INTERNALIZATION OF CONGESTION AT
U.S. HUB AIRPORTS

by

I. Ater

Working Paper No 5/2010   July 2010

Research No. 07890100

Internalization of Congestion at U.S. Hub Airports[*]

Itai Ater

Tel Aviv University

July 12, 2010

Abstract

I study delays and congestion patterns in U.S. airports during high-volume periods of flights. I find that these periods are longer the larger the share of flights which is operated by a hub airline. Furthermore, these longer banks exhibit shorter delays than high-volume periods where several airlines operate. These results lend support to recent theoretical work on congestion, and may suggest that congestion management solutions implemented at hub airports dominated by one airline could have only a limited impact on congestion itself.

JEL classification: H23; L50; L93; R41;

Keywords: Congestion; Air Transportation; Air Delays;

1   Introduction

Delays and congestion in the airline industry are a major concern[1] and policymakers are considering solutions, such as congestion pricing or restricting the number of flights during

1

high-demand periods in order to reduce congestion.[2] Successful implementation of solutions to congestion depends on understanding the airlines' scheduling decisions, particularly how airlines determine their schedules given the impact of these decisions on the congestion that they bear.

The early theoretical literature on congestion pricing illustrated that scarcity of public infrastructure results in congestion and delays, because commuters ignore the impact of their scheduling decisions on other commuters' travel time. More recent theoretical papers emphasized that airlines, which operate many flights at a particular airport, should internalize congestion. These papers have argued that more concentrated airports should exhibit less congestion because an airline's incentive to reduce congestion increases with the share of flights it operates. The fact that the existing evidence generally does not support these theoretical models posits conceptual difficulties in designing the right mechanism to reduce congestion.

In searching for evidence of this internalizing behavior, empirical research has explored whether flights in airports, which are dominated by one airline exhibit shorter delays. These papers did not explicitly distinguish between time periods with a higher or lower volume of flights. Analyzing data from both low and high volume periods could explain why strong evidence for the predicted congestion-concentration relationship was not found, because the incentive to internalize congestion arises mainly during high-volume periods.

To address this issue, I focus here on hub airports and study the empirical relationship between congestion and market-structure determinants only during high-volume periods of flights, known as *flight banks*. This paper also uses a rich set of control variables, including airport runway capacity, airport gates, weather and aircraft characteristics, and measures of congestion that are closely related to the scarcity of the airport's runway during takeoffs and landings. I find strong evidence of internalization behavior. Importantly, focusing on high-

---

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]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.

volume periods also enables me to explore the channel through which internalization takes place. In particular, I show that hub airlines internalize congestion by scheduling banks with lower flight density. I also show that more concentrated banks are longer and exhibit lower flight density. These longer banks are characterized by shorter flight delays.

In Section 2 I discuss the relevant literature, and Section 3 includes a simple framework for a hub-carrier scheduling decision that guides the empirical analysis. This simple framework provides intuitive predictions for internalizing behavior: more concentrated banks are longer and have lower flight density, and longer banks exhibit shorter delays. Furthermore, as the unit cost of queuing rises, the longer is the bank period chosen by the hub-carrier.

In my empirical analysis, I follow this framework and provide evidence consistent with each of the framework's implications. First, I examine, for both arriving and departing banks, how the scheduled length of the bank period varies with the bank concentration level. I account for the potential endogeneity of the bank concentration measure using the concentration of airport gates, and discuss the validity of that instrument in Section 5. I find that arriving banks are longer than departing banks, and that an increase of one standard deviation in bank concentration is associated with 5.63 and 7.7 minutes longer departing and arriving banks, respectively. The difference between arriving and departing banks is consistent with the unit cost of queuing being higher during arriving banks.[3]

Next, I explore the relationship between the length of the bank period and flight delays, created during departing and arriving queues. During departing queues the measure of delay, defined as taxi-out delay, is based on a flight taxi-out time: the elapsed time from leaving the airport gate to wheels off the runway. During arriving queues the measure of delay, defined as airtime delay, is based on flight airtime between takeoff at the airport of origin and landing at the hub airport. Specifically, I use the fastest hub-bound flight airtime in each origin airport - hub-airport pair as a benchmark, and then subtract this benchmark from each actual flight airtime to obtain the airtime delay measure for each particular flight.

---

[3]During arriving banks, when airplanes wait for their turn to land, queuing cost is higher 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.

The advantage of these delay measures is that they are closely related to the scarcity of the airport runway infrastructure during the congested period. In Figures 1 and 2, I plot the relationship between concentration level and the taxi-out and airtime delay measures during bank periods, respectively. As shown in the figures there is a clear negative relationship between concentration and these delay measures during bank periods.

My estimates show that longer banks are associated with shorter flight delays during both arriving and departing queues. The changes in the length of departing and arriving bank periods (5.63 and 7.7 minutes, respectively) mentioned above translate, on average, into 0.4 minutes shorter delays during departing banks and 0.75 minutes shorter delays during arriving banks for each flight.

Overall, my empirical findings support internalizing behavior by hub-carriers. One interpretation of these results is that potential time savings at highly concentrated banks are limited, because hub airlines already are able to attain a lower level of delay at these airports. My findings also suggest that congestion management tools would have a larger impact on operation times of departing flights than on operation times of 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 and bank density regressions, as well as the regressions using the different delay measures as dependent variables. Section 6 concludes.

2 Related literature

Brueckner (2002) was the first to formalize the idea that airports which are dominated by one airline are less congested.[4] In general, the theoretical literature on airport congestion assumes

---

[4]The initial insight should be attributed to Daniel (1995). Brueckner (2002) also provided rudimentary evidence for internalization based on annual measures of delay at 25 U.S. airports. Other theoretical papers which examined aspects of airline internalization include: Brueckner (2005), Pels and Verhoef (2004), Zhang

that the daily pattern of flights at an airport can be divided into congested and non-congested periods. The analysis focuses on the congested period because airlines have an incentive to take into account the the impact of their scheduling decision on other flights they operate during that period. Although this line of research leads to the basic prediction that concentrated, high-volume periods are less congested, it does not clearly indicate how airlines internalize congestion.

In contrast, the deterministic theoretical literature on road congestion, and particularly Henderson (1981) and Henderson (1985),[5] illustrates how the length of the congested period increases and the level of delays falls following a social planner's intervention to reduce congestion. One shortcoming of these latter papers in the context of the airline industry, though, is that they only consider a fully competitive (atomistic) equilibrium or a fully monopolized (social planner) equilibrium. Still, the predictions of these models provide additional guidance for the empirical analysis performed here, assuming that the shift from fully competitive to fully monopolized market is continuous. I also follow this literature by assuming that the number of flights during the congested period is fixed.

The empirical papers that investigated whether airlines internalize congestion generally did not find that they did. Daniel (1995) used stochastic queuing models and detailed data from the Minneapolis-St.Paul hub airport; he concluded that internalization behavior by the hub-carrier is unlikely.[6] More recently, Morrison and Winston (2007) quantified the potential benefits from eliminating congestion at airports. They used calibration and alternative assumptions about the dominant carrier behavior and argued that, quantitatively, the difference between internalizing behavior and non-internalizing behavior is modest. In trying to explain the lack of supporting evidence for internalizing behavior, Brueckner and Van-Dender (2008) suggest that hub-carriers might over-schedule flights to preempt scheduling by other airlines.

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

---

and Zhang (2006), Basso and Zhang (2007), and Brueckner (2009).

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

[6]Daniel and Harback (2008) applied the same methodology to 27 airports and found generally similar results. See also Daniel and Pahwa (2000) and Daniel and Harback (2009).

hub-carriers suffer longer delays than flights performed by non-hub carriers. They attributed this finding to the tendency of hub-carriers to cluster flights in high-volume banks, leading to increased flight time. They also found evidence of shorter delays at more concentrated airports. Rupp (2009) extended Mayer and Sinai's analysis by adopting a different measure for delay, as well as a larger set of control variables. He did not find evidence for internalizing behavior. While these latter papers emphasized the importance of banks in generating delays, these papers neither identified banks nor explicitly used variation across banks to examine how bank structure, congestion, and delays are related. Furthermore, none of the papers explored the channel through which internalization takes place.

3 Economics of hub airports and theoretical framework

Hub-and-spoke networks enable airlines to reduce their aircraft operating cost by achieving higher load factors. Hub-carriers can take passengers from the same departure point to a hub airport, from which they can proceed to different destinations. Or, flights from the hub airport can take passengers to a specific destination, regardless of where they started their trip. Each spoke of the network can carry many more passengers to and from the hub than a direct route between individual city pairs. Consequently, the network is able to provide more frequent service in larger aircraft at a lower cost per passenger. Longer travel time and layover times at the hub airport are the costs of a hub system. To minimize those costs, hub-and-spoke networks schedule arrivals and departures at their hubs in banks of flights. Arrival banks consists of hub-bound flights from spoke cities, which land at approximately the same time. At the hub, connecting passengers then change aircraft, and the aircraft they disembarked prepares for its next operation. Departure banks consist of flights to spoke cities that depart at approximately the same time.

Because runway capacity constraints at hub airports prevent all bank flights from departing or arriving concurrently, hub-carriers schedule their bank flights over a period of time. By choosing a longer bank period, the hub-carrier can reduce congestion costs while increasing connecting passengers' layover time. Thus, during bank periods there is a basic tradeoff faced

6

by hub-carriers between congestion costs and layover/ground time costs.[7]

Airplane operators bear the externalized cost of congestion during bank periods because flights inflict delay/congestion costs on other flights scheduled around the same time. The closer in time airplanes are operated, the larger are the inflicted congestion costs. Consequently, an airline that operates multiple airplanes during a bank period will benefit from scheduling one flight away from other flights more than a carrier that operates one airplane during that bank period. In computing congestion costs, the hub-carrier considers the cost that 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 will be shorter and longer delays will be created during these banks. In addition, these shorter, dense, banks will experience longer delays.

Finally, for a higher unit cost of congestion, the incentive of airlines to avoid congestion rises. In that case, hub-carriers would reduce the density of bank flights by choosing a longer bank period.

To summarize, the predictions are: 1) that more concentrated banks are longer and are characterized by lower flight-per-minute measures; 2) departure banks are shorter than arriving banks, and are characterized by higher flights per minute; and 3) longer (arriving and departing) banks exhibit shorter delays. Figure 3 illustrates these predictions, except the one about changes in the marginal cost of queuing. These predictions can be viewed as extensions of the theoretical models developed by Henderson (1981) and Henderson (1985).[8]

---

[7]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.

[8]The figure also shows that flights, scheduled 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. I test this prediction as well.

4 Data, variable construction and descriptive statistics

4.1 Data

The data for the empirical analysis comes 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.[9] The ten reporting carriers in October 2000 were: 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; weight; number of engines; and year of manufacture.[10] Measures of the number of hourly landing and departing operations that an airport can handle under different weather conditions come from the "Airport Capacity Benchmark Report".[11] In addition, FAA measures for unimpeded taxi-out time (derived by the FAA by airline-airport-season) are used to derive the delay measures discussed in Section 4.3. I focus on flights departing from and arriving at 16 U.S. hub airports in October 2000.[12] Table 1 displays descriptive statistics of the 16 hub airports.

I also compiled data on the number of gates that each airline leased in an airport in the second half of 2000. That data come from competition plan reports, which were submitted

---

[9]The database is available at *www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp*

[10]The FAA Aircraft Reference File and the Aircraft Registration Master File databases contain these data and can be downloaded from *http : //www.faa.gov/aircraft/air_cert/*. The aircraft characteristics I use are its year of manufacture, number of seats, and number of engines.

[11]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.

[12]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.

by airports to the FAA in 2000 and 2001.[13] Finally, weather conditions at each airport for everyday in October 2000 are from the National Climatic Data Center, which operates weather stations at each of the hub airports in the research sample.[14]

4.2   Bank structures

My 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 begin and end. For example, on 10/16/2000 Delta Airlines operated seven departing banks in Cincinnati International Airport, one of them started at 08:31 AM and ended at 09:16 AM. The appendix contains a detailed description of the bank identification procedure, and Figures A1, A2, and A3 show the derived bank structure in three hub airports: Cincinnati, Detroit, and Philadelphia on October 4, 2000.

In October 2000 approximately 60% of the flights in my data arrived at one of the 16 selected hub airports, and about the same proportion 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, but only 45% of the flights arriving during non-bank periods and 40% of the flights departing during non-bank periods. Figure 4 displays the relationship between an airport's overall concentration and the average concentration of departing banks at that airport. Because hub-carriers predominantly operate during bank periods, banks are more concentrated than the overall concentration of the airport. This finding supports the assumption made by Mayer and Sinai (2003), who exploited the distinction between hub and non-hub carriers operating in the same airport, and assumed that hub-carriers are more likely to operate during congested bank periods.

---

[13]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 (Forhtcoming) for a more complete description of competition plan reports.

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

For each bank at each hub airport, the following variables are constructed: the number of flights operating during the bank; the length of time of the bank; and its concentration level, as 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 the beginning or the end of the bank.[15] This 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.

4.3   Measuring delays

Airlines report the scheduled and actual time of each flight departure and arrival. Based on these reported measures, there are two measures of delay common in the literature: 'actual vs. scheduled' and 'actual vs. optimal actual benchmark'. The first measure, the difference between the flight's actual time and scheduled time, is intuitive.[16] Indeed, if a scheduled time of flight arrival represents the airline or passengers' expectations, 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.[17] However, the 'actual vs. scheduled' measure is probably inadequate for examining the impact of airport structure on congestion during peak periods, because airlines anticipate longer travel times during peak periods and build this excess travel time into their schedules.

The 'actual vs. optimal actual benchmark' measure is derived based on a flight's actual time of operation compared to an optimal performance benchmark.[18] It is therefore not subject to manipulation by airlines and is useful for investigating how the hub-airport and network structure affect flights' time performance. One important advantage of the 'actual vs. actual' delay measure is that for each flight the dataset contains its taxi-out time and airtime

---

[15]Thus, if a bank starts at 8:00 AM and ends at 9:00 A.M. then a bank position for 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 AM or 9:00 AM is 0.

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

[17]Papers that primarily relied on this measure of delays are: Brueckner (2002), Rupp (2009), Mazzeo (2003), Forbes (2008). See also Forbes and Lederman (Forthcoming) for a paper that focuses on departure delays at the gate.

[18]For example, the fastest actual flight time in the same directional route, as in Mayer and Sinai (2003).

measures. This decomposition enables to investigate the relationship between bank, airport characteristics and delays before takeoff and before landing, when the scarcity of the runway is most relevant.

Specifically, to construct the airtime delay measure I first compute the fastest airtime among all flights arriving at a hub airport from the same origin airport. Then I subtract this benchmark from each flight airtime to obtain the airtime delay measure for a particular flight. The taxi-out time benchmark is the FAA's unimpeded taxi-out, a measure of unimpeded elapsed time from a carrier gate in a particular airport to takeoff. I subtract this benchmark from a flight taxi-out time to obtain the relevant delay measure.[19]

5 Estimation and results

5.1 Bank length and flight density

To estimate how the length of bank j in airport k varies with the bank concentration, I use the following specifications:

$$Length_{jk} = \beta_1 Bank - Conc_j + \beta_2 Bank - Flights_j + \beta_3 Runway_k$$
$$\beta_3 Weekend_j + \beta_4 Tourist_k + \beta_5 Remain - Flights_j + \epsilon_{jk} \quad (1)$$

$$Operation - Rate_{jk} = \beta_1 Bank - Conc_j + \beta_2 Bank - Flights_j + \beta_3 Runway_k$$
$$\beta_3 Weekend_j + \beta_4 Tourist_k + \beta_5 Remain - Flights_j + \epsilon_{jk} \quad (2)$$

The unit of observation is a bank. The analysis is performed separately for arriving and departing banks unless specified differently. The length of a bank is measured in minutes. The bank operation rate is the ratio of the number of bank flights to bank length. The hypothesis is that more concentrated banks are longer and exhibit lower flight density. The number of bank flights and the airport runway capacity are additional control variables. The underlying assumption is that hub-carriers first choose the number of flights they intend to operate during

---

[19]Morrison and Winston (2008) adopted a similar measure of delay but not in the context of the internalization question.

a bank and then the length of the bank.

I also use two categorical variables as proxies for passenger preferences toward layover time. First, I include the categorical variable 'Weekend,' equals to one when the bank operates on a Saturday or Sunday and zero otherwise. Airlines will likely choose longer banks during the weekend when the average passenger-value of time is lower. I also include the categorical variable 'Tourist' for departing and arriving banks at Miami International Airport. The bank period is likely to be longer in airports where many of the passengers are tourists.

In addition, I include as an additional control variable, defined as 'Remain-Flights', a measure of aircraft utilization during the day. Presumably, the more remaining aircraft operations there are during the day, the higher is the hub-carrier's incentive to reduce ground time. To derive this measure, I calculate the number of remaining daily flights for each aircraft and then derive an average measure for a bank aircraft's remaining flights in a day.

The length of the bank period and the bank operation rate probably are also affected by the (unobserved) number of bank connecting passengers. The more connecting passengers relative to total bank passengers, the larger is the incentive of the hub-carrier to reduce layover time. Because the share of connecting passengers is likely to be correlated with the share of flights operated by the hub-carrier, 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. Typically, airport lease agreements are long-term contracts,[20] 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.

I report the results for the first-stage instrumental variable regression in Table 3. As expected, the airport-gates variable is positively correlated with bank concentration. Furthermore, this measure is probably not correlated with the share of connecting passengers at a particular bank during a day because the measure of gate concentration is invariant-airport-

---

[20]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).

specific. However, using airport gates as an instrumental variable implies that variation across airports is the main source of variation in the estimation. It also hinders the use of airport fixed-effects to control for other differences across airports, such as the type of population served by each airport.[21] Note that in the delay regressions that follows, I do use variation within airports and control for unobserved differences between airports by including airport fixed effects.

The IV regression results are shown in Table 4. Columns 1 and 2 correspond to arriving and departing banks, respectively. In all of the regressions, the coefficient on the bank concentration coefficient is positive and significant, implying that more concentrated banks are longer. The coefficients on the number of bank flights are positive; the runway capacity coefficients are negative and statistically significant, as expected.[22] Other coefficients generally have the expected signs. Weekend banks typically are longer, as 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. They suggest that hub-airlines choose longer banks as their share of bank flights increases.

In columns 4-6, I report regression results using as the dependent variable the bank operation rate. The results support internalization behavior, with more concentrated banks exhibiting lower operation rates. Other control variables have the expected signs.

5.1.1 Scheduling decisions across arriving and departing banks

The higher the unit cost of congestion, the higher is the incentive of hub-carriers to increase the length of the bank, and consequently to reduce the time an airplane spends in a queue. I exploit the distinction between arriving and departing banks to explore this relationship, assuming that for arriving banks the unit cost of congestion is higher than that for departing

---

[21] In all airports, the variation across days and weeks is small. In addition, in some hub airports there is little within-airport variation in bank concentration.

[22] I obtain similar qualitative results when I include the ratio of bank flights and runway capacity as a control variable instead of these two variables separately.

banks.[23] Note that I use schedule 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 the theoretical framework in Section 3. The results of the pooled-banks regressions are shown in columns 3 and 6 in Table 4. I add a dummy variable, $D(arr)$, to the bank-length and operation rate specification – which equals one in arriving banks and zero otherwise. As expected, the results imply that arriving banks are more than three minutes longer than departing banks, and that arriving banks have lower density than departing banks.

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 suggests that dominant airlines, operating in concentrated banks and choosing longer bank periods, experience fewer delays than less concentrated banks in which several airlines operate concurrently.

The analysis that follows refers only to flights scheduled during bank periods. I use two measures of delays as dependent variables: 1) taxi-out delay, which focuses on the queue before takeoff, as aircraft wait for their turn to depart; 2) airtime delay, which focuses on the queue before landing, as aircraft wait their turn to land.

Thus, the specification for aircraft n used for flight i operating during bank j at airport k on day m is:

$$
\begin{aligned}
Delay_{ijkmn} = \beta_1 Bank - Length_j + \beta_2 Capacity_k + \beta_3 Bank - Flights_j + \\
\beta_4 Bank - Pos_{i,j} + \beta_5 Weather_{km} + \beta_6 Aircraft_n + \epsilon_{ijkmn}
\end{aligned}
\tag{3}
$$

The control variables can be divided into two groups. The first, which includes variables that are determined by airlines prior to the actual operation of the flight and the realization of delay, are: airport runway capacity; the scheduled number of bank flights; the bank length;

---

[23]During arriving banks, when airplanes wait for their turn to land, queuing cost is higher than the unit cost of congestion during departing banks when airplanes wait on the ground.

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 the airlines.

Table 5 displays the regression results when the taxi-out delay measure is the dependent variable.[24] In all of regressions, the coefficient on the length of the bank is negative and statistically significant. The coefficient on 'Runway capacity' is also negative, suggesting that 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. In addition, weather conditions are important and have the expected signs.[25]

In Table 6, I present the regression results using airtime delay as the dependent variable. These results again indicate that longer banks are associated with shorter delays. They lend additional support to internalization behavior by airlines. In all of 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.[26]

5.3 Discussion of results

The empirical analysis here includes several pieces of evidence for internalizing behavior by hub-carriers. The results suggest that hub airlines can lower the density of bank flights, and consequently reduce congestion, by scheduling longer banks. Indeed, beginning in 2002 hub-carriers, such as American Airlines, which were looking for ways to reduce costs, implemented

---

[24]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.

[25]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.

[26]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.

de-peaking strategies: they essentially increased connecting passengers' layover time while reducing congestion and delays.

I use the estimates of the bank length regression (columns 1 and 2 in Table 4) together with estimates of the delay regressions (column 1 in Table 5 and 6) to obtain a crude measure of potential savings. I consider how an increase of one standard deviation in bank concentration would affect the length of that bank. Conceptually, introducing congestion pricing also aims at increasing the concentration of banks, by requiring airlines to pay for the congestion cost they inflict on other airlines that operate during the bank period. My findings suggest that arriving banks would be $(0.15 * 51.329 =)7.7$ minutes longer whereas departing banks would increase by $(0.17 * 33.167 =)5.63$ minutes. On average, these changes in bank length translate into approximately $(7.7 * 0.098 =)0.75$ minutes shorter airtime delays for each flight arriving during a bank, and $(5.63 * 0.071 =)0.4$ minutes shorter taxi-out time for each flight departing 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 3 minutes of taxi-out time and 2 minutes of airtime delay. Thus, it might be worthwhile to allocate more resources to improving airline performance under severe weather conditions.

The analysis in this paper assumes that airlines choose their schedules simultaneously, taking other airlines' decisions as exogenous. This assumption seems plausible given the complexity of an airline-network scheduling decision, in which airplanes and crew undertake multiple flight operations everyday. This also could explain why fringe carriers, who are constrained by their overall network operations, schedule their flights during bank periods. For example, a fringe carrier departing flights are likely to arrive during a bank period at the other airport, where this carrier is the hub-carrier.

6 Concluding remarks

Air delays and congestion have become a major policy issue in recent years. Traditionally, economists have proposed congestion pricing solutions to reflect the real value of scarce runway

capacity. However, economists disagree on how to implement these solutions, and on whether carriers operating a large share of flights should be charged a lower fee, because they already internalize congestion externalities inflicted on their flights.

This paper investigates the relationship between congestion and the structure of hub airports. Specifically, I study how congestion varies at hub airports across high-volume time periods, known as flight banks. One advantage of focusing on bank flights at hub airports is that it allows me to compare airports with relatively similar patterns of operations. Extending the sample to non-hub airports would require addressing basic differences between the two types of airports.

I find evidence consistent with internalizing behavior. In particular, I find that hub airlines choose longer banks as their share of bank flights increases. These longer banks are associated with shorter flight delays.

The empirical findings may suggest that an attempt to reduce congestion externalities will have only a limited impact on congestion at highly concentrated airports, because hub-airlines already internalize congestion. In addition, the results suggest that introducing congestion pricing at non-concentrated banks or airports could yield better time savings than doing so at highly concentrated hub-airports. Finally, policymakers should consider treating hub-airlines differently from fringe carriers, because the dominant carriers already internalize congestion and schedule their flights accordingly.

Future research could compare the effectiveness of alternative policy prescriptions, and quantify the potential savings from intervening at departing or arriving banks. The results also could shed light on potential efficiency gains that might arise following a merger between two airlines operating at an airport, as congestion costs would be likely to fall in that case. Finally, the vast literature on the airline industry and its hub and spoke network generally has ignored the explicit role of airport banks. Future research could explore how airline performance and traveler welfare are affected by the structure of banks.

17

References

Arnott, R., Palma, A. D. and Lindsey, R.: 1990, Economics of a bottleneck, *Journal of Urban Economics* **27**, 111–130.

Arnott, R., Palma, A. D. and Lindsey, R.: 1993, A structural model of peak - period congestion: A traffic bottleneck with elastic demand, *American Economic Review* **83(1)**, 161–179.

Basso, L. and Zhang, A.: 2007, Congestible facility rivalry in vertical structures, *Journal of Urban Economics* **61**(2), 218–237.

Brueckner, J. K.: 2002, Airport congestion when carriers have market power, *American Economic Review* **92**(5), 1357–1375.

Brueckner, J. K.: 2005, Internalization of airport congestion: A network analysis, *International Journal of Industrial Organization* **23**, 599–614.

Brueckner, J. K.: 2009, Price vs. quantity approaches to airport congestion management, *Journal of Public Economics* **93**, 681–690.

Brueckner, J. K. and Van-Dender, K.: 2008, Atomistic congestion tolls at concentrated airports? seeking a unified view in the internalization debate, *Journal of Urban Economics* **64**, 288–295.

Ciliberto, F. and Williams, J.: Forhtcoming, Limited access to airport facilities and market power in the airline industry, *Journal of Law and Economics* .

Daniel, J. I. and Harback, K. T.: 2008, (when) do hub airlines internalize their self-imposed congestion delays?, *Journal of Urban Economics* **63**, 583612.

Daniel, J. I. and Harback, K. T.: 2009, Pricing the major u.s. hub airports, *Journal of Urban Economics* **66**(1), 3356.

Daniel, J. I. and Pahwa, M.: 2000, Comparison of three empirical models of airport pricing, *Journal of Urban Economics* **47**, 1–38.

18

Forbes, S. J.: 2008, The effect of air traffic delays on airline prices, *International Journal of Industrial Organization* **26**, 1218–1232.

Forbes, S. and Lederman, M.: Forthcoming, Does vertical integration affect firm performance? evidence from the airline industry, *Rand Journal of Economics* .

GAO: 1990, Airline competition: industry operating and marketing practices limit market entry.

Henderson, V. J.: 1981, The economics of staggered work hours, *Journal of Urban Economics* **9**, 349–364.

Henderson, V. J.: 1985, Economic theory and the citites, *Academic Press, Inc.* **2nd edition**.

Mayer, C. and Sinai, T.: 2003, Network effects, congestion externalities, and air traffic delays: Or why all delays are not evil, *American Economic Review* **93**(4), 1194–1215.

Mazzeo, M. J.: 2003, Competition and service quality in the u.s. airline industry, *Review of Industrial Organization* **22**(4), 275–296.

Morrison, S. and Winston, C.: 2007, Another look at airport congestion pricing, *American Economic Review* **97**(5), 1970–1977.

Morrison, S. and Winston, C.: 2008, The effect of faa expenditures on air travel delays, *Journal of Urban Economics* **63**, 669–678.

Pels, E. and Verhoef, E.: 2004, The economics of airport congestion pricing, *Journal of Urban Economics* (55), 257–277.

Rupp, N.: 2009, Do carriers internalize congestion costs? empirical evidence on the internalization question, *Journal of Urban Economics* **65**, 24–37.

Vickrey, W. S.: 1969, Congestion theory and transport investment, *American Economic Review* **59**(2), 251–260.

Zhang, A. and Zhang, Y.: 2006, Airport capacity and congestion when carriers have market power., *Journal of Urban Economics* (60), 229–247.

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

Table 1: Hub airport characteristics in October 2000

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

Hub Airport	Hub-carrier	# of monthly departing & arriving banks	Operation rates during departing & arriving banks (flights per min.)	Mean departing bank length (min.)	Mean arriving bank length (min.)	Mean departing & arriving 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

Table 2: Hub airport bank structures

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 concentration, 2sls first stage regressions		
VARIABLES	Arriving banks	Departing banks	Pooled banks
Bank Flights	-0.001***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)
Gates Conc	0.526***	0.531***	0.530***
	(0.034)	(0.033)	(0.033)
Tour	-0.175***	-0.260***	-0.228***
	(0.010)	(0.008)	(0.008)
Weekend	0.007	0.000	0.003
	(0.009)	(0.009)	(0.009)
Remain Flights	0.009***	-0.019***	-0.005***
	(0.001)	(0.001)	(0.001)
Arriving Bank			-0.004***
			(0.001)
Constant	0.595***	0.651***	0.631***
	(0.024)	(0.027)	(0.025)
Observations	4032	4305	8337
R-squared	0.283	0.305	0.270

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

Table 3: First stage IV regressions

The Table displays the results of the first stage IV regression presented in Table 4. As expected, gates concentration is positively correlated with bank concentration.

	Dep. Var.: Bank length, 2sls regressions			Dep. Var.: Operation rate, 2sls regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Arriving banks	Dep. banks	Pooled banks	Arriving banks	Dep. banks	Pooled banks
Bank Conc	51.329***	33.167***	42.225***	-0.919***	-0.413***	-0.668***
	(3.739)	(3.322)	(2.803)	(0.048)	(0.100)	(0.059)
Bank Flights	0.749***	0.670***	0.728***	0.009***	0.012***	0.010***
	(0.016)	(0.017)	(0.014)	(0.000)	(0.001)	(0.000)
Runway	-0.109***	-0.106***	-0.111***	0.002***	0.003***	0.002***
	(0.005)	(0.006)	(0.004)	(0.000)	(0.000)	(0.000)
Tour	16.126***	22.045***	20.246***	0.009***	-0.023***	-0.010***
	(0.992)	(0.809)	(0.723)	(0.002)	(0.003)	(0.002)
Weekend	0.174	1.121*	0.690	-0.393***	-0.459***	-0.452***
	(0.590)	(0.594)	(0.533)	(0.015)	(0.024)	(0.016)
Remain Flights	-0.578***	1.312***	0.495***	-0.007	-0.033*	-0.021*
	(0.113)	(0.124)	(0.069)	(0.011)	(0.017)	(0.012)
Arriving Bank			3.004***			-0.084***
			(0.133)			(0.004)
Constant	-7.935***	-2.033	-5.811**	0.983***	0.591***	0.803***
	(2.877)	(2.881)	(2.503)	(0.044)	(0.092)	(0.057)
Observations	4032	4305	8337	4057	4332	8389
R-squared	0.326	0.250	0.294	0.398	0.439	0.436

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

Table 4: Bank length estimation results

In columns 1-3, bank length is used as the dependent variable and in columns 4-6, bank operation rate (flight per minute) is used as the dependent variable. Columns 1 and 2 (4 and 5) correspond to arriving and departing banks, respectively. Column 3 (6) 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 and have lower operation rates. Other coefficients generally have the expected signs. For example, banks with more flights are longer and higher runway capacity is associated with shorter banks. The pooled data estimation results also suggest that arriving banks are longer and exhibit lower operation rate which is consistent with the higher marginal cost of queuing time during arrival queues. Standard errors are clustered over an airport-day pair.

			Dep. Var: Taxiout delay, OLS regressions			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Bank Length	-0.071***	-0.062***	-0.065***	-0.064***	-0.076***	-0.065***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.007)	(0.016)
Bank Flights	0.146***	0.162***	0.193***	0.192***	0.139***	0.170***
	(0.007)	(0.008)	(0.011)	(0.011)	(0.007)	(0.021)
Runway Capacity	-0.020***	-0.035***			-0.018***	-0.053***
	(0.003)	(0.004)			(0.003)	(0.009)
Flight Bank Pos	1.150***	0.852***	1.082***	1.092***	1.137***	0.533
	(0.181)	(0.186)	(0.185)	(0.184)	(0.209)	(0.510)
Thunderstorm	3.599***	3.376***	3.445***	2.978***	3.549***	14.728***
	(0.727)	(0.735)	(0.728)	(0.694)	(0.766)	(1.557)
Rain	1.260***	1.177***	0.877**	1.111***	1.391***	4.696***
	(0.352)	(0.362)	(0.356)	(0.371)	(0.353)	(0.711)
Snow	4.099***	4.330***	3.912***	3.788***	4.305***	7.368***
	(1.323)	(1.315)	(1.300)	(1.315)	(1.665)	(2.732)
Heavy Fog	1.106**	1.213***	0.407	-0.120	1.236**	7.337***
	(0.459)	(0.460)	(0.481)	(0.480)	(0.489)	(1.060)
	(0.532)	(0.605)	(1.049)	(1.053)	(0.651)	(1.391)
Weather Char.	+	+	+	+	+	+
Carrier FE	-	+	+	+	-	+
Airport FE	-	-	+	+	-	-
Day FE	-	-	-	+	-	-
Aircraft Char.	-	-	-	-	+	-
Observations	130927	130927	130927	130927	85953	130927
R-squared	0.043	0.053	0.074	0.080	0.049	0.066

*** 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 FAA unimpeded carrier-airport delay measure from each flight taxi-out time. In all regressions, the coefficient on the bank length variable is negative and statistically significant. Runway capacity is also negative suggesting that 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 characteristics have large and significant impact on delays. 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 and are consistent with an internalizing behavior. Additional weather controls (not reported) are dummy indicators for drizzle, fog, mist and haze. Standard errors are clustered over the bank in which the flight operates.

		Dep. Var: Airtime delay, OLS regressions				
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Bank Length	-0.098***	-0.068***	-0.053***	-0.055***	-0.087***	-0.094***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.008)
Bank Flights	0.138***	0.162***	0.139***	0.143***	0.141***	0.152***
	(0.008)	(0.008)	(0.013)	(0.012)	(0.007)	(0.008)
Runway Capacity	-0.024***	-0.055***			-0.026***	-0.031***
	(0.002)	(0.003)			(0.002)	(0.002)
Flight Bank Pos	2.590***	2.558***	2.709***	2.713***	2.833***	2.576***
	(0.241)	(0.237)	(0.235)	(0.234)	(0.242)	(0.202)
Distance					0.011***	0.010***
					(0.000)	(0.000)
Constant	17.694***	23.943***	18.325***	17.092***	7.540***	10.214***
	(0.422)	(0.554)	(0.531)	(0.599)	(0.581)	(0.416)
Thunderstorm	2.545***	1.839***	1.729***	1.755***	2.186***	2.277***
	(0.436)	(0.409)	(0.404)	(0.426)	(0.418)	(0.458)
Rain	1.877***	1.680***	1.449***	1.275***	1.566***	1.257***
	(0.298)	(0.268)	(0.265)	(0.279)	(0.270)	(0.272)
Snow	9.564***	8.277***	7.344***	7.141***	8.526***	9.452***
	(1.321)	(1.323)	(1.322)	(1.336)	(1.144)	(1.404)
Heavy Fog	1.595***	1.587***	0.812**	0.725**	1.085***	0.777**
	(0.397)	(0.374)	(0.360)	(0.366)	(0.372)	(0.337)
Weather Char.	+	+	+	+	+	+
Carrier FE	-	+	+	+	-	-
Airport FE	-	-	+	+	-	-
Day FE	-	-	-	+	-	-
Aircraft Char.	-	-	-	-	+	-
Observations	123811	123811	123811	123811	80661	116675
R-squared	0.030	0.060	0.087	0.092	0.256	0.232

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

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. Weather characteristics also have large and significant impact on delays. Additional weather controls (not reported) are dummy indicators for drizzle, fog, mist and haze. Standard errors are clustered over the bank in which the flight operates.
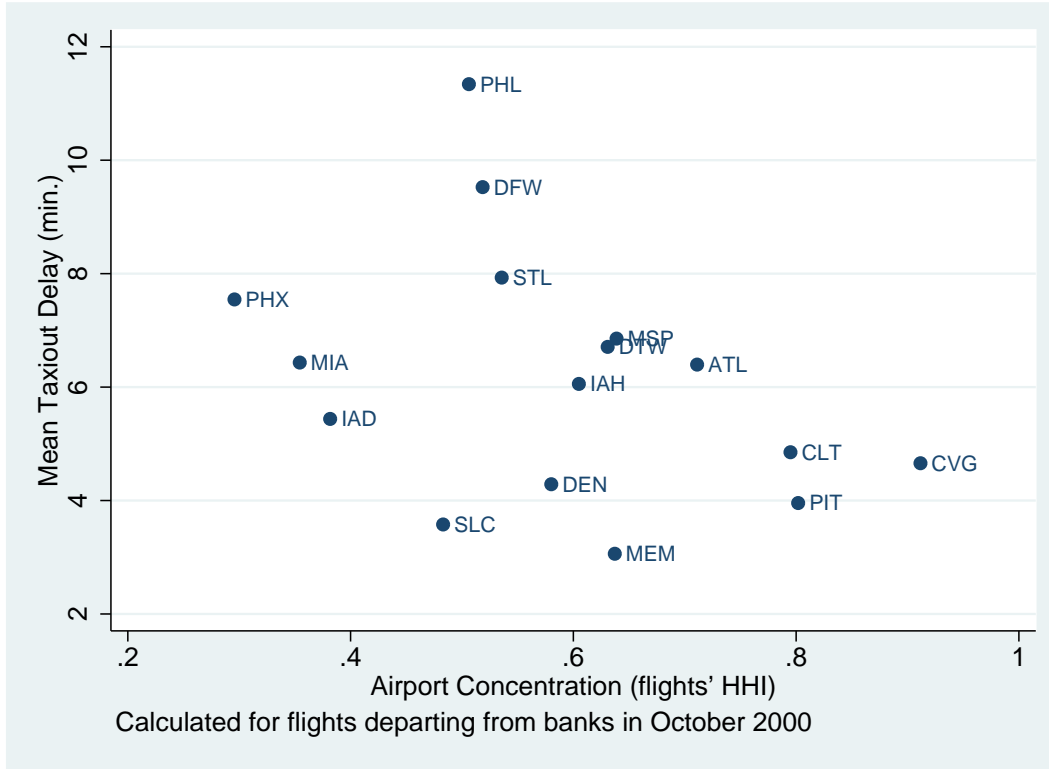
Figure 1: The relationship between airport concentration and taxi-out delay

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 in 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.
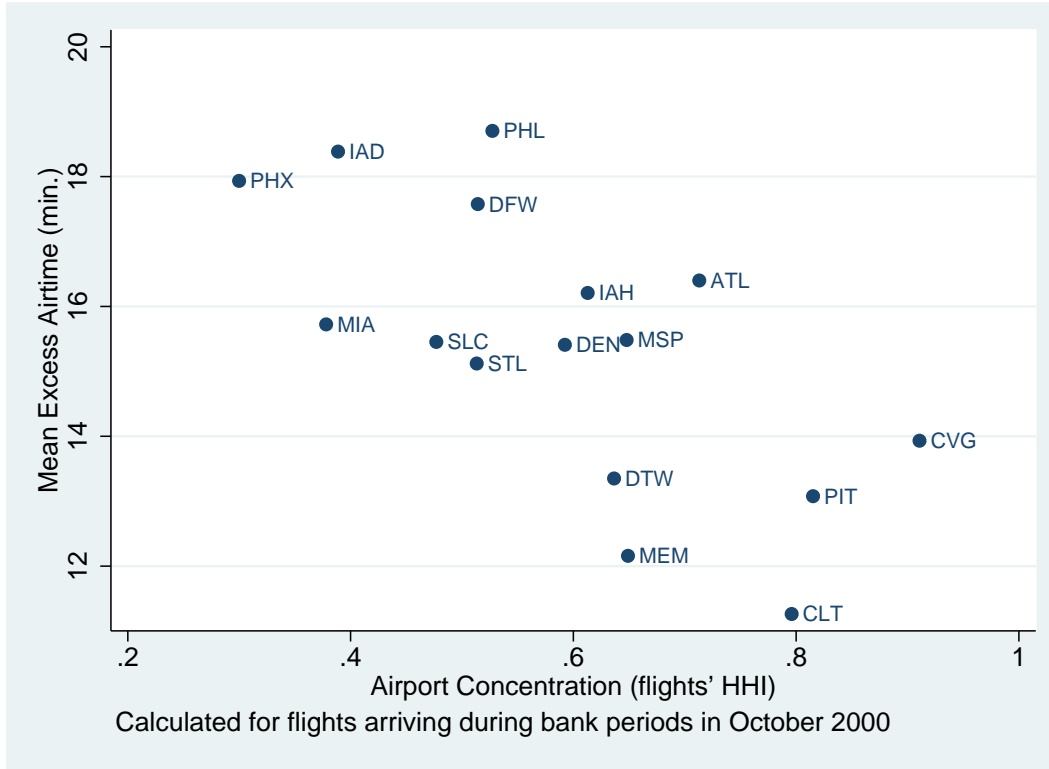
Figure 2: The relationship between airport concentration and excess airtime delay

The Figure displays a negative empirical relationship between airport concentration and airtime delay. A flight airtime delay is derived relative to the fastest airtime of a flight on the same directional route in the same month. Airtime delay is used as a proxy for queuing time before landing, while airplanes wait for their turn to land. 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.
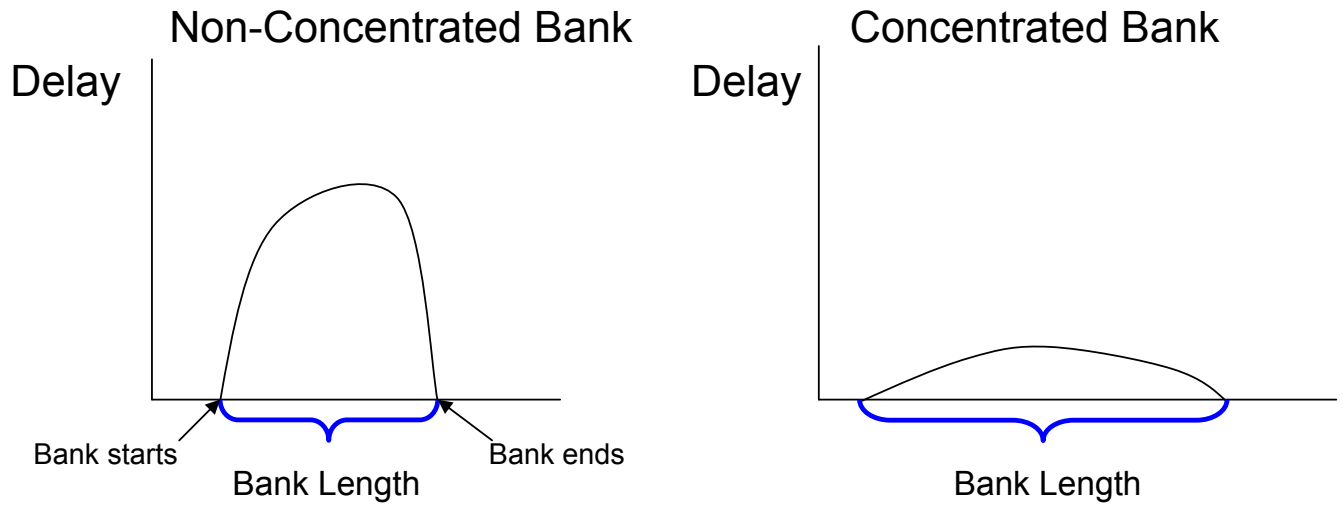
Figure 3: Graphic illustration of the theoretical framework

The Figure displays the congested period in non-concentrated and concentrated markets/banks as predicted by the theoretical framework. Bank periods are longer and delays are shorter in concentrated banks than in less concentrated 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).
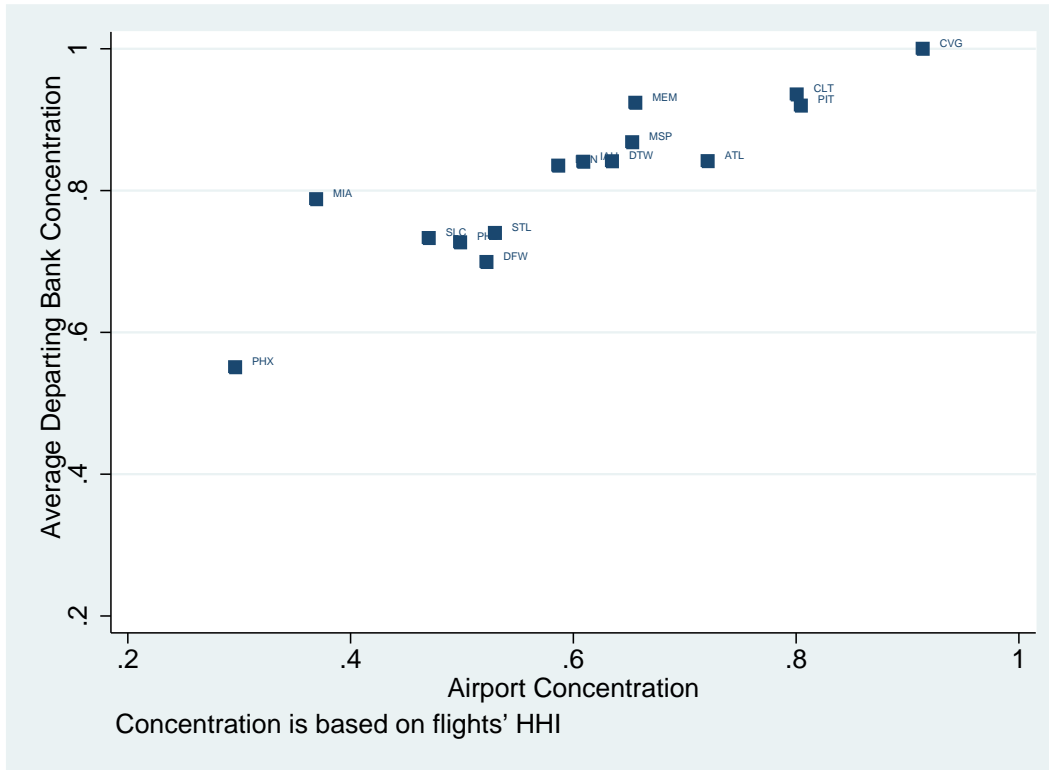
Figure 4: Bank and airport concentration

The Figure plots departing bank concentration levels against 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 operate during non-bank periods. Nevertheless, non-hub carriers still operate during bank periods.