

## **THE IMPACT OF DELAYS ON AIRLINE FREQUENCIES UNDER DIFFERENT ROUTE STRUCTURES**

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**Abstract:** In this paper, we examine the relationship between airline frequencies and delays under different route structures taking advantage of aggregated data of large US airports for the period 2005-2013. We run regressions using airline and airport fixed effects to control for different heterogeneities in data. Results of the empirical analysis show airlines operating under hub-and-spoke route structures increase frequencies in response to more frequent delays, while airlines operating fully-connected route structures do reduce frequencies. This may explain that the percentage of delayed flights is higher in hub airports than in other airports controlling for other relevant factors.

**Keywords:** airlines; airports; fully-connected networks; hub-and-spoke networks; delays

**JEL Classification Numbers:** L13; L93; H23; R41.

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# THE IMPACT OF DELAYS ON AIRLINE FREQUENCIES UNDER DIFFERENT ROUTE STRUCTURES

## 1. Introduction

Network airlines have increasingly concentrated their services in a small number of hub airports in which they channel a high proportion of total flights. In their hub airports, the dominant network carrier exploits the transfer traffic through coordinated banks of arrivals and departures. By operating hub-and-spoke route configurations (HS), they are able to reduce their costs taking advantage of density economies, and they can offer higher flight frequencies which are highly valued by business and connecting passengers.<sup>1</sup>

Unlike network airlines (which operate HS route configurations), low-cost carriers operate fully-connected (FC) route structures in which most air services are point-to-point. While low-cost carriers may also concentrate their traffic in a few airports, the exploitation of density economies is particularly relevant for network carriers. As pointed out in Flores-Fillol (2010), by adding a new route to an existing hub-and-spoke network carriers gain access to one new local market and to many connecting markets.

Baumgarten et al. (2014) suggest that hub-and-operations may aggravate congestion problems at peak times because more flights are operated for a given capacity during banks. Furthermore, a larger number of connecting passengers lead to an increasing complexity of airport and airline operations. Hence, congestion problems are particularly associated to hub airports. In this regard, such congestion problems may be generated by the strategic behavior followed by the hubbing airline. Daniel and Harback (2008) show dominant airlines at many major US hub airports concentrate their flights at peak times, constraining non-hubbing airlines to cluster their traffic in the uncongested periods. They do not observe this effect in non-hub airport.

The potentially negative effects associated with congestion may be substantial both for passengers and airlines. In this regard, several empirical studies have assessed the effects of delays on both airlines and passengers. For example, Britto et al. (2012) examine the impact of delays on consumer and producer welfare for a sample of US routes. They find that delays raise prices and reduce demand. From their results, a 10%

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<sup>1</sup> It is generally accepted that the route operations of airlines are subject to density economies (Brueckner and Spiller, 1994), and that airlines can attract more connecting passengers in a hub-and-spoke structure by increasing service frequency than by increasing aircraft size (Wei and Hansen, 2006).

decrease in delays would imply a benefit of \$1.50-\$2.50 per passenger, while the gains for airlines of reducing delays are about three times higher. Peterson et al. (2013) use a recursive-dynamic model to examine the costs of flight delays for both airlines and passengers. They find that a 10% reduction in delayed flights increases net US welfare by \$17.6 billion.

The studies of airport congestion center primarily the attention on the relationship between delays and airport concentration (see for example Brueckner, 2002; Mayer and Sinai, 2003; Daniel, 1995; Rupp, 2009; Santos and Robin, 2010; Ater, 2012; Bilotkach and Pai, 2014). While several studies have analyzed the determinants of delays, less attention has been put on the impact of delays on airline frequencies.<sup>2</sup> The exceptions are the works of Pai (2010) and Zou and Hansen (2014).

Pai (2010) finds that every 1 min delay increase at the origin and destination airports could result in 2 and 3 fewer flights per month using data for a sample of US routes. On the contrary, Zou and Hansen (2014) find a positive relationship between frequencies and delays using also a sample of US routes. In the latter study, it is suggested that airlines could reduce frequencies when delays increase due to higher operation costs. However, they justify the positive relationship that they find by noting that congested flight segments may be associated with higher yields. In addition, the airline operating the congested flight segment may be very concerned about losing market power as the abandoned slots could be taken over by its competitors.

Our contribution is set in the context of this scarce literature that examines the impact of delays on airline frequencies. In particular, we run regressions to examine the relationship between airline frequencies and delays under different route structures using aggregated data of large US airports for the period 2005-2013. We study how airlines adjust frequencies to airport congestion under HS and FC route structures.

The hypothesis to test is that airlines operating HS networks may have incentives to keep frequencies high even if congestion at their hub airports is worsening. In this regard, Fageda and Flores-Fillol (2014) show that airlines may prefer to develop HS networks because of the exploitation of economies of traffic density, even if this comes at the expense of higher congestion costs both for passengers and airlines.

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<sup>2</sup> Several empirical studies have examined the determinants of airline frequencies at the route level. These previous studies have generally focused on the effects of route or airport competition (see for example; Schipper et al., 2002; Bilotkach et al., 2010, 2013; Brueckner and Luo, 2013; Fageda, 2014).

The rest of this paper is organized as follows. In the next section, we explain the data used in the empirical analysis. Then, we specify the empirical model and state our expectations for the explanatory variables. The following section deals with various econometric issues and then we report the regression results. The last section contains our concluding remarks.

## **2. Data**

We have data for 50 large US continental airports, including all hubs and the country's most congested, during the period 2005-2013. Data on airline frequencies and flight shares at the airport level have been obtained from RDC Aviation (Capstats statistics) that represent an aggregation of the T-100 dataset collected by the US Department of Transportation. Since we focus on US domestic traffic, intercontinental flights are excluded from the analysis. We just consider airlines that at least provide one flight per week in the considered airport. The unit of observation of our regressions is the pair airline-airport so that our final sample comprises 4259 observations.

We also consider variables that may affect demand of flights in the airports of our sample. In this regard, we use data on population and GDP per capita, obtained from the US census, which refer to the Metropolitan Statistical Area (MSA) where the airport is located.

An important issue in our analysis is the distinction between network airlines that operate under hub-and-spoke route structures and other airlines (usually low-cost airlines) that operate under fully-connected route structures. Table 1 provides a list of the airlines included in our dataset. Alaska airlines, American Airlines, Continental, Delta, Northwest, United and US airways are considered network airlines.

### **Insert Table 1 here**

All network airlines are integrated in an International alliance (i.e., Oneworld, Star Alliance, and SkyTeam) in the period under study. The only exception is Alaska airlines that have code-share agreements with several airlines integrated in airline alliances. Note also that all network airlines rely extensively on regional carriers to feed their flights. These regional carriers may be subsidiaries or they may have signed contracts with the major network carrier.<sup>3</sup>

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<sup>3</sup> Our data set assigns the flight to the major carrier in those cases where it is operated by a regional carrier on behalf of the major carrier.

By definition, hub airports are those airports in which a dominant network carrier exploits the transfer traffic through coordinated banks of arrivals and departures. In this regard, hub airports usually have two characteristics; they are big and a network carrier concentrates a high proportion of its flights.

Hence, our dataset includes the following hub airports: Portland (PDX) and Seattle (SEA) for Alaska airlines; Dallas (DFW), Miami (MIA), and Chicago (ORD) for American Airlines; Cleveland (CLE), Houston (IAH), and Newark (EWR) for Continental; Atlanta (ATL), Cincinnati (CVG), New York (JFK), and Salt Lake City (SLC) for Delta; Detroit (DTW), Memphis (MEM), and Minneapolis (MSP) for Northwest; Chicago (ORD), Denver (DEN), San Francisco (SFO), and Washington Dulles (IAD) for United; and Charlotte (CLT), Philadelphia (PHL), and Phoenix (PHX) for US Airways.<sup>4</sup>

Our analysis assumes that network airlines operate in an HS manner at their hub airports, while the rest of airlines provide point-to-point connections. This is a simplification because all airlines can offer connecting services at any airport when their frequencies are sufficiently high. However, we consider this a sensible assumption given that the bulk of HS operations in the US domestic market are the services of network airlines at their hub airports.

Concerning airlines operating under fully-connected route structures, Southwest is the airline with the largest volume of passengers in US domestic traffic and it has a leading position in several airports of our sample. Although Southwest passengers could take advantage of some connecting flights, its network can still be considered as FC. Southwest only uses one type of plane, it does not have regional subsidiaries to feed its main airports, and flights are not clustered in coordinated banks of arrivals and departures. In this same vein, Boguslaski et al. (2004) show that the bulk of Southwest's traffic is found on dense point-to-point routes.

We measure congestion at the airport level. We define the levels of congestion as the percentage of originating flights that have been delayed by more than fifteen minutes at

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<sup>4</sup> Several network airlines have undertaken a de-hubbing process in the considered period. For example, the share of American airlines in Saint Louis was 57% in 2005 and it is just 12% in 2013, while that the share of US Airways in Pittsburg was 68% in 2005 and it is just 29% in 2013. Thus, we do not consider these two airports as hub airports although they were hubs in a previous period. Note that the share of Delta in Cincinnati was 92% in 2005 and it is 64% in 2013. Although it seems that Delta is gradually dismantling its hub in Cincinnati, still maintains a high volume of connection operations at this airport. Thus, this airport is considered as a hub airport.

a given airport.<sup>5</sup> Data regarding delays have been obtained from the US Department of Transportation. Figure 1 shows the evolution of delayed flights at airports of our sample. While data in this figure shows a peak in 2007, the percentage of delayed flights has been higher than 20% in all years of the considered period with the exception of 2012. Thus, a high proportion of flights in the US domestic market are affected by delays in a relatively long period of time.

**Insert figure 1 here**

Table 2 shows some features of the airports included in our sample.<sup>6</sup> In the case of hub airports, the share of the dominant airline (in terms of total airport departures) is usually well above 50%. The exceptions are New York (JFK), Chicago (ORD) and Phoenix (PHX) where two airlines have relatively large shares, and Denver (DEN) and Portland (PDX). In the period considered, the percentage of delayed flights at hub airports was well above 20%, and it was close to 30% in the most congested airports (New York - EWR and JFK), Chicago (ORD), and Philadelphia (PHL). Salt Lake City (SLC), Seattle (SEA), Portland (PDX) and Phoenix (PHX) are the only hub airports with a percentage of delayed flights below 20%.

**Insert Table 2 here**

Several non-hub airports are dominated by Southwest. Indeed, the share of Southwest is above 50% in Albuquerque (ABQ), Baltimore (BWI), Dallas (DAL), Houston (HOU), Chicago (MDW), Oakland (OAK) and Sacramento (SMF). Southwest is also clearly the leading airline in other airports as Las Vegas (LAS), San Diego (SAN) and San Antonio (SAT) with a share higher than 40%. Overall, the levels of concentration in airports dominated by Southwest may be as high as in hub airports. The percentage of delayed flights at Southwest-dominated airports is usually around 20% or

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<sup>5</sup> Previous empirical studies of the determinants of delays (Mayer and Sinai, 2003; Rupp, 2009; Santos and Robin, 2010) use data at the flight level and measure congestion as the difference between the actual and scheduled time and/or the difference between the actual and the minimum feasible time of the flight. For the purposes of our empirical analysis, which is the study of the influence of delays on the frequency choices of airlines at the airport level, such a disaggregated analysis is not needed.

<sup>6</sup> Several merger operations have taken place in the considered period. Indeed, since 2010 flights of Northwest are operated by Delta so that the dominant network carrier in Minneapolis (MSP), Detroit (DTW) and Memphis (MEM) is Delta and not Northwest since 2010. In the same vein, since 2012 flights of Continental are operated by United so that the dominant network carrier in Cleveland (CLE), Houston (IAH) and Newark (EWR) is United and not Continental since 2012. The merger between American Airlines and US Airways was made effective at the end of 2013 but the integration is not yet completed so that it does not affect our analysis.

less, so that it seems that the levels of congestion are generally lower than those at hub airports. The non-hub airports where Southwest is not the clearly the dominant airline generally present low concentration levels and their congestion levels are similar to those reported by Southwest dominated airports. However, Boston (BOS) and New York (LGA) report relatively high percentages of delayed flights.

### 3. The empirical model

Table 3 reports the results of a regression using data at the airport level. In this estimation, we consider the determinants of airport delays including the size of the airport, the concentration index in terms of total frequencies, climatic variables (temperature, precipitation)<sup>7</sup>, and a dummy for slot-controlled airports.<sup>8</sup> Controlling for all these variables, we find that the percentage of delayed flights is higher in hub airports. While this regression is made just for descriptive purposes, it provides some evidence that congestion is particularly worrying in hub airports and that the problem of congestion is not only related to the size of the airport, the levels of concentration or the weather.

#### Insert Table 3 here

The hypothesis that we want to test is that airlines operating under HS structures tend to react less to delays than airlines operating under FC structures. This could explain why the percentage of delayed flights is higher in hub airports than in other airports, even after controlling for other variables that may have a strong impact on such percentage. Hence, we estimate the following equation for airline  $i$  at airport  $a$  from urban area  $u$ :

$$\begin{aligned} \text{Freq}_{i,a,t} = & \beta_0 + \beta_1 \text{Pop}_{u,t-1} + \beta_2 \text{GDPpc}_{u,t-1} + \beta_3 \text{HHI}_{a,t-1} + \beta_4 D_a^{\text{slot}} + \beta_5 D_{i,a}^{\text{hubs\_smaller\_merged\_airline}} \\ & + \beta_6 \text{Delays}_{a,t-1} + \beta_7 D_{i,a}^{\text{HS}} + \beta_8 D_{i,a}^{\text{HS}} \times \text{Delays}_{a,t-1} + \beta_9 D_{i,a}^{\text{FC}} + \beta_{10} D_{i,a}^{\text{FC}} \times \text{Delays}_{a,t-1} + \\ & + \mu'_t + \varepsilon \end{aligned}$$

The dependent variable ( $\text{Freq}_{i,a,t}$ ) is the total number of annual flights that each airline offers at the corresponding airport. The data for the explanatory variables are for

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<sup>7</sup> Data for climatic variables have been obtained from the web site of the National Oceanic and Atmospheric Administration (NOAA)

<sup>8</sup> Only four airports are slot-constrained in US: Two of them can be considered hub airports (Chicago O'Hare, and New York-JFK) and the other two are not hub airports Washington-Ronald Reagan, New York –La Guardia).

the previous year because airline frequencies at the airport level in period  $t$  are influenced by airport and airline features in period  $t-1$ .

Among the explanatory factors, we include variables related to local demand: population ( $Pop_{u,t-1}$ ) and GDP per capita ( $GDPpc_{u,t-1}$ ). We can expect a positive sign for the coefficients associated with the population and income variables. Airlines may have incentives to increase the number of flights on routes departing from airports located in areas with a higher local demand. Thus, the demand for airline services should be higher in airports located in more populated and richer urban areas.

A variable for the concentration index at the airport level is also considered ( $HHI_{a,t-1}$ ). The Hirschman-Herfindalh index is calculated as the sum of the squares of the shares of airlines in terms of flight frequencies. Frequencies of airlines operating in more concentrated airports may be higher because yields may be higher and also due to a better exploitation of density economies. We also include a dummy variable that takes the value one for slot-constrained airports ( $D_a^{slot}$ ) as slot constraints may affect frequency choices of airlines.

Furthermore, we include a variable that is aimed to control for the mergers that have taken place during the considered period ( $D_{i,a}^{hubs\_smaller\_merged\_airline}$ ). This variable takes the value one for merged airlines operating in the hubs of the smaller airline (see footnote 4). In this regard, Bilotkach et al. (2013) show that the merger of Delta and Northwest led to a re-organization of the route structure in favor of the hubs of the larger airline

Along with these control variables, we consider a measure of airport congestion ( $Delays_{a,t-1}$ ), which is constructed as the percentage of total flights at the airport suffering a delay in excess of fifteen minutes. According to Zou and Hansen (2014), airlines could reduce frequencies when delays increase due to higher operation costs but they could also increase frequencies when delays increase due to higher yields and avoid losing market power.

Furthermore, we consider dummy variables for airlines that operate under HS and FC networks ( $D_{i,a}^{HS}$  and  $D_{i,a}^{FC}$ ). Finally, we include two variables that are formed from the interaction between the dummy variable for airlines operating under HS and FC networks and the measure of congestion ( $D_{i,a}^{HS} \times Delays_{a,t-1}$  and  $D_{i,a}^{FC} \times Delays_{a,t-1}$ ).

Controlling for local demand, the frequencies of network airlines at their hub airports (i.e., airlines operating HS networks) should be higher than the frequencies of other airlines. The reason for this is the exploitation of connecting traffic, which is independent of local demand. Thus, we expect a positive sign for the coefficient



associated with  $D_{i,a}^{HS}$ . The expected sign of the coefficient associated with  $D_{i,a}^{FC}$  is less clear because this variable captures different types of FC route structures, depending on the econometric specification chosen (as we explain below).

The relationship between frequencies and delays for airlines operating under HS networks is determined by coefficients  $\beta_6$  and  $\beta_8$ , while the same relationship for airlines operating under FC networks is determined by coefficients  $\beta_6$  and  $\beta_{10}$ . Thus, we can test whether airlines react differently to congestion according to the network structure they operate by examining the estimated coefficients of  $\beta_8$  and  $\beta_{10}$ . If network airlines react less to delays at their hubs, we would expect  $\beta_8 > 0$  and  $\beta_8 > \beta_{10}$ . This is the main hypothesis to test in this study.

Equation (1) also includes time fixed effects ( $\mu$ ). The time fixed effects capture shocks common to all airports and airlines that have taken place in the period considered.

#### **4. Estimation and results**

The estimation of Eq. (1) is made using the fixed effects estimator, which allows us to control for any omitted time-invariant variable that is correlated with the variables of interest. Another advantage of the fixed effects model is that it allows us to account for different types of heterogeneity in the data. We follow two different approaches to control for heterogeneities in our data.

First, we use airline fixed effects to control for airline heterogeneity. In this regression, we can identify the different behavior of airlines operating at the same airport. The dummy variable  $D_{i,a}^{HS}$  refers to network airlines' flights from/to their hubs (e.g., Delta's flights from/to Atlanta-ATL), while  $D_{i,a}^{FC-a}$  refers to the flights of non-hubbing airlines operating at the same hub airports (e.g., American Airline's flights from/to Atlanta-ATL). We may consider that airlines offering flights in hub airports that are not the hubbing airline are operating under FC route structures in such airports. For example, Delta exploits the transfer traffic through coordinated banks of arrivals and departures in Atlanta so that it concentrates a large share of total flights there. On the contrary, American Airlines use Atlanta mainly to provide direct services to its hubs while Frontier may be offering some point-to-point services with origin or destination in Atlanta. Thus, this regression does not distinguish between network or low-cost carriers in the identification of airlines operating under FC route structures.

Second, we use airport fixed effects to control for airport heterogeneity. Here, we can identify the different behavior of airlines operating in different airports. Hence,  $D_{i,a}^{HS}$  is

the same as that in the regression with airline specific effects and  $D_{i,a}^{FC-b}$  is associated with dominant airlines operating in non-hub airports. We consider as dominant those airlines that have a share greater than 50% of total flights originating at the airport. Hence, this regression makes the distinction between network airlines operating in their hub airports (eg., American Airlines's flights from/to Dallas-DFW) and low-cost airlines operating in their main airports (e.g., Southwest's flights from/to Dallas-DAL). American Airlines and Southwest both concentrate a very high proportion of total flights in Dallas-DFW and Dallas-DAL, respectively. However, American Airlines exploits the transfer traffic through coordinated banks of arrivals and departures in Dallas-DFW while the bulk of the activity of Southwest in Dallas-DAL is based on point-to-point services.

We follow these two different but complementary approaches as a robustness check. Certainly, network airlines in their hub airports are operating under HS route structures. On the contrary, airlines operating in different contexts are primarily operating under FC route structures.

An important econometric challenge in our analysis is the possible simultaneous determination of frequencies and delays. Note here that the frequency variable is at the airline-airport level, while the delays variable is at the airport level. This should mitigate any endogeneity problem.

This being said, we deal with this potential bias by using further lags of the delays variable as instruments. A typical shortcoming of the lags approach is that the correlation between several lags may be high if the variable of interest has a strong inertia. However, this is not the case in the data that we use. The correlation between the delays variable and its lagged values is 0.76, 0.58, 0.40, and 0.24 for one, two, three, and four lags, respectively. Lagged delays of more than four years are highly non-significant in the first-stage regression of the instrumental variables procedure. In the table of results, we report tests of instrument appropriateness: the Hansen test where the null hypothesis is that the instruments are exogenous, and the Kleibergen-Paap LM where the null hypothesis is that the instruments are not strong. The Hansen test determines the selection of the lags that we use as instruments of the delays variable.

Another econometric issue that should be mentioned is the high correlation between the variables  $D_{i,a}^{HS}$  and  $D_{i,a}^{HS} \times \text{Delays}_{a,t-1}$ , and between the variables  $D_{i,a}^{FC}$  and  $D_{i,a}^{FC} \times \text{Delays}_{a,t-1}$ , respectively. This may pose a multicollinearity problem that could distort the individual identification of these variables. However, the results of the regressions

excluding either  $D_{i,a}^{HS}$  and  $D_{i,a}^{FC}$  or  $D_{i,a}^{HS} \times \text{Delays}_{a,t-1}$  and  $D_{i,a}^{FC} \times \text{Delays}_{a,t-1}$  are qualitatively identical to the regressions that include all the variables.<sup>9</sup>

Table 4 shows the descriptive statistics of the variables used in the empirical analysis. All the variables show sufficient variability to provide robust estimations. Recall here that the unit of observation of our analysis is the pair airline-airport although some variable of our analysis are taken at the airport or urban level.

**Insert Table 4 here**

Table 5 shows the results of the estimation of Eq. (1) using airline and airport fixed effects. Standard errors are robust to heterocedasticity and clustered by year to account for any autocorrelation problem. The overall explanatory power of the model is high in both airline and airport fixed-effects regressions.

**Insert Table 5 here**

The impact of the population and income variables on frequencies does not seem to be relevant in our regressions, although the coefficient of the population variable is positive and statistically significant at the 10% level in the airline fixed effects regression. It should be borne in mind that the estimations capture the within rather than the between data variation. In this regard, the airport and year fixed effects may capture part of the effect of population and income. The dummy variables for slot constrained airports and for merged airlines operating in the hubs of the smaller airline are not significant either in any regression.

The coefficient associated to the airport concentration variable is positive and statistically significant both in the airport and airline fixed effects regressions. Hence, it seems that frequencies of airlines in more concentrated airports are higher. Higher yields and a better exploitation of density economies by airlines operating in more concentrated airports could explain this result.

As expected, the coefficient of  $D_{i,a}^{HS}$  is positive and statistically significant in all the regressions. Additionally, the coefficients of  $D_{i,a}^{FC-a}$  and  $D_{i,a}^{FC-b}$  are also positive and statistically significant. As expected, frequencies of airlines operating under HS route structures will be higher than those of other airlines as they be offering both direct and

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<sup>9</sup> The results of these additional regressions are available from the authors on request.

connecting services. Less clear is the interpretation of results for the  $D_{i,a}^{FC-a}$  and  $D_{i,a}^{FC-b}$  as they refer to different types of airlines.

The coefficient associated with the delays variable is positive and statistically significant in the airline fixed effects regression, while such coefficient is negative but not statistically significant in the airport fixed effects regression. However, the relationship between frequencies and delays is jointly determined by the coefficients associated with the delays and the interaction variables. In fact, our main interest lies on the interaction variable since we focus on identifying the different behavior of airlines operating under HS and FC networks.

We find that airlines operating HS networks increase frequencies as the percentage of delayed flights in their hub airports increases. The coefficient associated with the interaction variable  $D_{i,a}^{HS} \times \text{Delays}_{a,t-1}$  is positive and statistically significant both in the airline and airport fixed effects regressions. Furthermore, note that the magnitude of the coefficient of this interaction variable is higher than that of the delays variable in the airport fixed effects regression.

By contrast, the coefficient associated with the interaction variable  $D_{i,a}^{FC} \times \text{Delays}_{a,t-1}$  is always negative and statistically significant. In the airline fixed effects regression, the magnitude of the coefficient of the interaction variable is similar to that of the delays variable. Recall that  $D_{i,a}^{FC-a}$  refers to non-hubbing airlines operating at hubs in the airline fixed effects regressions. Thus, our results indicate that airlines operating in other airlines' hub airports may be more prone to cut frequencies than hubbing airlines in reaction to more frequent delays at such airports.

In the airport fixed effects regressions,  $D_{i,a}^{FC-b}$  refers to dominant airlines in non-hub airports. Hence, dominant airlines operating in non-hub airports (ie; Southwest) clearly decrease frequencies as delays at such airports increase as long as the coefficients of the delays and interaction variables are negative.

In short, we find evidence of a differentiated behavior between airlines operating HS and FC networks. Indeed, the estimated coefficients of the interaction variables clearly indicate this result since  $\beta_8 > 0$  and  $\beta_8 > \beta_{10}$ . Hence, we conclude that airlines operating HS networks may have strong incentives to maintain high frequencies in their hubs even when congestion at those hubs increases.

Results of our analysis may provide an explanation of different results found in previous studies that examine the impact of delays on airline frequencies. While Pai (2010) find a negative relationship between frequencies and delays, Zou and Hansen

(2014) obtain evidence of the opposite result. We find a positive relationship between airline frequencies and delays when airlines operate under HS route structures, while we find that this relationship is negative when airlines operate under FC route structures.

## **5. Concluding remarks**

The dominance of the network airlines has benefitted the hub airports and their corresponding urban areas. Indeed, the traffic is higher than that generated solely by local demand because a large proportion of passengers in hub airports are connecting passengers. Furthermore, the number and geographical scope of destinations may be also higher in hub airports. However, a negative effect associated with hub airports concerns congestion which imposes costs to both passengers and airlines. In congested hubs, a high proportion of flights are affected by delays, cancellations and missed connections.

Results of our empirical analysis show airlines operating HS route structures increase frequencies in response to more frequent delays, while airlines operating FC networks do reduce frequencies. Thus, airlines operating HS networks seem to ignore the costs in terms of airport congestion implied by their route structure choice.

Our results are in line of those obtained by Daniel and Harback (2008), which show that dominant airlines at many major US hub airports concentrate flights in departure/arrival banks in peak periods, constraining non-hubbing airlines to cluster their traffic in the uncongested periods. It could be that our aggregate measure of delays serves as a proxy for concentrated flight banks of dominant hub carriers. In such a case, the positive effect of delays on frequencies that we find for airlines operating HS networks could be related to the benefits from having dominated banks of departures/arrivals at their hub airports.

The empirical findings of this study are also consistent with the analysis of Zou and Hansen (2014) which find a positive relationship between airline frequencies and airport delays. It may be the case that yields are particularly high in congested flight segments operated by network airlines in their hub airports and hubbing airlines may particularly reluctant to give up slots in their hub airports.

Our results suggest that policy measures promoting direct connections away from hubs may have social benefits in case that the problem of congestion becomes too severe. Policy makers and airport operators could use such tools as congestion tolls, capacity investment, and a better marketing of the cities in which non-hub airports are

located. Additionally, the rules determining the allocation and use of slots in the US could also be re-designed so as to create incentives for airlines to increase the size of their aircraft and reduce their flight frequencies.

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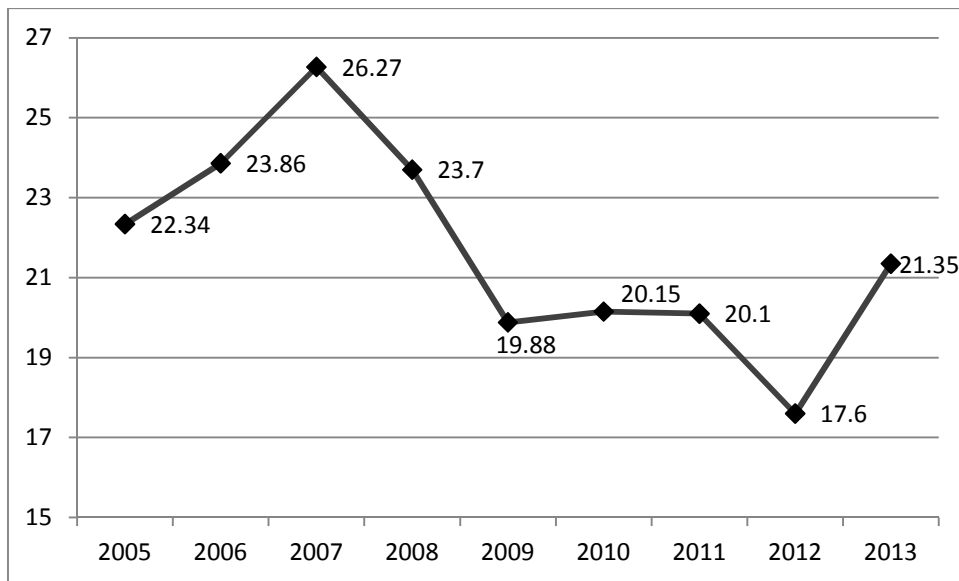
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## TABLES AND FIGURES

**Table 1. List of airlines included in our sample**

Network airlines	Low-cost airlines
Alaska airlines	AirTran
American Airlines	Allegiant air
Continental	Cape air
Delta	Frontier
Northwest	Great Lakes airlines
United	Jet Blue
US airways	Pacific Wings
	Republic airlines
	Southwest
	Spirit airlines
	Sun Country airlines
	USA3000 Airlines
	Virgin America

**Figure 1. Evolution of the percentage of delayed flights at airports of our sample**





**Table 1. Characteristics of the airports included in the sample (mean values in 2005-2013)**

<b>Airport</b>	<b>Delays</b>	<b>Departures</b>	<b>HHI</b>	<b>Share dominant airline</b>
Albuquerque (ABQ)	16.5	50,729	0.33	Southwest (54.3%)
Atlanta (ATL)	25.4	423,500	0.57	Delta (73.3%)
Austin (AUS)	17.2	60,882	0.24	Southwest (40.3%)
Hartford (BDL)	19.9	43,728	0.18	US Airways (23.2%)/Southwest (22.7%)
Nashville (BNA)	20.4	78,370	0.26	Southwest (45.8%)
Boston (BOS)	24.5	160,641	0.13	US Airways (19.7%)/Delta (17.4%)
Baltimore (BWI)	21.3	134,066	0.35	Southwest (56.5%)
Cleveland (CLE)	20.8	99,099	0.43	Continental (66.6%) in 2005-2011/United (73.3%) in 2012-2013
Charlotte (CLT)	23.4	224,642	0.73	US Airways (85.7%)
Columbus (CMH)	21.2	58,940	0.16	Delta (21.4%)/Southwest (19.8%)
Cincinnati (CVG)	21.8	110,485	0.65	Delta (79.1%)
Dallas (DAL)	20.6	62,191	0.82	Southwest (90.2%)
Washington (DCA)	21.9	138,096	0.28	US Airways (46.6%)
Denver (DEN)	22.4	288,766	0.29	United (47.1%)
Dallas (DFW)	24.9	295,620	0.69	American Airlines (83.4%)
Detroit (DTW)	25.3	209,909	0.60	Northwest (74.4%)/Delta (81.4%)
New York (EWR)	31.1	156,175	0.50	Continental (69.9%) in 2005-2011/United (76.2%) in 2012-2013
Fort Lauderdale (FLL)	22.6	99,059	0.13	Southwest (23.4%)
Houston (HOU)	22.9	72,963	0.76	Southwest (87.1%)
Washington (IAD)	24.5	136,697	0.52	United (70.2%)
Houston (IAH)	21.9	217,221	0.72	Continental (86.7%) in 2005-2011/United (87.5%) in 2012-2013
Indianapolis (IND)	20.1	63,014	0.15	Northwest (21.6%) in 2005-2009/Delta (26.7%) in 2010-2013
New York (JFK)	28.7	124,180	0.27	Jet Blue (35.0%)/Delta (34.9%)
Las Vegas (LAS)	21.3	183,366	0.29	Southwest (49.9%)
Los Angeles (LAX)	19.3	239,165	0.18	United (28.9%)
New York (LGA)	27.2	182,981	0.23	US Airways (29.2%)/Delta (27.9%)
Kansas (MCI)	20.2	86,363	0.19	Southwest (36.2%)
Orlando (MCO)	20.2	149,058	0.16	Southwest (30.2%)
Chicago (MDW)	22.7	111,033	0.67	Southwest (81.1%)

Memphis (MEM)	20.8	84,778	0.58	Northwest (76.6%)/Delta (76.4%)
Miami (MIA)	26.7	83,076	0.50	American airlines (68.6%)
Milwaukee (MKE)	22.3	69,267	0.25	Frontier (47.3%) in 2005-2010/AirTran (21.7%) from 2011-2013
Minneapolis (MSP)	23.4	200,386	0.58	Northwest (75.4%) in 2005-2009/Delta (77.5%) in 2010-2013
New Orleans (MSY)	19.5	51,819	0.19	Southwest (34.5%)
Oakland (OAK)	17.4	74,808	0.59	Southwest (76.1%)
Chicago (ORD)	29.2	391,806	0.40	American Airlines (39.4%)/United (49.6%)
Portland (PDX)	15.3	92,987	0.25	Alaska airlines (40.8%)
Philadelphia (PHL)	27.5	204,892	0.50	US Airways (68.8%)
Phoenix (PHX)	19.2	196,410	0.34	Southwest (41.2%)/US Airways (33.3%)
Pittsburg (PIT)	22.1	75,874	0.23	US Airways (38.9%)
Raleigh-Durham (RDU)	22.1	76,019	0.17	American Airlines (22.3%)/Delta (21.1%)
Fort Myers (RSW)	19.3	36,973	0.12	Delta (16.5%)/AirTran (13.9%)
San Diego (SAN)	17.5	99,464	0.23	Southwest (42.3%)
San Antonio (SAT)	17.1	55,153	0.24	Southwest (42.5%)
Seattle (SEA)	19.7	158,026	0.33	Alaska Airlines (54.5%)
San Francisco (SFO)	24.5	154,485	0.32	United (53.4%)
Salt Lake City (SLC)	17.2	154,485	0.55	Delta (72.7%)
Sacramento (SMF)	17.3	56,477	0.33	Southwest (54.1%)
Santa Ana (SNA)	16.9	51,754	0.19	Southwest (34.1%)
St. Louis (STL)	20.1	113,701	0.25	American Airlines (30.3%)/Southwest (32.5%)

**Table 3. Results of estimates of delays at the airport level (Ordinary Least Squares)**

	<b>All airports</b>
Frequencies <sub>a,t</sub>	0.000014 (2.18e-06)***
HHI <sub>a,t</sub>	1.80 (0.86)**
Rain <sub>a,t</sub>	0.08 (0.009)***
Temperature <sub>a,t</sub>	-0.04 (0.018)**
D <sup>slot</sup>	3.74 (0.59)***
D <sup>Hub</sup>	0.77 (0.39)**
Intercept	18.48 (1.27)***
Time fixed effects	YES
R <sup>2</sup>	0.58
Test F (joint significance)	43.12***
Number observations	450

Note 1: Standard errors in parenthesis (robust to heteroscedasticity and clustered by year).

Note 2: Statistical significance at 1% (\*\*\*), 5% (\*\*), 10% (\*)

**Table 4. Descriptive statistics of the variables used in the empirical analysis**

<b>Variable</b>	<b>Mean</b>	<b>Standard Deviation</b>
<b>Annual frequencies of the airline at the airport level (Freq<sub>i,a,t</sub>)</b>	13622.7	31553.06
<b>Annual Frequencies at the airport level</b>	139939.7	89542
<b>Concentration at the airport level (HHI index)</b>	0.34	0.18
<b>Population of the metropolitan area –million inhabitants (Pop<sub>u,t-1</sub>)</b>	4707663	4536939
<b>Per capita income of the metropolitan area –US current dollars (GDPpc<sub>u,t-1</sub>)</b>	50326.8	8811.3
<b>Percentage of delayed flights at the airport(Delays<sub>a,t-1</sub>)</b>	21.77	4.74
<b>Dummy for dominant network airlines operating at the hub airport (D<sub>i,a</sub><sup>HS</sup>)</b>	0.045	0.20
<b>Dummy for airlines operating at the hub airport (D<sub>i,a</sub><sup>FC-a</sup>)</b>	0.012	0.11
<b>Dummy for dominant non-network airlines operating at their base airports (D<sub>i,a</sub><sup>FC-b</sup>)</b>	0.036	0.48

**Table 5. Results of estimates of airline frequencies at the airport level  
(Instrumental variables regression)**

	<b>Airline fixed effects</b>	<b>Airport fixed effects</b>
Pop <sub>u,t-1</sub>	0.00013 (0.00008)*	-0.0002 (0.0011)
GDPpc <sub>u,t-1</sub>	-0.003 (0.03)	0.11 (0.17)
HHI <sub>a,t-1</sub>	12379.67 (2103.63)***	13317.55 (6899.69)**
D <sub>a</sub> <sup>Slot</sup>	1475.57 (1430.66)	-
D <sub>i,a</sub> <sup>hubs_smaller_merged_airline</sup>	-9849.46 (9959.81)	2103.07 (14274.09)
Delays <sub>a,t-1</sub>	1010.01 (232.39)***	-207.41 (679.21)
D <sub>i,a</sub> <sup>HS</sup>	60937.35 (20536.06)***	37869.9 (18478.9)**
D <sub>i,a</sub> <sup>FC_a</sup>	12570.39 (3795.39)***	-
D <sub>i,a</sub> <sup>FC_b</sup>	-	59358.91 (2750.07)***
D <sub>i,a</sub> <sup>HS</sup> X Delays <sub>a,t-1</sub>	2132.43 (874.64)***	3378.78 (771.12)***
D <sub>i,a</sub> <sup>FC_a</sup> X Delays <sub>a,t-1</sub>	-877.25 (186.42)***	-
D <sub>i,a</sub> <sup>FC_b</sup> X Delays <sub>a,t-1</sub>	-	-302.21 (82.13)***
Time fixed effects	YES	YES
R <sup>2</sup>	0.66	0.66
Test F (joint significance)	47.25***	73.23***
Kleibergen-Paap LM statistic (Ho: equation is underidentified)	569.93***	104.55***
Hansen J statistic (Ho: equation is overidentified)	1.82	0.21
Number observations	4259	4259

Note 1: Standard errors in parenthesis (robust to heteroscedasticity and clustered by year).

Note 2: Statistical significance at 1% (\*\*\*), 5% (\*\*), 10% (\*)

Note 3: Instruments of lagged delays are three and four delays.