than flight time of operation. Another approach for alleviating congestion is to directly regulate the number of flights operated during a congested period, as implemented in slot-constrained airports.

[3] The airport concentration is measured by the herfindahl index of flights at the airport.

time periods with a higher or lower volume of flights and found either no or weak evidence for internalizing behavior. Analyzing data from low and high volume periods could explain why strong evidence for the predicted congestion-concentration relationship was not found since the incentive to internalize congestion arises mainly during high-volume periods of flights.

To address this concern, this paper focuses on hub airports and studies the empirical relationship between congestion and concentration only during high-volume periods of flights, known as *flight banks*. In addition, this paper employs a rich set of control variables such as airport runway capacity, airport gates, weather and aircraft characteristics and focuses on flight delays that are closely related to the scarcity of the public airport runway during takeoffs and landings. I find a strong negative relationship between the level of delays and concentration. Importantly, focusing on high-volume periods of flights not only results in better assessment of the relationship between concentration and delays, but also enables me to explore the channel through which internalization takes place. In particular, I provide evidence implying that hub airlines internalize congestion by scheduling banks with lower flight density. I show that more concentrated banks are longer and that longer banks are characterized by shorter flight delays.

Section 3 contains a simple framework of a hub-carrier scheduling decision that guides the empirical analysis. According to the framework, a hub carrier can reduce congestion by increasing the length of the bank. The incentive of the hub-carrier to reduce congestion increases with its share of bank flights. The simple framework provides intuitive predictions for internalizing behavior: more concentrated banks are longer and longer banks exhibit shorter delays. Furthermore, as the unit cost of queuing rises, the longer the bank period chosen by the hub carrier. In addition, airplanes operating during longer bank periods incur increased aircraft ground time between subsequent flights.

In the empirical analysis, I follow the suggested framework and provide evidence consistent with each of the framework implications. I start by examining, for both arriving and departing banks, how the scheduled length of the bank period varies with the bank concentration level. I find that an increase of one standard deviation in bank concentration is associated with 6.96 and 9.42 minutes longer departing and arriving banks, respectively. The estimated regression of bank length suffers from potential endogeneity of the bank concentration variable. In particular, the decision by the hub carrier on the length of the bank is affected by the (unobserved) share of connecting passengers which is likely correlated with the bank concentration variable. I account for this endogeneity concern by using the concentration of airport gates as an instrument for bank concentration and discuss the validity of the instrument in section 5.[4]

After establishing a positive relationship between the length of the bank and bank concentration, I explore the relationship between the length of the bank period and flight delays. The analysis is performed separately for departing and arriving banks, and I adopt measures of flight delays created during departing and arriving queues. The measure of delays during departing queues is based on a flight taxi-out time, the elapsed time from leaving the airport gate to wheels off the runway. Specifically, I subtract an airport-carrier measure of unimpeded taxi-out time from a flight taxi-out time to obtain the departure queue delay measure. The measure of delay during arriving queues is based on flight airtime, between takeoff at the origin airport and landing at the hub airport. Specifically, the airtime delay benchmark was constructed by computing the fastest hub-bound flight airtime in each pair of origin airport - hub-airport.[5] I then subtract this benchmark from each flight airtime to obtain the airtime delay measure for each particular flight. The advantage of these measures is that they are closely related to the scarcity of the airport runway infrastructure during the congested period.

I find that longer banks are associated with shorter flight delays during both arriving and departing queues. In particular, the above changes in the length of departing and arriving bank periods (6.96 and 9.42 minutes, respectively) translate, on average, into 0.5 minutes

[4]One important implication of using airport gates as an instrument is that the main source of variation in identifying the relationship between concentration and bank length is across airports variation rather than within airport variation.

[5]For example, the fastest airtime in the San Francisco - Denver route is one benchmark.

shorter delays during departing banks and 0.9 minutes shorter delays during arriving banks for each flight operating during a bank. The different findings regarding arriving and departing banks and particularly that arriving banks are longer than departing banks are consistent with the unit cost of queuing being higher during arriving banks.[6] To examine aircraft ground time between subsequent flights, I focus only on flights departing during departing banks and find that the length of arriving and departing banks is positively associated with aircraft ground time.

The findings of the empirical analysis are consistent with the predictions of the theoretical framework and thus suggest that dominant carriers do internalize congestion. One interpretation of these results is that potential time savings at highly concentrated banks are limited since hub airlines are already able to attain a lower level of delays at these airports. My findings also suggest that congestion management tools would have a larger impact on departing flights rather than on arriving flights.

The remainder of the paper is organized as follows. Section 2 provides a review of the relevant literature. In Section 3, I describe the theoretical framework, which guides the empirical estimation and derives testable implications. In Section 4, I describe the data, provide descriptive statistics and explain how the variables used in the empirical estimation were constructed. Section 5 includes the estimation results of the bank length regressions, the different delay measures and aircraft ground time. Section 6 concludes.

2 Related Literature

Brueckner (2002) was the first to formalize[7] the idea that concentrated airports should exhibit less congestion.[8] In general, the theoretical literature on internalization by airlines assumes

[6] During arriving banks, when airplanes wait for their turn to land, queuing cost is larger than the unit cost of congestion during departing banks when airplanes wait on the ground. Consequently, airlines can avoid congestion during arriving banks by choosing longer bank periods.

[7] The initial insight should be attributed to Daniel (1995).

[8] Brueckner (2002) also provided rudimentary evidence for internalization based on annual measures of delay

that the daily pattern of flights at an airport can be divided into congested and non-congested periods of flights. The focus of the analysis is on the congested period since during that period airlines have an incentive to internalize the impact of their scheduling decision on other flights they operate. Though this line of research derives the basic prediction that concentrated high-volume periods are less congested, it does not provide clear guidance on how airlines internalize congestion.

In contrast, the deterministic theoretical literature on road congestion and particularly Henderson (1981) and Henderson (1985)[9] illustrates how the length of the congested period increases and the level of delays falls following a social planner intervention to reduce congestion. A shortcoming of these papers in the context of the airline industry is that they consider either a fully competitive (atomistic) equilibrium, or fully monopolized (social planner) equilibrium. Nevertheless, the predictions of these models are used as additional guidance for the empirical analysis performed here, assuming that the change from fully competitive market to fully monopolized market is continuous.

Empirical papers which investigated whether airlines internalize congestion generally concluded that airlines do not internalize congestion. Daniel (1995) used stochastic queuing models and data from Minneapolis-St. Paul hub airport and concluded that internalization behavior by the hub-carrier is unlikely.[10] More recently, Morrison and Winston (2007) quantified the potential benefits from eliminating congestion at airports. They used calibration and alternative assumptions on the dominant carrier behavior and argue that the quantitative difference between internalizing behavior and non-internalizing behavior is modest.

This paper is most closely related to the paper by Mayer and Sinai (2003). Mayer & Sinai highlighted the role of hubbing and network effects in generating delays and demonstrated

at 25 U.S. airports. Other theoretical papers which examined aspects of airline internalization include: Brueckner (2005), Pels and Verhoef (2004), Zhang and Zhang (2006), Basso and Zhang (2007), Brueckner and Van-Dender (2008), Brueckner (2009).

[9] See also Vickrey (1969) as well as Arnott, Palma and Lindsey (1990), Arnott, Palma and Lindsey (1993).

[10] Daniel and Harback (2008) applied the same methodology to 27 airports and found generally similar results. See also Daniel and Pahwa (2000).

that flights operated by hub-carriers suffer longer delays than flights performed by non-hub carriers. Mayer & Sinai attributed this finding to hub-carriers tendency to cluster flights in high-volume banks leading to increased flight time. They also found evidence for shorter delays at more concentrated airports.[11] Though acknowledging the importance of banks in generating delays, these papers neither identified banks nor used variation across banks to examine how bank structure, congestion and delays are related. In addition, none of the papers explored the channel through which internalization takes place.

3 Theoretical Framework

Hub-and-spoke networks enable airlines to reduce their aircraft operating cost by achieving higher load factors. Hub carriers carry passengers from the same origin but with different destinations on the same flight to the hub. Passengers with different originations but the same destination share the flights from the hub. Each spoke of the network carries many more passengers to and from the hub than a direct route between individual city pairs would. Consequently, the network can provide more frequent service in larger aircrafts at a lower cost per passenger. Longer travel time and layover times at the hub are the costs of a hub system. To minimize costs, hub-and-spoke networks schedule arrivals and departures at hubs in banks of flights. Arrival banks consist of hub-bound flights from spoke cities landing at approximately the same time. At the hub, connecting passengers change aircraft and the aircraft they disembarked prepares for the next operation. Departure banks consist of flights to spoke cities that depart at approximately the same time.

Assuming that all aircraft in an arrival or departure bank have similar mixes of connecting passengers, they all have the same preferred time of operation. Without capacity constraints at hub airports, all arriving flights operated by a hub airline would arrive at a par-

[11] Rupp (2009) extended Mayer & Sinai's analysis by adopting a different measure for delay as well as a larger set of control variables and did not find evidence for internalizing behavior.

ticular time, and all departing flights would depart at a particular time later. Since capacity constraints do play a role hub airlines schedule their arriving and departing bank of flights over a time period. By choosing a longer bank period, hub-airlines reduce congestion costs but increase connecting passengers' layover time. Thus, the basic tradeoff faced by hub carriers is between congestion costs and layover/ground time costs.[12]

Airplane operators bear the externalized cost of congestion because flights inflict delay/congestion costs on other flights scheduled close in time. The closer in time airplanes are operated, the larger the inflicted congestion cost. Consequently, an airline that operates multiple airplanes benefits from scheduling a flight away from other flights more than a single airplane carrier would benefit from rescheduling.[13] In computing congestion costs, the hub carrier considers the cost each airplane inflicts on other hub-carrier airplanes. A carrier operating a single flight during a bank does not take into account any impact on other flights' cost of congestion. Consequently, we expect that when several airlines operate during the bank, the bank is shorter and longer delays are created during these shorter, dense, banks.

Other implications of the suggested framework are that if the unit cost of congestion is higher, the incentive of hub airlines to avoid congestion increases and they are expected to reduce the density of bank flights by choosing a longer bank period. Figure 1 illustrates the main predictions of the theoretical framework. These predictions can be viewed as extensions for the theoretical models developed by Henderson (1981) and Henderson (1985).[14] Finally, the tradeoff faced by hub airlines between congestion and layover time suggests that scheduling longer banks will result in longer aircraft ground time between subsequent flights.

[12]These costs include reduced willingness to pay by consumers to flights that include long connections as well as the costs associated with lower utilization of the airline fleet of aircraft.

[13]The benefit for the multi-airplane carrier is accrued for each of its airplanes.

[14]The figure suggests another implication, flights operating closer to the center of the bank suffer longer delays. These flights are exposed to more adjacent flights than flights scheduled at either the beginning or the end of the bank.

4 Data, Variable Construction and Descriptive Statistics

4.1 Data

The dataset for the empirical analysis was compiled from several sources. The main source is the "On-Time Performance Dataset," which includes data on all scheduled and actual domestic flights operated by airlines carrying more than 1% of U.S. domestic passengers.[15] The ten reporting carriers in October 2000 are: Alaska, America West, American, Continental, Delta, Northwest, Southwest, Trans World, United and US Airways. For each flight the following information is provided: carrier, date of flight, flight origin and destination, scheduled departure and arrival time, actual gate push back time and actual gate arrival time, actual airtime, taxi-in time, taxi-out time, and the aircraft tail number. Using the aircraft tail number, I add data on the following characteristics of the aircraft: the number of aircraft seats; manufacturer; weight; number of engines and year of manufacture.[16] Measures of the number of hourly landing and departing operations that an airport can handle under different weather conditions were obtained from the "Airport Capacity Benchmark Report".[17] In addition, FAA measures for unimpeded taxi-out time (derived by the FAA by airline-airport-season) are used to derive the delay measures as discussed in section 3.3. I focus on flights departing from and arriving at 16 U.S. hub airports in October 2000.[18] Table 1 displays descriptive statistics of the 16 hub airports.

[15] The database is available at $www.transtats.bts.gov/OT - Delay/OT - DelayCause1.asp$

[16] The FAA Aircraft Reference File and the Aircraft Registration Master File databases contain these data and can be downloaded from $www.faa.gov/licenses - certificates/aircraft - certification/aircraft - registry/$.

[17] The full report is available at: $http : //www.faa.gov/about/office - org/headquarters - offices/ato/publications/bench/$. The report contains three measures for airport capacity derived based on different weather conditions. The reported estimation results are based on the medium range capacity measure but the results are qualitatively similar for the other measures.

[18] A hub airport is defined as an airport in which more than 50% of a carrier passengers are connecting passengers. The dataset includes all U.S. hub-airports except Chicago-O'hare, which is a slot-constrained airport. To obtain the total number of an airport enplanements I use the T100 database, which consists of the total thruput of passengers who used each airport. The number of non-connecting passengers (passengers who use the airport as either their origin or final destination) was constructed using the DB1B database. The DB1B database contains a survey of 10% of all the flight fares sold in the U.S. domestic market (I thank Chris Mandel from the Department of Transportation for his help in obtaining these data.).

I also compiled data on the number of gates each airline leased in an airport in the second half of 2000. Data on gates were extracted from competition plan reports, which were submitted by airports to the FAA in 2000 and 2001.[19] Finally, weather conditions at each airport for everyday in October 2000 were obtained from the National Climatic Data Center, which operates weather stations at each of the hub airports in the research sample.[20]

4.2 Bank Structures

The unit of analysis is a *bank* of flights. For each of the 16 hub airports, I use airlines' flight schedules to identify when each of the departing and arriving banks was scheduled to start and end. For example, on 10/16/2000 Delta airlines operated a departing bank in Cincinnati International Airport, which started at 08:31 a.m. and ended at 09:16 a.m. In Figures 2, 3 and 4 the derived bank structure in three hub airports: Cincinnati, Detroit and and Philadelphia on 4 October, 2000 is presented. The appendix contains a detailed description of the bank identification procedure.

Approximately 60% of the flights in October 2000 and included in the dataset arrived at one of the selected 16 hub airports and 60% of the flights departed from one of the 16 hub airports. Among flights operating in hub airports, 70% arrive during bank periods and more than 75% depart during bank periods. Hub airlines operate about 90% of the flights arriving or departing during bank periods, whereas hub airlines operate only 45% of the flights arriving during non-bank periods and 40% of the flights departing during non-banks. Figure 5 displays the mean taxi-out time for flights scheduled to depart during bank and non-bank periods. The Figure illustrates that operating during bank periods entails longer taxi-out

[19] Among the provisions of the Wendell H. Ford Aviation Investment and Reform Act for the 21st Century (AIR 21), enacted in April 2000, is the requirement that an airport competition plan be filed annually with the Federal Aviation Administration (FAA) by the operators of certain airports before they can receive grants under the Airport Improvement Program (AIP) or be authorized to impose a new passenger facility charge (PFC). The requirement for a competition plan applies to airports serving more than 0.5% of U.S. domestic passengers at which one or two airlines control more than 50% of the enplaned passengers. See Ciliberto and Williams (2009) for a more complete description of the competition plan reports.

[20] The weather data can be found and downloaded at *http://cdo.ncdc.noaa.gov/ulcd/ULCD*.

times. Figure 6 displays the relationship between an airport overall concentration and the average concentration of the banks at that airport. Since hub-carriers predominantly operate during bank periods, banks are more concentrated than the airport overall concentration.

For each bank at each hub airport, the following variables are constructed: the number of flights operating during the bank; its length from the time it began till it ended, and its concentration level measured by flights' HHI. Based on the bank length, I also construct a variable denoting the location of a flight within a bank relative to beginning or the end of the bank. Thus, if a bank starts at 8:00 a.m. and ends at 9:00 a.m. then a bank position of a flight operating at 8:30 is $\frac{30}{60} = 0.5$, at 8:10 or 8:50 is $\frac{10}{60} = \frac{1}{6}$, and at 8:00 a.m. or 9:00 a.m. is 0. The measure of flight bank position is used to investigate whether flights arriving or departing closer to the center of the bank experience longer delays. Table 2 provides additional characteristics of bank structures at the 16 hub airports. In Figures 7 and 8, the distributions of the length of banks and the number of flights per bank are presented.

4.3 Measuring Delays

Airlines report the scheduled and actual time of each flight departure and arrival. Based on these reported measures, the literature has adopted two measures of delay: 'actual vs. scheduled' and 'actual vs. optimal actual benchmark'.[21]

The first measure, the difference between the flight actual time and scheduled time, is intuitive.[22] Indeed, if a scheduled time of flight arrival represents the airline or passengers' expectation regarding the time of arrival, then arriving earlier or later than expected may entail costs or benefits for both passengers and airlines. Moving away from the expected time of arrival could have a detrimental impact on subsequent operations.[23] It is likely, however,

[21]See Ater (2007) for a third type of delay measure which uses only the scheduled departure and scheduled arrival time of a flight to derive a 'scheduled vs. optimal scheduled benchmark' delay measure.

[22]The FAA defines a *delayed* flight as a flight that arrives 15 minutes or more after its schedule arrival time.

[23]Papers that primarily relied on this measure of delays are: Brueckner (2002), Rupp (2009), Mazzeo (2003) and Forbes (2008).

that the 'actual vs. scheduled' measure is an inappropriate measure to examine the impact of airport structure on congestion during peak periods, as airlines anticipate longer travel times during peak periods and build these excess travel time into their schedules.[24]

The other measure discussed in the literature does not focus on the deviation from the expected time of a flight. The 'actual vs. optimal actual benchmark' measure is derived based on a flight actual time of operation[25] compared to an optimal performance benchmark.[26] This measure is not subject to manipulation by airlines and has been used to investigate how the hub-airport and network structure affect flights' time performance.[27] An important advantage of the 'actual vs. actual' delay measure is that for each flight the dataset contains several measures of actual flight times: taxi-out time, the time an aircraft spends between leaving the origin airport gate and takeoff; airtime, the time between wheels off at the origin airport till touching the ground at the destination airport; taxi-in time, the elapsed time between wheels-on at the destination airport runway and arriving at the airport gate. This decomposition enables me to investigate the relationship between bank and airport characteristics and queuing time at two bottlenecks: before aircraft takeoff and before aircraft landing. The two bottlenecks are the result of common airport runway facility, which can be viewed as a 'public good'.

Thus, in this paper, I adopt an 'actual vs. actual' measure of delay, using the taxi-out time and airtime data to derive the before takeoff and before landing delay measures. Specifically, the airtime delay measure was constructed by first computing the fastest airtime among all flights arriving at a hub airport from the same origin airport.[28] I then subtracted this benchmark from each flight airtime to obtain the airtime delay measure for a particular flight. The taxi-out time benchmark is the FAA unimpeded taxi-out, a measure for unimpeded elapsed

[24] Known also as schedule padding. For example, Ater (2007) shows that the maximum scheduling padding in October 2000 was 43 minutes for the same directional route.

[25] For example, from the time the airplane leaves the gate at the origin airport till it arrives at the gate at the destination airport.

[26] For example, the fastest actual flight time in the same directional route.

[27] See Mayer and Sinai (2003)

[28] There are other factors that could affect airtime, such as: aircraft type, weather conditions, runways, routing, congestion on the way. I do control for some of these factors in the estimation.

time from a carrier gate in a particular airport to takeoff. This benchmark was then subtracted from a flight taxi-out time to obtain the relevant delay measure.[29] To provide initial evidence for the negative relationship between these measures of delay and airport concentration, Figures 9 and 10 display the negative relationship between the airport concentration level and the mean delay measure during bank periods at that airport.

5 Estimation and Results

The empirical section relies on the theoretical framework outlined in section 3 and contains two main parts. In the first part I examine the relationship between an airline scheduling decision regarding the length of the bank period and market structure determinants. Scheduling decisions by airlines can be interpreted as the outcome of a simultaneous scheduling game, where the number of flights offered by each carrier is exogenous but the time of operation is endogenously determined. In the second part I explore how the length of the bank period is associated with flight delays generated during bank periods. I also provide evidence on the relationship between bank concentration and delays. Finally, I investigate whether airplanes operating during longer banks remain on the ground for a longer time between subsequent flights.

5.1 Bank Structure and Scheduling Decisions

In this section, I provide evidence on the link between the length of departing and arriving banks and market structure determinants, such as the number of bank flights, airport runway capacity and the concentration of the bank. The hypothesis is that more concentrated banks are longer since hub carriers at these banks have a greater incentive to reduce congestion at the bank. Other factors that may affect the length of the bank are the airport runway

[29] Morrison and Winston (2008) adopted this measure of delay but not in the context of the internalization question. Note that this benchmark does not account for potential differences in the location of gates leased by the same airline in an airport.

capacity and the overall number of bank flights. I, thus, add the ratio of bank flights and airport runway capacity as a control variable.[30] In addition, I use two categorical variables to proxy for passenger preferences over layover time. Presumably, if passengers' layover time is more expensive, then airlines will tend to choose shorter bank periods and reduce layover time. First, I include the categorical variable 'Weekend,' which equals one when the bank operates on either Saturday or Sunday and 0 otherwise. It is expected that airlines will choose longer banks during the weekend, when the average passenger value of time is lower. Also included is the categorical variable 'Tourist' for departing and arriving banks at Miami Intl. Airport as it is expected that the bank period is longer in airports where many of the passengers are tourists. Another potential consideration for the length of a bank is the level of aircraft utilization during the day. The greater the number of remaining aircraft operations during the day, the higher the incentive is to reduce the ground time. Accordingly, we could expect banks characterized by airplanes with relatively a large number of remaining flights to be shorter. To obtain a measure of the number of remaining flights for each aircraft, I calculated the number of remaining daily flights for each aircraft[31] and then derived an average measure of a bank's remaining flights in a day. I define this measure as 'Remain-Flights'.

In the empirical estimation, a unit of observation is a bank, and the analysis is performed separately for arriving and departing banks unless mentioned differently. The length of a bank is measured by minutes and the base specification examining how does the length of bank j in airport k vary with the bank concentration is as follows:

$$\begin{aligned} Bank-Length_{jk} = \beta_1 Bank-Conc_j + \beta_2 Bank-Flights-Runway_j + \\ \beta_3 Weekend + \beta_4 Tourist_k + \beta_5 Remain-Flights_j + \epsilon_{jk} \end{aligned} \tag{1}$$

[30] I use the ratio of bank flights and airport capacity rather than add them as separate regressors since the airport gate instrument I use already exploits the variation across airports.

[31] Clearly, this measure diminishes over the day.

The length of the bank period is also affected by the (unobserved) number of bank connecting passengers. The larger the share of connecting passengers out of total bank passengers the larger the incentive of the hub carrier to reduce layover time. The share of connecting passengers is likely to be correlated with the share of flights operated by the hub carrier, and thus, an omitted variable bias may arise. To control for the potential endogeneity of the bank concentration coefficient, I use the herfindahl concentration measure of airport gates as an instrument. Airport lease agreements are typically long-term contracts[32] and the extent of service an airline can offer at the airport is affected by the number of gates it leases. Hence, banks at airports characterized by highly concentrated gate structure are also likely to be highly concentrated. In Table 3, I report the results for the first stage instrumental variable regression. As expected, the airport gates variable is positively correlated with the bank concentration.[33] Furthermore, it is likely that this measure is uncorrelated with the share of connecting passengers at a particular bank during a day since the measure of gate concentration is invariant-airport-specific. Using airport gates as an instrumental variable, however, implies that variation across airports is the main source of variation in the estimation and it also hinders using airport fixed-effects to control for other differences across airports, such as the type of population served by each airport.[34] Note also that in the delay regression below I do use variation within airports and control for unobserved differences between airports by including airport fixed effects.

The IV regression results are displayed in Table 4. Columns 1 and 2 correspond to arriving and departing banks, respectively. In all the regressions the coefficient on the bank concentration coefficient is positive and significant implying that more concentrated banks

[32] The 1990 study by the Government Accounting Office reported that 22 percent of the gates at the 66 largest airports were for 3-10 years duration; 25 percent were for 11 - 20 years duration; and 41 percent were for more than 20 years duration, GAO (1990).

[33] I also reject the exogeneity of the bank concentration variable.

[34] In all airports, the variation across days and weeks is very small. In addition, in some hub airports there is little within-airports variation in bank concentration. Hence, to some extent, the loss from not exploiting within-airport variation is limited.

are longer. The coefficient on the ratio of bank flights and runway capacity is positive and statistically significant, as expected. Other coefficients generally have the expected signs. Weekend banks are typically longer so too are banks at airports serving relatively more tourists. The coefficient on 'Remain-Flight' is negative and significant in the arriving bank regression - suggesting that banks earlier in the day are more congested - but is negative for the departing and pooled bank regressions. Overall the results are consistent with internalizing behavior by hub carriers, and suggests that hub-airlines choose longer banks as their share of bank flights increases.

5.1.1 Scheduling Decisions across Arriving and Departing Banks

The unit cost of congestion likely affects hub airlines' decisions regarding the length of the bank. The higher the unit cost of congestion the higher the incentive of hub carriers to increase the length of the bank and consequently reduce the time an airplane spends in a queue. I exploit the distinction between arriving and departing banks to explore this relationship, assuming that the unit cost of congestion for arriving banks is higher than that of departing banks.[35] Note that I use scheduled data to determine the length of a bank period. Thus, safety considerations regarding time difference between flight arrivals are unlikely to affect my findings. Hence, evidence that arrival banks are longer than departing banks is consistent with an internalization behavior. The results of the pooled banks regressions are presented in columns 5 and 6 in Table 4. In particular, I add to the bank length specification a dummy variable, $D(arr)$, which equals to one in arriving banks and zero otherwise. The results imply that arriving banks are more than 3 minutes longer than departing banks, which is consistent with higher marginal cost of queuing time during arriving banks.

[35] During arriving banks, when airplanes wait for their turn to land, queuing cost is larger than the unit cost of congestion during departing banks when airplanes wait on the ground. Consequently, airlines can avoid congestion during arriving banks by choosing longer bank periods.

5.2 Delays and Bank Length

In this section, I primarily seek to document the negative relationship between different measures of flight delays and the length of the bank. A negative relationship would suggest that dominant airlines, operating in concentrated banks and choosing longer bank period, attain a lower level of delays relative to banks, where several airlines operate concurrently.

The analysis below refers only to flights scheduled during bank periods and utilizes two categories of delays as dependent variables. The first category, taxi-out delay, focuses on the queue before takeoff, as aircraft wait for their turn to depart. The second category, airtime delay, focuses on the queue before landing, as aircraft wait for their turn to land. In both categories, airport runway capacity is interpreted as the scarce resource over which airlines compete.[36]

In each of the regression analyses (for departure and arrival banks), an observation is a flight. The base specification for aircraft n used for flight i operating during bank j at airport k on day m is as follows:

$$\begin{aligned} Delay_{ijkmn} = \beta_1 Bank - Length_j + \beta_2 Capacity_k + \beta_3 Bank - Flights_j + \\ \beta_4 Bank - Pos_{i,j} + \beta_5 Weather_m + \beta_6 Aircraft_n + \epsilon_{ijkmn} \end{aligned} \tag{2}$$

Standard errors are clustered over an origin airport-flight number pair. The control variables in the above specifications can be divided into two groups. The first group includes variables that are determined by airlines prior to the actual operation of the flight and the realization of delay. These variables are the airport runway capacity, the scheduled number of bank flights, the bank length and the relative position of the flight within the bank. The second group of control variables includes daily weather variables, which are not controlled by

[36] Hence, the taxi-in time, which corresponds to the flight segment post-landing is unlikely to be affected by this scarce airport resource.

the airlines. Thus, one can view airlines as engaging in a two-stage game. In the first stage, airlines determine the schedule of flights. In the second stage, delay is realized given the first stage outcome, as well as the daily weather conditions.

Table 5 displays the regression results when the taxi-out delay measure is used as the dependent variable.[37] In all regressions, the coefficient on the length of the bank is negative and statistically significant. The coefficient on 'Runway capacity' is also negative suggesting that, *ceteris paribus*, the scarcity of the runway has a detrimental impact on delays. Similarly, the coefficient on the number of bank flights is positive indicating that larger banks are associated with longer delays. The relative location of the flight within the bank is positive suggesting that flights scheduled either at the beginning or towards the end of the bank wait less for their turn to depart. Finally, weather conditions have the expected signs.[38]

In Table 6, I present regression results using the airtime delay as the dependent variable. The regression results indicate that longer banks are associated with shorter delays and lend additional support to an internalization behavior by airlines. In all the regressions the bank length and the runway capacity coefficients are negative and significant. Furthermore, the coefficients on bank flights and the flight bank position are all positive. The flight distance variable, added in columns 4-5, is positive suggesting that longer flights incur longer airtime delays.[39]

[37] In columns 5, the dependent variable is the sum of the taxi-out delay measure and the flight departure delay. Departure delay is the difference between the actual time a flight left the origin airport gate and the time it was scheduled to leave the gate. In this regression, I restrict the sample to departure delays shorter than 20 minutes.

[38] Note also that adding aircraft characteristics entails losing about 40% of the observations. There are two main reasons for this. First, the FAA registry data does not include the characteristics of aircraft which are no longer operating or were sold to non-U.S. entities. Second, some airlines report their aircraft nose numbers rather than the tail numbers.

[39] A potential explanation for this finding is that airlines operating in shorter routes can foresee better the landing conditions at the destination airport. Consequently, they are more likely to adjust their schedule to avoid operating when conditions at the destination airport require that.

5.3 Analysis of Aircraft Ground Time

Internalization behavior suggests that hub airlines operating a larger share of the bank flights will schedule longer banks. As a result, hub airlines reduce the cost of congestion but may incur additional costs due to longer passengers' layover time and lower utilization of their fleet. In this section, I investigate whether airplanes that operate during longer banks experience longer ground time. Using the aircraft tail number, I identify the daily sequence of flights by each aircraft and the aircraft ground time between subsequent flights and employ the following specification:

$$\begin{aligned} Ground-Time_{jklmn} &= \beta_1 Bank-Length_m + \beta_2 Bank-Length_n \\ &+ \beta_3 Bank-Flights_m + \beta_4 Bank-Flights_n + \beta_5 Distance_{jk} \\ &+ \beta_5 Distance_{jl} + \beta_6 Hub-Carrier_j + \epsilon_{jmn} \end{aligned} \tag{3}$$

An observation is an aircraft and the dependent variable is the aircraft ground time between subsequent flights. In the regression analysis I consider only flights that depart during bank periods and restrict the sample to aircraft that remained less than 180 minutes on the ground between subsequent flights.[40] The coefficients of interest are β_1 and β_2 and standard errors are clustered over an aircraft tail number. In column 4 I add aircraft characteristics, and in column 5 I focus on flights operated by the hub airline. All the the coefficients of interest are positive and significant In the regressions displayed in Table 7, implying that aircraft operating during longer banks spend longer time on the ground between adjacent flights.

5.4 Using Bank Concentration to Explain Delays

Existing literature on the relationship between congestion and concentration typically examined the empirical relationship between congestion and concentration. To provide a compar-

[40] The results are not sensitive to other time restrictions.

ison with previous literature, I report the results of estimating delays as a function of bank concentration. Specifically, I replace the bank length variable in equation 2 with the bank concentration variable. The results for taxi-out and airtime delays are reported in Tables 8 and 9 and document a negative relationship between bank concentration and delays. The regression results confirm the clear negative patterns displayed in Figures 9 and 10.

5.5 Discussion of Results

The empirical analysis consists of several pieces of evidence for an internalizing behavior by hub carriers. The results suggest that hub airlines are able to lower the density of bank flights and consequently reduce congestion by scheduling longer banks. Indeed, starting at 2002 hub airlines, looking for ways to reduce costs, have implemented de-peaking strategies that essentially increased passengers' layover time and at the same time reduce congestion and delays. The empirical findings may also imply that policy intervention should consider treating hub-airlines differently than fringe carriers, since dominant carriers already internalize congestion and schedule their flights accordingly. The findings may also suggest that an attempt to reduce congestion externalities will have a limited impact on congestion at highly concentrated airports since hub-airlines already internalize congestion. To provide a crude measure of potential savings, I rely on the bank length regression and consider how an increase of one standard deviation in bank concentration would affect the length of the corresponding bank. My findings suggest that departing banks would increase by (0.17* 40.95) 6.96 minutes whereas arriving banks would be (0.15*62.78) 9.4 minutes longer. Using the coefficients from the delay regressions, I find that these changes in bank length translate, on average, into approximately (6.96*0.071) 0.5 minutes shorter taxi-out time during departing banks and (9.4*0.098) 0.9 minutes shorter airtime delays during arriving banks for each flight operating during a bank. The results also underscore the adverse effect of weather on airlines' time performance. For example, a thunderstorm is associated with an additional three minutes of taxi-out time and two minutes of excess airtime. Thus, this may warrant allocating more resources to improving airline performance under severe weather conditions.

6 Concluding Remarks

Air delays and congestion have become a major policy issue in recent years. Traditionally, economists proposed congestion pricing solutions to reflect the real value of scarce runway capacity. Economists, however, disagree on how to implement these solutions and whether airlines should be charged a uniform fee for operating at a particular time, or alternatively whether dominant carriers operating a large share of flights, should be charged a lower fee, because these airlines already internalize congestion externalities inflicted on their own flights.

This paper investigates the relationship between congestion and the structure of hub airports. Specifically, I study how congestion varies across high-volume time periods at hub airports, known as flight banks. An advantage of focusing on bank flights at hub airports is the ability to compare airports with relatively similar patterns of operations. Extending the sample of airports to non-hub airports would require addressing basic differences between these two types of airports. I find a clear negative relationship between market/bank concentration and the level of delays, as a measure of congestion. Furthermore, using bank as the unit of analysis enables me to explore how hub airlines internalize congestion. I find that hub airlines choose longer banks as their share of bank flights increases. These longer banks are associated with shorter flight delays. Thus, the results suggest that introducing congestion pricing at non-concentrated banks or airports could yield better time savings than at highly concentrated hub-airports. Future research could offer better estimates of the potential savings as well as compare the effectiveness of alternative policy prescriptions. The results also shed light on efficiency gains that may arise following a merger between two airlines operating at an airport, as congestion costs are likely to fall. Lastly, the vast literature on the airline industry and its hub & spoke network has generally ignored the explicit role of airport banks. Future research could explore how airline performance and traveler welfare are affected by the structure of banks.

7 Appendix A

The identification of banks relies on flights operated only by the relevant hub carrier in each airport. To identify the arriving banks, the number of arriving flights for each minute of every day and hub airport was derived and then the average number of flights arriving at the airport in a 21 minute time window was computed.[41] To exploit the structure of arriving and departing banks, the number of departing flights in each minute was considered as negative, when this average was computed.[42] Based on the 21 minute operation rates, I compute also the daily operation rate and its standard deviation. An arriving bank threshold is defined as the operation level at one standard deviation above the daily operation rate. An arriving bank period occurs when the average 21 minute operation rate is higher than the positive threshold. The bank period starts and ends when the per minute operation rate falls below the daily average operation rate.[43] The structure of departing banks is derived equivalently.

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[41] The number of flights operating ten minutes before and ten minutes after a particular minute, divided by 21.

[42] Thus, if the same number of arriving and departing flights operate in a 21 minute window of a particular minute then the average operation rate is zero. If there are more arriving flights than departing flights (for example, during arriving bank) then the operation rate will be above zero.

[43] Specifically, the bank boundaries are identified by the last hub carrier flight which still operates above the daily average.

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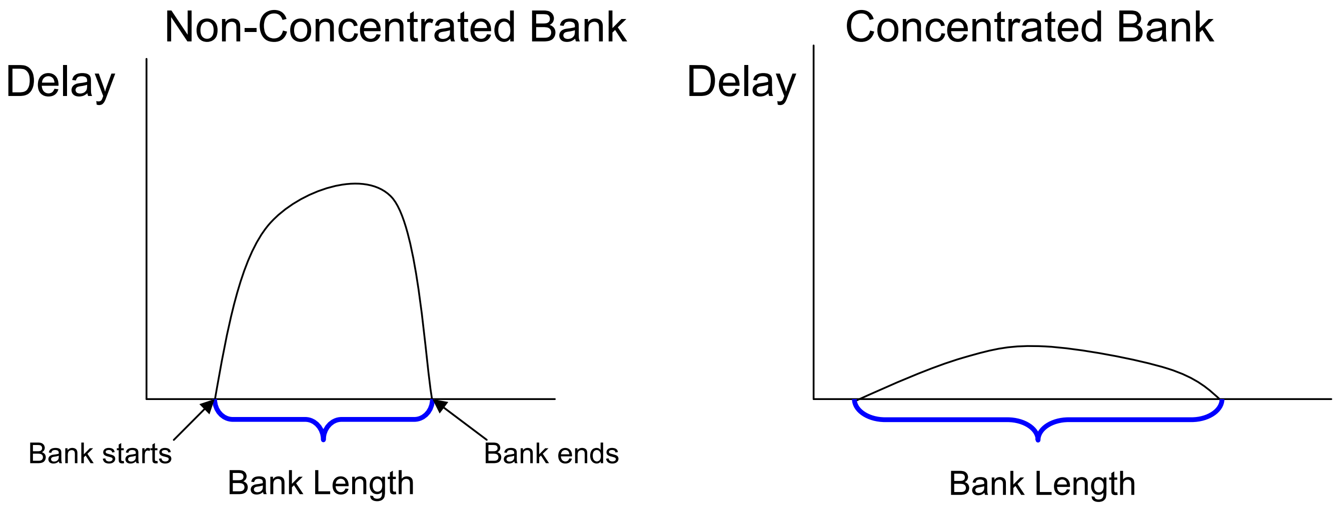

Figure 1: Graphic Illustration of the Theoretical Framework

The Figure displays the congested period in competitive and concentrated markets/banks as postulated by the theoretical framework. Bank periods are longer and delays are shorter in concentrated banks than in competitive banks. The Figure also shows that flights scheduled to operate closer to the center of the bank experience longer delays. The depicted pattern of congestion is similar to the pattern of congestion illustrated by Henderson (1981).

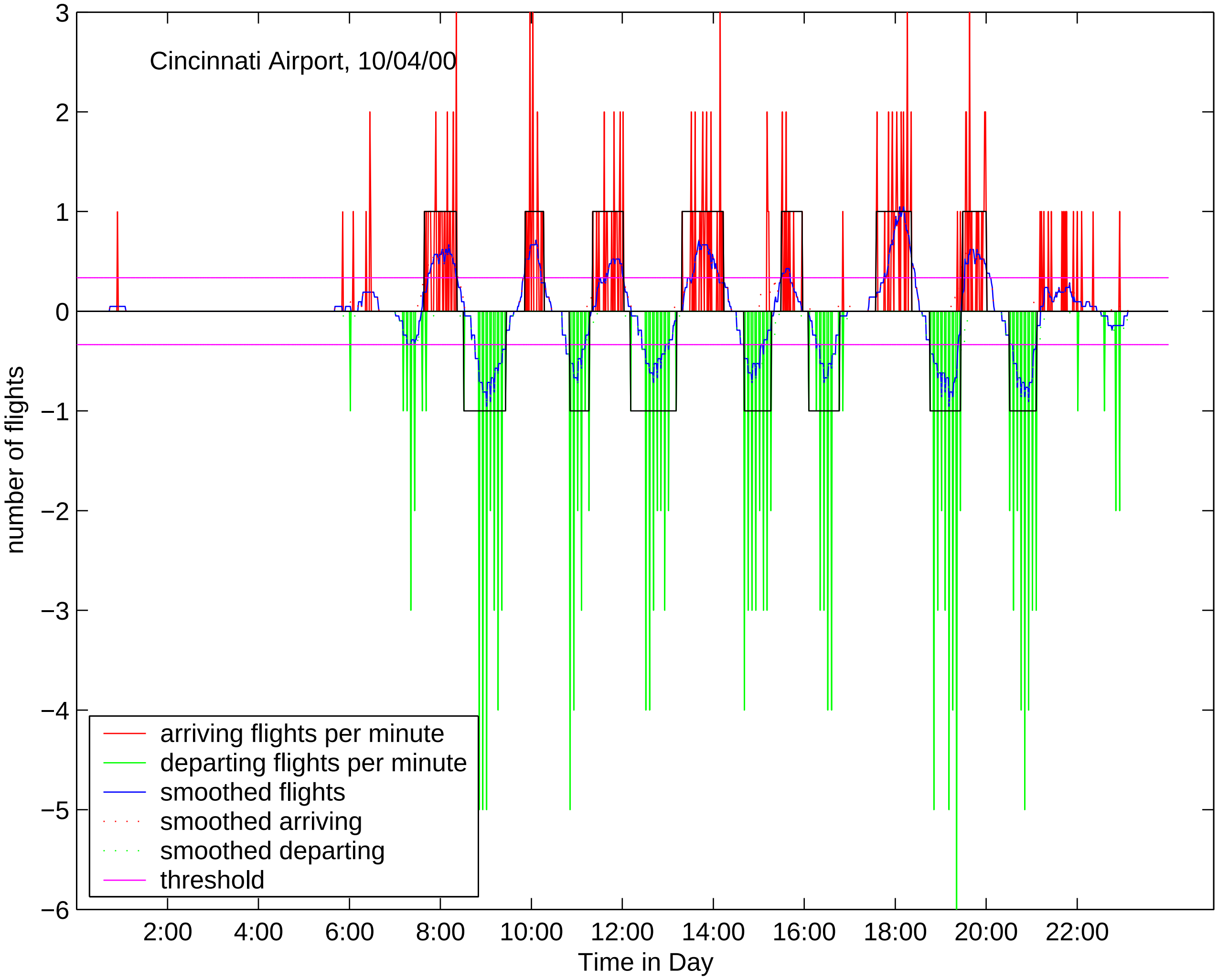

Figure 2: Bank Structure in Cincinnati Airport

The Figure illustrates the algorithm used to identify banks in Cincinnati Airport, where Delta Airlines operates as a hub carrier. The smooth line depicts the average 21-minute operation rate based on the number of arriving and departing flights. An arriving (departing) bank occurs when the 21-minute operation rate is higher (lower) than one standard deviation of the daily average operation rate. The rectangles denote the banks.

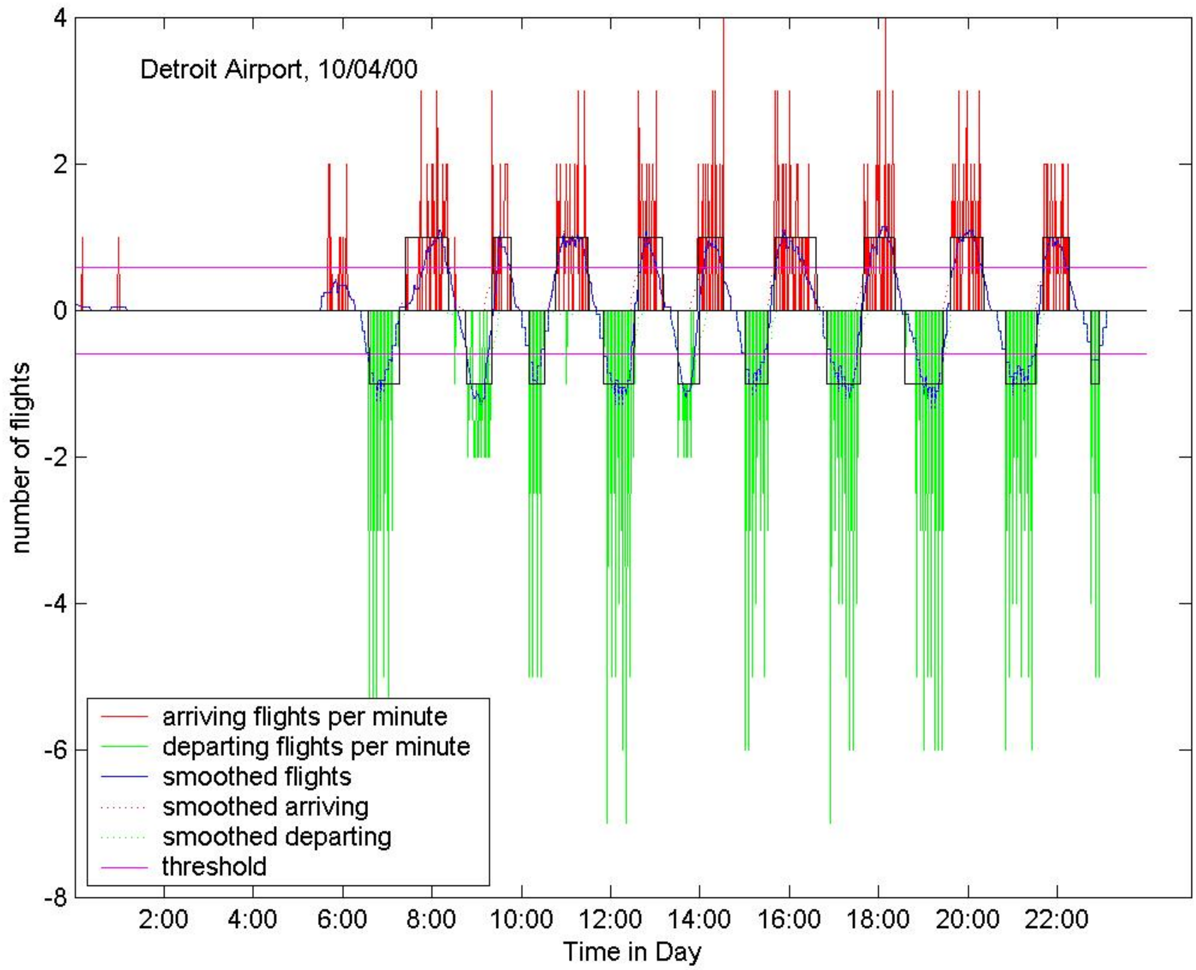

Figure 3: Bank Structure in Detroit Airport

The Figure illustrates the algorithm used to identify banks in Detroit Airport, where Northwest Airlines operates as a hub carrier. The smooth line depicts the 21-minute operation rate based on the number of arriving and departing flights. An arriving (departing) bank occurs when the 21-minute operation rate is higher (lower) than one standard deviation of the daily average operation rate. The rectangles denote the banks.

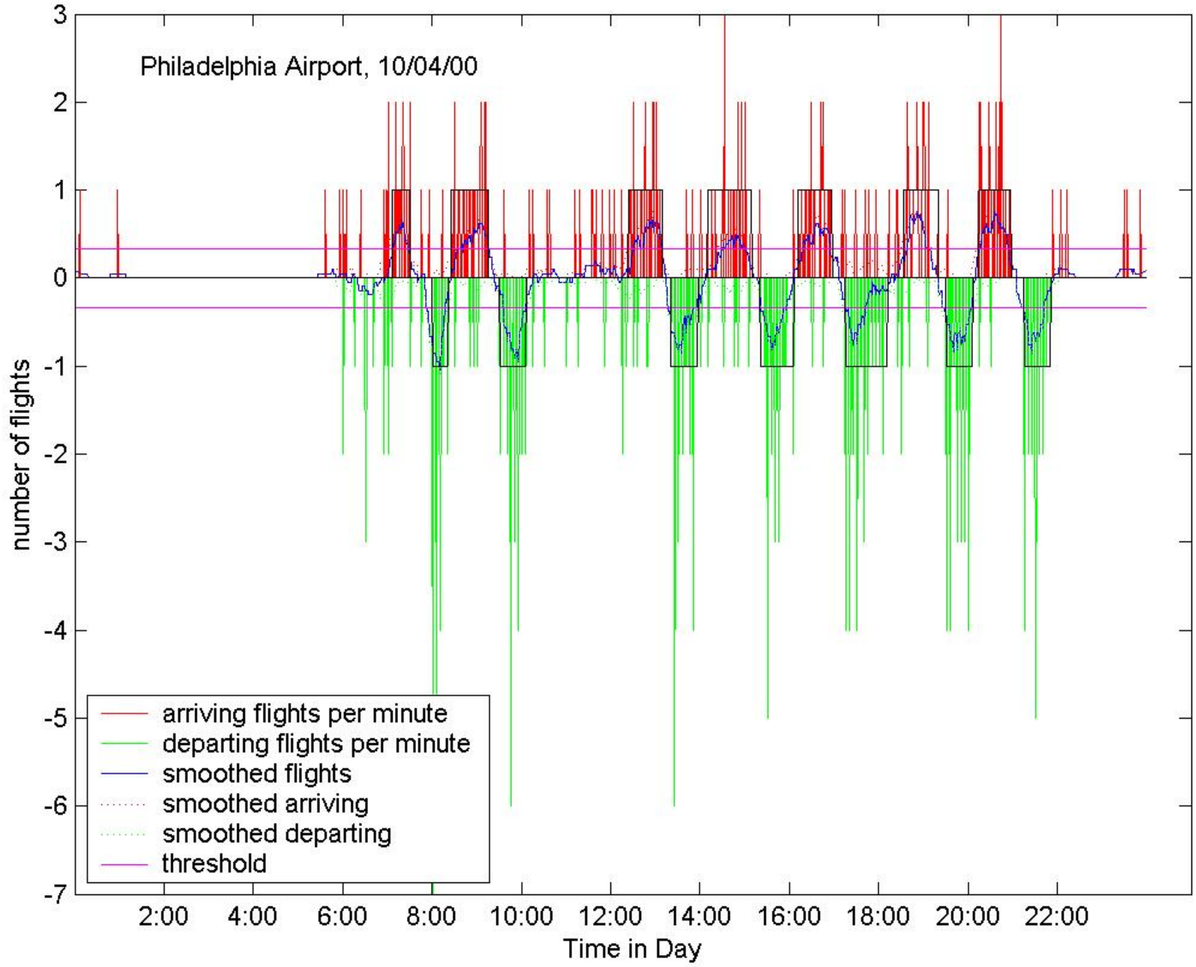

Figure 4: Bank Structure in Philadelphia Airport

The Figure illustrates the algorithm to identify banks in Philadelphia Airport, where US Airways operates as hub carrier. The smooth line depicts the 21 minutes operation rate based on the number of arriving and departing flights. An arriving (departing) bank occurs when the 21-minute operation rate is higher (lower) than one standard deviation of the daily average operation rate. The rectangles denote the banks.

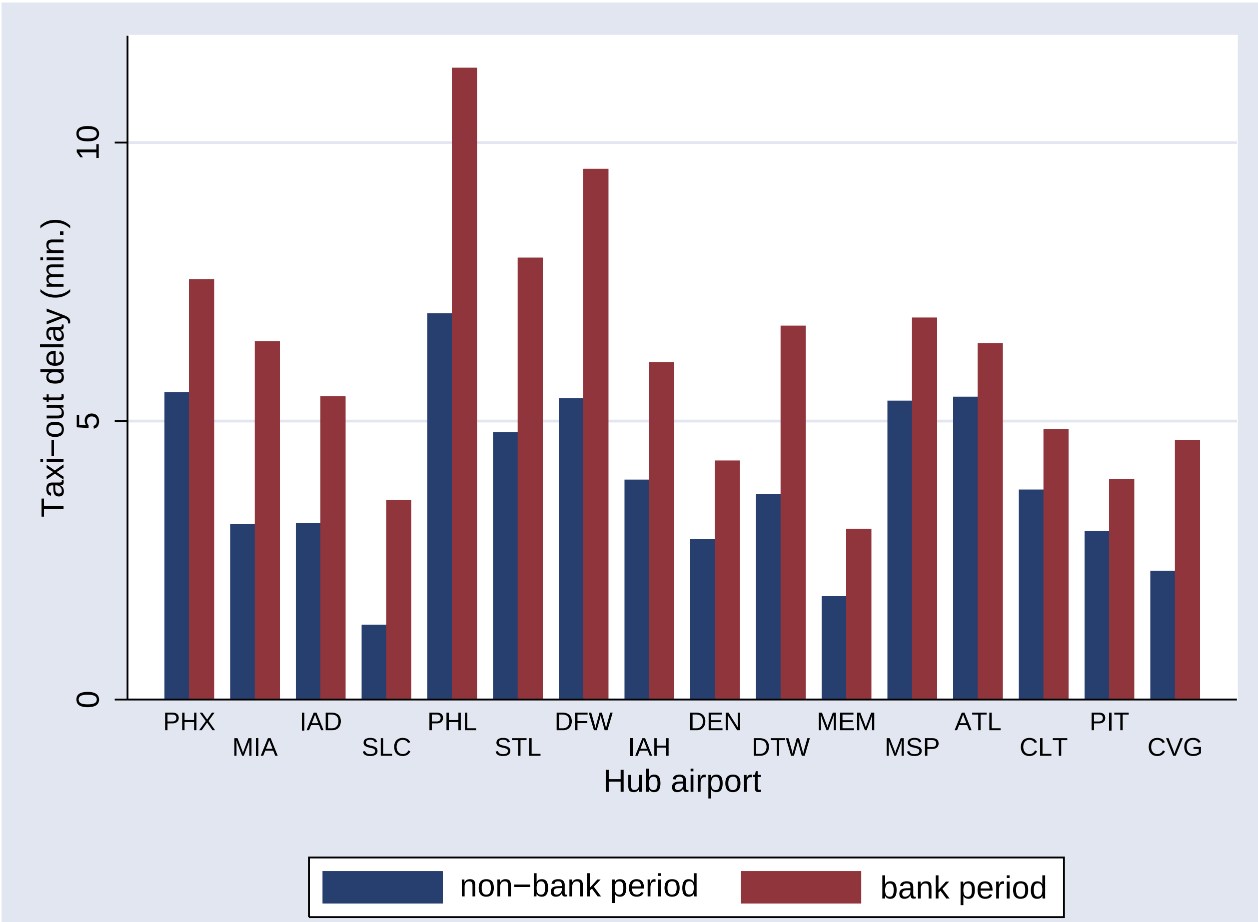

Figure 5: Taxi-out Time during bank and non-bank periods in hub airports

Figure 5 displays the mean taxi-out time for flights operating during bank and non-bank periods at the 16 hub airports. Hub-airports (The horizontal axis) are sorted by their concentration levels, where highly concentrated airports are on the right side of the Figure. More flights operate during bank periods and taxi-out time during these periods is longer than during non-bank periods. Furthermore, taxi-out at more concentrated hub-airports is generally shorter.

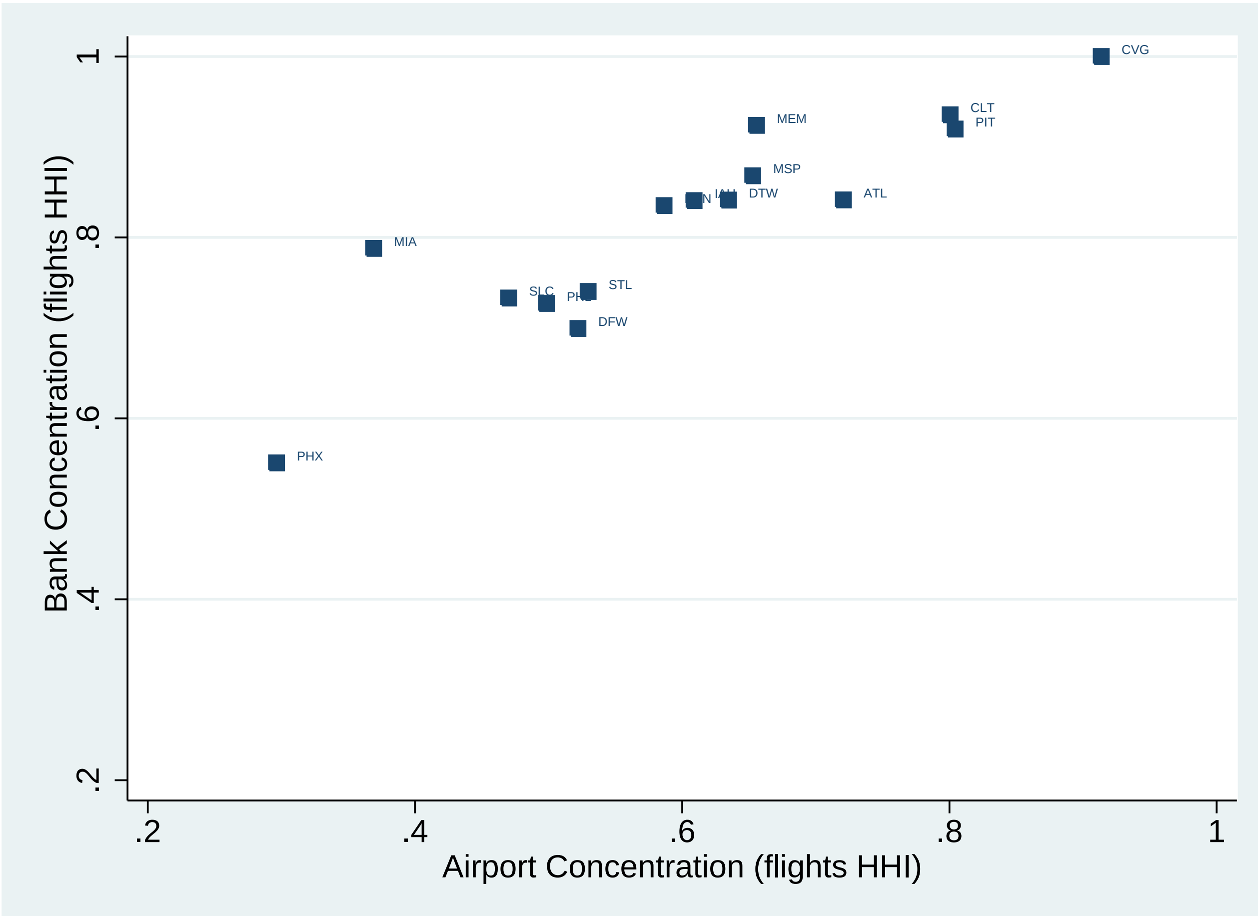

Figure 6: Bank and Airport Concentration

Figure 6 plots bank concentration levels as a function of the hub airport concentration levels. It demonstrates that banks are more concentrated than the airport they operate in. For example, the concentration level in Miami Intl. Airport is less than 0.4, whereas the average bank concentration is nearly 0.8. Thus, hub carriers predominantly operate during banks, and non-hub carriers generally prefer to operate during non-bank periods. Nevertheless, non-hub carrier still operate during bank periods.

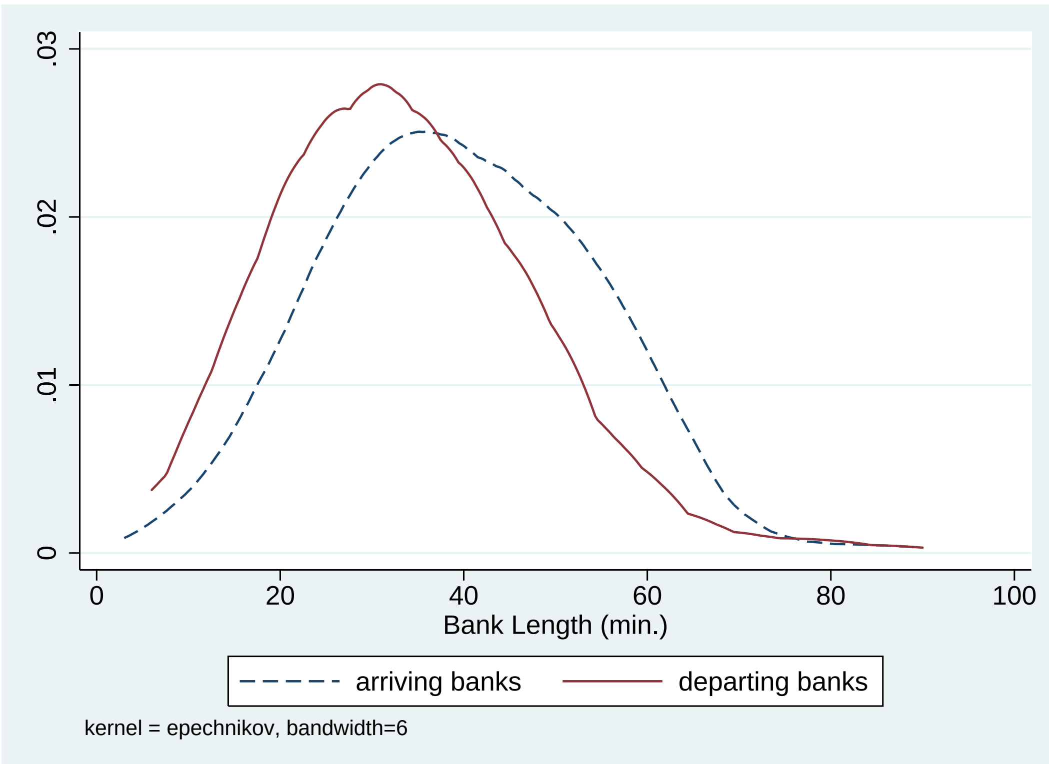

Figure 7: Kernel Distributions of Length of Departing and Arriving Bank Periods

The Figure displays the distribution of the length of bank periods. The mass of departing banks lasts for less than 30 minutes whereas arriving banks are typically longer.

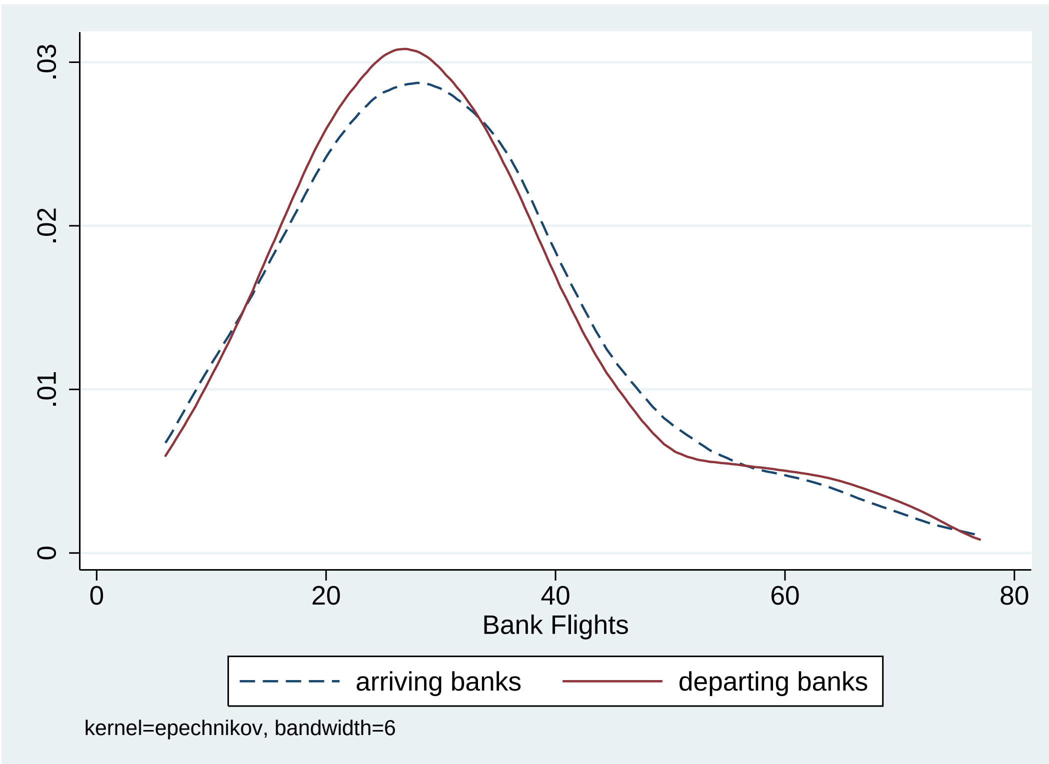

Figure 8: Kernel Distributions of Volume of Flights During Departing and Arriving Banks

Kernel distributions of bank flight volume are presented in Figure 8. A representative bank consists of roughly 30 flights.

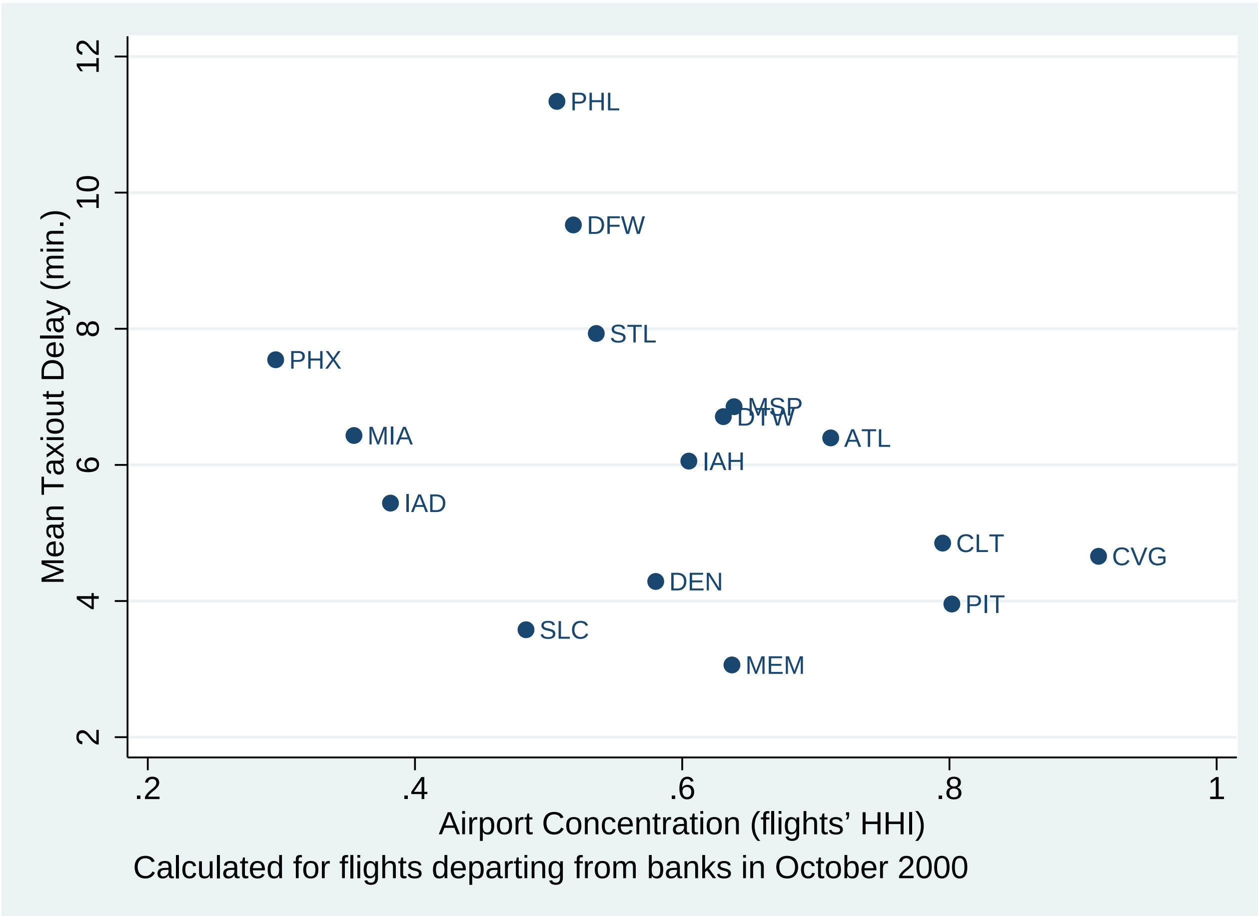

Figure 9: The Relationship between Airport Concentration and Taxi-out Delay

The Figure shows a negative empirical relationship between airport concentration and taxi-out delay. The taxi-out delay is a measure of airplane queuing time before departure, as airplanes wait for their turn to use the airport runway. Taxi-out time during bank periods is typically longer at less concentrated hub-airports. This finding is consistent with an internalizing behavior by dominant carriers, whose incentive to take into account the impact of their scheduling decisions on congestion is higher the greater their share of the flights.

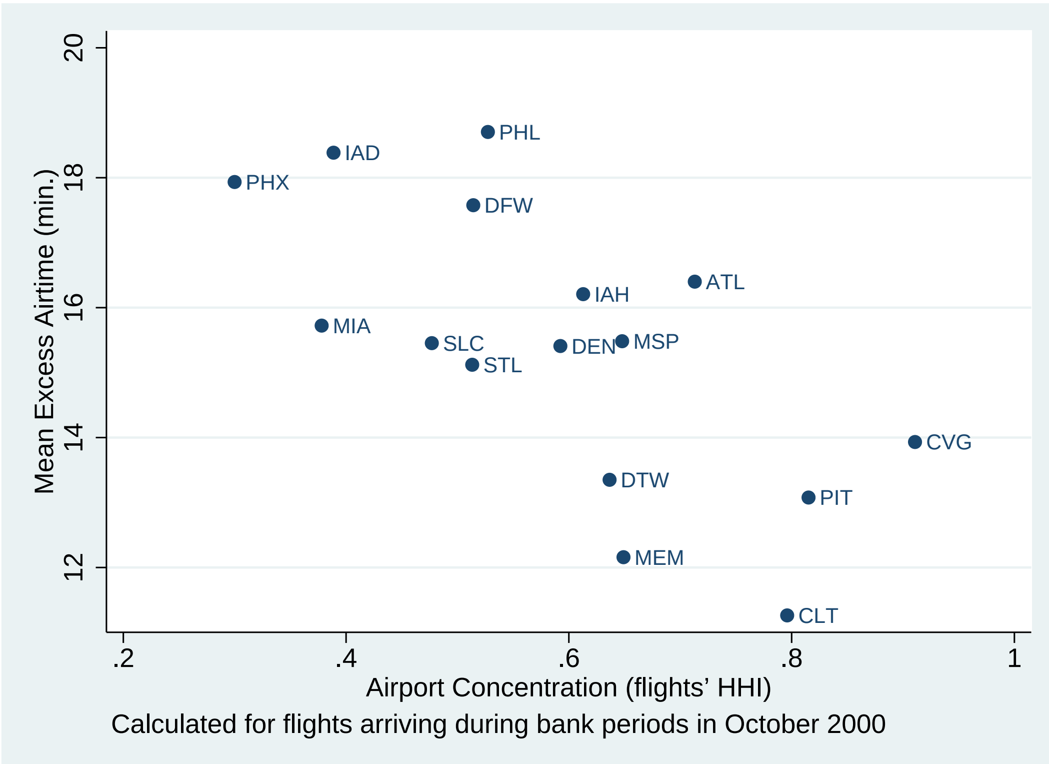

Figure 10: The Relationship between Airport Concentration and Excess Airtime Delay

The Figure displays a negative empirical relationship between airport concentration and excess airtime delay. A flight excess airtime is derived relative to the fastest airtime of a flight on the same directional route in the same month. Excess air-time is used as a proxy for queuing time before landing, while airplanes wait for their turn to land on the airport runway. This negative relationship is consistent with an internalizing behavior by dominant carriers, whose incentive to take into account the impact of their scheduling decisions on congestion is higher the greater their share of the flights.

Table 1: Hub Airport Characteristics

Airport	Airport concentration*	Dominant carrier	Dominant carrier share of passengers	Share of dominant carrier connecting passengers*	Capacity (operations per hour)
Atlanta	0.71	Delta	0.72	0.66	173
Charlotte	0.8	US Airways	0.9	0.8	128
Cincinnati	0.91	Delta	0.64	0.69	122
Denver	0.58	United	0.64	0.62	194
Dallas-Fort Worth	0.52	American	0.58	0.63	241.5
Detroit	0.63	Northwest	0.68	0.58	170.5
Washington Dulles	0.38	United	0.59	0.51	117
Houston	0.61	Continental	0.72	0.65	130.5
Memphis	0.65	Northwest	0.7	0.74	153.5
Miami	0.37	American	0.53	0.61	111
Minneapolis-St. Paul	0.65	Northwest	0.71	0.59	113.5
Philadelphia	0.49	US Airways	0.64	0.51	99
Phoenix	0.29	Southwest	0.31	0.69*	113.5
Pittsburgh	0.8	US Airways	0.87	0.71	146
Salt Lake City	0.47	Delta	0.71	0.62	115
St. Louis	0.53	Trans World	0.72	0.77	93.5

*Notes: (1) Concentration is measured by flights' HHI (2) Share of connecting passengers is the dominant carrier share of connecting passengers out of the carrier total passengers (3) In Phoenix, the share of connecting passengers relates to America West, the second largest carrier.

Table 2: Hub Airport Bank Structures

Hub Airport	Hub carrier	# of departing & arriving banks	Operation Rates during dep. & arr. banks (flights per min.)	Mean dep. bank length (min.)	Mean arr. bank length (min.)	Mean dep. & arr. bank concentration
Atlanta	Delta	309 , 279	1.18 (0.3) ; 1.12(0.1)	47 (8.2)	48.9 (8)	0.83 , 0.88
Charlotte	US Airways	310 , 310	0.98 (0.3) ; 0.73(0.2)	31.5 (6.7)	43.4 (7.4)	0.93 , 0.9
Cincinnati	Delta	246 , 218	0.55(0.15) ; 0.57(0.1)	40.5 (12)	38.2 (10.5)	0.99 , 0.99
Denver	United	362 , 371	0.93(0.3) ; 0.77(0.24)	19.3 (6.8)	24.6 (7.6)	0.88 , 0.83
Dallas	American	309 , 277	1.76(0.5) ; 1.3(0.2)	32.2 (11.4)	45.3 (9.8)	0.7 , 0.69
Detroit	Northwest	301 , 274	1.1(0.1) ; 0.95(0.2)	34.4 (11)	40.6 (10.2)	0.84 , 0.89
Washington Dulles	United	210, 185	0.45(0.15) ; 0.36(0.2)	28.6 (6.4)	32.4 (15)	0.77 , 0.78
Houston	Continental	329 , 275	1.18(0.2) ; 0.88(0.14)	22.8 (6.4)	32.9 (11.6)	0.85 , 0.86
Memphis	Northwest	124 , 124	0.6(0.1) ; 0.52(0.1)	52.7 (16)	59.7 (12)	0.91 , 0.91
Miami	American	181 , 154	0.39(0.1) ; 0.38(0.13)	52 (27)	57.4 (32.7)	0.62 , 0.9
Minneapolis	Northwest	276 , 257	1.07(0.2) ; 0.73(0.1)	33.8 (6.9)	52 (6.9)	0.84 , 0.86
Philadelphia	US Airways	217 , 217	0.83(0.2) ; 0.68(0.1)	39.3 (10.1)	43.3 (8.3)	0.73 , 0.84
Phoenix	America West	338 , 343	1.05(0.3) ; 0.96(0.3)	26.4 (8.43)	27.8 (6.42)	0.58 , 0.54
Pittsburgh	US Airways	247 , 221	0.79(0.2) ; 0.77(0.2)	42.6 (17.7)	44.4 (15)	0.91 , 0.93
Salt Lake City	Delta	248 , 248	0.53(0.1) ; 0.54(0.3)	36.8 (10.5)	39.7 (14.9)	0.73 , 0.79
St. Louis	Trans World	333 , 312	1.1(0.25) ; 0.84(0.2)	28.7 (6.95)	35.4 (8)	0.74 , 0.87

The Table contains monthly characteristics of banks at the 16 hub airports, where a hub airports is defined as an airport, in which 50% of a carrier passengers are connecting passengers.

* The numbers in parentheses reflect the standard deviation of the corresponding variable.

	Dep. Var: Bank Conc, 2sls first stage regressions		
	Arriving Banks	Departing Banks	Pooled Banks
	(1)	(2)	(3)
VARIABLES			
Gates Conc	0.493***	0.500***	0.497***
	(0.014)	(0.015)	(0.011)
Bank Flights/Runway	-0.132***	-0.381***	-0.288***
	(0.023)	(0.024)	(0.017)
Remain Flights	0.011***	-0.019***	-0.005***
	(0.001)	(0.001)	(0.001)
Tour	-0.152***	-0.251***	-0.212***
	(0.014)	(0.010)	(0.009)
Weekend	0.008*	0.001	0.004
	(0.004)	(0.005)	(0.003)
Arriving Bank			-0.004***
			(0.002)
Constant	0.567***	0.696***	0.645***
	(0.010)	(0.011)	(0.007)
Observations	4032	4305	8337
R-squared	0.264	0.302	0.257

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: First Stage IV regressions

The Table displays the results of the first stage IV regression presented in Table 3. As expected, gates concentration is positively correlated with bank concentration.

	Dep. Var: Bank Length, IV Regressions		
	Arriving Banks	Departing Banks	Pooled Banks
	(1)	(2)	(3)
VARIABLES			
Bank Conc	62.780***	40.950***	52.013***
	(2.745)	(2.707)	(1.953)
Bank Flights/Runway	98.933***	91.371***	98.703***
	(2.320)	(2.336)	(1.665)
Tour	16.631***	23.641***	21.590***
	(1.577)	(1.288)	(1.009)
Weekend	-0.057	1.067**	0.559*
	(0.444)	(0.424)	(0.313)
Remain Flights	-0.809***	1.502***	0.517***
	(0.116)	(0.130)	(0.081)
Arriving Bank			3.107***
			(0.145)
Constant	-30.727***	-23.467***	-28.899***
	(2.276)	(2.605)	(1.780)
Observations	4032	4305	8337
R-squared	0.152	0.127	0.144

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Bank Length Estimation Results

In all columns a bank length is used as the dependent variable. Columns 1 and 2 correspond to arriving and departing banks, respectively. Column 3 reports the estimation results of the pooled data using both arriving and departing banks. I account for potential endogeneity of the bank level of concentration using the concentration of airport gates. The results are consistent with an internalization behavior, where more concentrated banks are longer. Other coefficients generally have the expected signs. For example, the ratio of bank flights and airport runway is positive and the weekend banks are longer. The pooled data estimation results suggest that arriving banks are longer which is consistent with the higher marginal cost of queuing time during arrival queues.

	Dep. Var: Taxiout delay, OLS regressions				
	(1)	(2)	(3)	(4)	(5)
VARIABLES					
Runway Capacity	-0.020***	-0.035***	-0.022***	-0.018***	-0.033***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
Bank Flights	0.146***	0.162***	0.193***	0.139***	0.182***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.007)
Bank Length	-0.071***	-0.062***	-0.065***	-0.076***	-0.073***
	(0.005)	(0.005)	(0.007)	(0.005)	(0.007)
Flight Bank Pos	1.150***	0.852**	1.082***	1.137***	1.106**
	(0.377)	(0.371)	(0.351)	(0.401)	(0.457)
ThunderStorm	3.599***	3.376***	3.445***	3.549***	4.478***
	(0.179)	(0.177)	(0.177)	(0.222)	(0.233)
Rain	1.260***	1.177***	0.877***	1.391***	1.677***
	(0.101)	(0.101)	(0.096)	(0.124)	(0.130)
Snow	4.099***	4.330***	3.912***	4.305***	7.651***
	(0.492)	(0.478)	(0.461)	(0.637)	(0.709)
Heavy Fog	1.106***	1.213***	0.407***	1.236***	2.360***
	(0.139)	(0.139)	(0.137)	(0.167)	(0.188)
Constant	6.191***	10.075***	5.301***	3.778***	9.594***
	(0.316)	(0.510)	(0.870)	(0.557)	(0.641)
Carrier FE	-	+	+	-	+
Airport FE	-	-	+	-	-
Aircraft Char.	-	-	-	+	-
Observations	130927	130927	130927	85953	113425
R-squared	0.043	0.053	0.074	0.049	0.065

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

Table 5: Taxi-out Delay Estimation Results

In the Table, I present the results of the delay regression using the taxi-out delay measure. Taxi-out delay is derived by subtracting the unimpeded carrier-airport delay measure from a flight taxi-out time. Standard errors are clustered over a flight number. In all regressions, the coefficient on the bank length variable is negative and statistically significant. Runway capacity is also negative suggesting that, *ceteris paribus*, the scarcity of the runway has a detrimental impact on delays. Similarly, the coefficient on the number of bank flights is positive indicating that larger banks are associated with longer waiting times. The relative location of the flight within the bank is positive suggesting that flights scheduled either at the beginning or towards the end of the bank wait less for their turn to depart. Weather and aircraft characteristics typically have the expected signs. In column 5, the dependent variable is the sum of the taxi-out delay measure and the flight departure delay. The results are qualitatively the same in all the regressions.

	Dep. Var: Airtime delay, OLS regressions				
	(1)	(2)	(3)	(4)	(5)
VARIABLES					
Runway Capacity	-0.024***	-0.055***	-0.054***	-0.026***	-0.031***
	(0.004)	(0.005)	(0.011)	(0.004)	(0.003)
Bank Flights	0.138***	0.162***	0.139***	0.141***	0.152***
	(0.012)	(0.013)	(0.020)	(0.011)	(0.011)
Bank Length	-0.098***	-0.068***	-0.053***	-0.087***	-0.094***
	(0.011)	(0.011)	(0.013)	(0.011)	(0.012)
Flight Bank Pos	2.590***	2.558***	2.709***	2.833***	2.576***
	(0.774)	(0.756)	(0.739)	(0.689)	(0.611)
ThunderStorm	2.545***	1.839***	1.729***	2.277***	2.186***
	(0.163)	(0.145)	(0.134)	(0.187)	(0.151)
Rain	1.877***	1.680***	1.449***	1.257***	1.566***
	(0.148)	(0.119)	(0.094)	(0.146)	(0.127)
Snow	9.564***	8.277***	7.344***	9.452***	8.526***
	(0.988)	(0.929)	(0.797)	(1.086)	(0.853)
Heavy Fog	1.595***	1.587***	0.812***	0.777***	1.085***
	(0.188)	(0.177)	(0.138)	(0.191)	(0.167)
Distance				0.011***	0.010***
				(0.000)	(0.000)
Constant	17.694***	23.943***	24.473***	7.540***	10.214***
	(0.666)	(1.015)	(2.306)	(1.216)	(0.632)
Carrier FE	-	+	+	-	-
Airport FE	-	-	+	-	-
Aircraft Char.	-	-	-	+	-
Observations	123811	123811	123811	80661	116675
R-squared	0.030	0.060	0.087	0.256	0.232

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Airtime Delay Estimation Results

Table 6 presents the regression results using the airtime delay measure. To derive this measure, the fastest airtime flight in October 2000 was calculated for each directional route. I then subtract this benchmark from each flight airtime flying in the same directional route. The regression results indicate that longer banks are associated with shorter delays and lend additional support for an internalization behavior by airlines. Thus, in all the regressions the bank length and the runway capacity coefficients are negative and significant. Furthermore, the coefficients on bank flights and the flight bank position are all positive. The flight distance variable, added in columns 4-5, is positive suggesting that longer flights are more likely to incur airtime delays.

	Dep. Var: Aircraft Ground Time, OLS regressions				
	(1)	(2)	(3)	(4)	(5)
VARIABLES					
Departing Bank Length	0.147***	0.098***	0.048***	0.145***	0.146***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
Arriving Bank Length	0.221***	0.210***	0.192***	0.228***	0.229***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)
Departing Bank Flights	0.017	-0.005	0.043***	-0.001	0.014
	(0.013)	(0.013)	(0.013)	(0.015)	(0.017)
Bank Flights	-0.017	-0.055***	0.019	-0.011	-0.007
	(0.012)	(0.012)	(0.015)	(0.013)	(0.014)
Hub Carrier	7.358***	3.435***	7.014***	4.365***	
	(0.351)	(0.330)	(0.403)	(0.376)	
Distance (current)	0.005***	0.005***	0.005***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distance (previous)	0.004***	0.004***	0.004***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age				0.273***	0.250***
				(0.020)	(0.020)
Seats (#)				0.083***	0.082***
				(0.004)	(0.004)
Engines (#)				-0.281	0.782
				(0.549)	(0.537)
Constant	32.658***	40.399***	40.716***	22.880***	25.218***
	(0.576)	(0.658)	(1.302)	(1.382)	(1.317)
Carrier FE	-	+	+	-	-
Airport FE	-	-	+	-	-
Observations	89762	89762	89762	60282	56341
R-squared	0.073	0.121	0.138	0.081	0.079

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

Table 7: Ground Time Analysis

Table 7 displays regression results using aircraft ground time as dependent variable. The regression examines whether longer banks are associated with longer aircraft ground time. The sample of flights includes only flights that arrived during a bank period and depart during the subsequent departing bank. In column 4 I add aircraft characteristics, and in column 5 I focus only on flights operated by hub carriers. The results suggest that aircraft ground time is longer as the length of banks increases.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Dep. Var: Taxiout delay, OLS regressions				
Runway Capacity	-0.011***	-0.023***	-0.014***	-0.010***	-0.038***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.006)
Bank Flights	0.094***	0.115***	0.144***	0.088***	0.107***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.013)
Bank Conc	-5.918***	-4.692***	-1.004*	-5.558***	-8.419***
	(0.387)	(0.478)	(0.524)	(0.450)	(1.121)
Flight Bank Pos	0.772**	0.548	0.753**	0.700*	0.268
	(0.378)	(0.372)	(0.353)	(0.407)	(0.861)
ThunderStorm	3.427***	3.309***	3.421***	3.405***	14.626***
	(0.174)	(0.176)	(0.177)	(0.218)	(0.474)
Rain	0.898***	1.010***	0.871***	1.121***	4.420***
	(0.098)	(0.098)	(0.096)	(0.122)	(0.289)
Snow	4.094***	4.500***	3.932***	4.472***	7.597***
	(0.496)	(0.481)	(0.461)	(0.642)	(1.526)
Heavy Fog	1.087***	1.133***	0.423***	1.271***	7.185***
	(0.138)	(0.138)	(0.137)	(0.166)	(0.450)
Constant	8.860***	11.096***	4.768***	6.713***	22.633***
	(0.375)	(0.578)	(0.915)	(0.632)	(1.447)
Carrier FE	-	+	+	-	+
Airport FE	-	-	+	-	-
Aircraft Char.	-	-	-	+	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Taxi-out Delay Estimation Results

In the Table, I present the results of the delay regression using the taxi-out delay measure. The specification is similar to the bank length regression (Table 6) except that the bank concentration variable is used instead of the bank length variable. Standard errors are clustered over a flight number. In all regressions, the coefficient on the bank concentration variable is negative and statistically significant. Runway capacity is also negative suggesting that, *ceteris paribus*, the scarcity of the runway has a detrimental impact on delays. Similarly, the coefficient on the number of bank flights is positive indicating that larger banks are associated with longer waiting times. The relative location of the flight within the bank is positive suggesting that flights scheduled either at the beginning or towards the end of the bank wait less for their turn to depart. Weather and aircraft characteristics typically have the expected signs. In column 5, the dependent variable is the sum of the taxi-out delay measure and the flight departure delay. The results indicate that more concentrated banks exhibit fewer delays and are consistent with internalizing behavior.

Dep. Var: Airtime delay, OLS regressions	(1)	(2)	(3)	(4)	(5)
VARIABLES					
Runway Capacity	-0.013***	-0.040***	-0.044***	-0.017***	-0.021***
	(0.004)	(0.005)	(0.011)	(0.003)	(0.003)
Bank Flights	0.050***	0.089***	0.078***	0.076***	0.079***
	(0.010)	(0.012)	(0.018)	(0.008)	(0.008)
Bank Conc	-11.841***	-7.512***	-2.313*	-5.443***	-6.392***
	(0.822)	(1.071)	(1.234)	(0.803)	(0.699)
Flight Bank Pos	2.457***	2.412***	2.565***	2.584***	2.030***
	(0.764)	(0.754)	(0.738)	(0.686)	(0.593)
ThunderStorm	2.241***	1.774***	1.692***	2.274***	2.053***
	(0.166)	(0.145)	(0.134)	(0.192)	(0.151)
Rain	1.321***	1.527***	1.448***	1.075***	1.272***
	(0.136)	(0.114)	(0.094)	(0.142)	(0.116)
Snow	8.432***	7.978***	7.372***	9.143***	8.007***
	(0.982)	(0.922)	(0.797)	(1.091)	(0.857)
Heavy Fog	1.603***	1.604***	0.809***	0.896***	1.172***
	(0.185)	(0.175)	(0.138)	(0.188)	(0.163)
Distance				0.011***	0.010***
				(0.000)	(0.000)
Constant	24.256***	26.614***	24.741***	9.628***	12.663***
	(0.914)	(1.232)	(2.352)	(1.462)	(0.822)
Carrier FE	-	+	+	-	-
Airport FE	-	-	+	-	-
Aircraft Char.	-	-	-	+	-
Observations	123811	123811	123811	80661	123810
R-squared	0.045	0.063	0.086	0.255	0.235

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Table 9: Airtime Delay Estimation Results

Table 9 presents the regression results using the airtime delay measure. The specification is similar to the bank length regression (Table 7) except that the bank concentration variable is used instead of the bank length variable. The regression results indicate that concentrated banks are associated with shorter delays and lend additional support for an internalization behavior by airlines. The flight distance variable, added in columns 4-5, is positive suggesting that longer flights are more likely to incur airtime delays.