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How do airlines react to airport congestion? The role of networks

Xavier Fageda [a,1], Ricardo Flores-Fillol [b,2]

[a] Department of Economic Policy, Universitat de Barcelona, Avinguda Diagonal 690, 08034 Barcelona, Spain
[b] Departament d'Economia and CREIP, Universitat Rovira i Virgili, Avinguda de la Universitat 1, 43204 Reus, Spain

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ABSTRACT

In this paper, we investigate the relationship between airline network structure and airport congestion. More specifically, we study the ways in which airlines adjust frequencies to delays (as a measure of airport congestion) depending on the network type they operate. Our results suggest that network structure has a fundamental impact. Thus, while airlines operating fully-connected configurations reduce frequencies in response to more frequent delays, airlines operating hub-and-spoke structures increase frequencies. Therefore, network airlines have incentives to keep frequencies high even if this is at the expense of a greater congestion at their hub airports. This result sheds light on previously unclear results in the literature.

1. Introduction

Network airlines increasingly concentrate their services at a small number of hub airports at which they channel a high proportion of their total flights. At these hubs, dominant network carriers exploit transfer traffic through coordinated banks of arrivals and departures. The operation of such hub-and-spoke (HS) configurations enables airlines to reduce their costs since they can exploit economies of traffic density and offer high flight frequencies, the latter being greatly valued by business and connecting passengers.[3] As Flores-Fillol (2010) points out, network carriers have strong incentives to add new routes to their HS networks because by doing so they gain simultaneous access to one new local market and many connecting markets. By offering a wide diversified range of destinations, hub airports contribute substantially to the competitiveness of firms located in the urban areas under their influence.[4] While low-cost carriers may also concentrate their traffic in just a few airports, they basically operate fully-connected (FC) networks in which most air services are point-to-point.

However, the concentration of traffic favored by HS networks has contributed to an increase in airport congestion. Baumgarten et al. (2014) suggest that HS operations may aggravate congestion problems at peak times because more flights are operated for a given capacity during banks. Furthermore, the larger number of connecting passengers results in an increasing complexity of airport and airline operations. Daniel and Harback (2008) show that dominant airlines at many major US hub airports concentrate their flights at peak times, thereby forcing non-hubbing airlines to cluster their traffic in uncongested periods. The potentially negative effects associated with congestion may be substantial both for passengers and airlines, as reported in several empirical studies. For example, Forbes (2008) uses data from New York-La Guardia airport (one of the four slot constrained airports in the US) to study price responses to flight delays. She finds an average price reduction per additional minute of delay of $1.42 for direct passengers; this price decrease amounts to $0.77 for connecting passengers. 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% decrease in delays implies 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 both for airlines

E-mail addresses: xfageda@ub.edu (X. Fageda), ricardo.flores@urv.cat (R. Flores-Fillol).
[1] Tel.: +34 934039721.
[2] Tel.: +34 977759851.

[3] 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 HS structure by increasing service frequency than by increasing aircraft size (Wei and Hansen, 2006).
[4] For instance, McDonald and McMillen (2000) discuss the centripetal force of Chicago O'Hare airport for industrial and commercial activities.

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and passengers, finding that a 10% reduction in delayed flights increases net US welfare by $17.6 billion.

HS networks, therefore, are associated with both positive and negative effects. The empirical challenge consists in ascertaining which of these two dominates. This paper aims at understanding the extent to which airlines react to airport congestion. More specifically, we seek to test the impact of airline network type on carriers' reactions to congestion: that is, do airlines operating HS and FC networks behave differently?

A closely related study to the one conducted here is provided by Bilotkach et al. (2013). Drawing on data for the period 2007–2011, they study the impact of the merger between Delta and Northwest on the distribution of traffic between primary and secondary hubs, considering the potential negative effect of increased congestion at the main hub airports. They report a post-merger redistribution of traffic in favor of primary hubs and *no effect of congestion* as a brake on this concentration of traffic. The authors claim that they are surprised by this apparent indifference of the merged entity (Delta-Northwest) to congestion and speculate that it might be due to the economic downturn following the financial crisis in 2008. Our study sheds further light on this puzzling outcome.

Most studies of airport congestion analyze the relationship between delays and airport concentration, focusing on the internalization debate. The internalization hypothesis states that airlines at heavily concentrated airports are likely to internalize the effects of self-imposed congestion.[5]

While several works analyze the determinants of delays, less attention has been devoted to the impact of delays on airline frequencies.[6] The exceptions are the studies published by Pai (2010) and Zou and Hansen (2014), which yield contradictory results. Using data for a sample of US routes, Pai (2010) finds a negative relationship between frequencies and delays. More precisely, he concludes that every extra minute of delay at the airports of origin or destination could result in 2–3 fewer flights per month. By contrast, Zou and Hansen (2014), also using a sample of US routes, find a positive relationship between frequencies and delays.

Our analysis seeks to reconcile the results in this scarce and incipient literature by undertaking a more general analysis in which we introduce a new relevant element: network structure. In particular, we undertake an empirical analysis of the US market during the period 2005–2013 to examine the relationship between airline frequencies and delays (as a measure of airport congestion) under different route structures. We study the different ways in which airlines adjust their frequencies to airport congestion depending on the network type they operate.

The results of the empirical analysis suggest that the effect of the network structure is fundamental. We provide some evidence about the different reaction to congestion of carriers operating HS networks (i.e., network carriers) as compared with carriers operating FC networks (i.e., mainly low-cost carriers). We find that while airlines operating FC configurations reduce frequencies in response to more frequent delays, airlines operating HS structures increase frequencies. Therefore, network airlines have incentives to keep frequencies high even if this is at the expense of greater congestion at their hub airports. The rationale behind this result would seem to lie in the higher yield associated with flight banks; the cost savings from an intense exploitation of economies of traffic density; and the strategic behavior of airlines that may adopt a preemptive strategy so as to avoid losing market power, which involves releasing slots that might be taken over by other competing airlines.[7]

Our results confirm the theoretical findings in Fageda and Flores-Fillol (2015), which suggest that congestion typically increases the profitability of HS networks (since frequencies are higher than those in FC networks). Our findings are also in line with the empirical results in Brueckner (2002), which show that delays are higher in hub airports after controlling for airport size and other airport attributes. Finally, our paper goes some way to accounting for the non-existent reaction to congestion by the merged Delta-Northwest airline reported in Bilotkach et al. (2013). This is unlikely to have been caused by the economic downturn in 2008, but rather represents an active decision on the part of the consolidated airline.

The rest of this paper is organized as follows. In the next section, we explain the data used in the empirical analysis. In Section 3, we specify the empirical model and state our expectations for the explanatory variables. Section 4 deals with various econometric issues and then we report the regression results and Section 5 provides some robustness checks. 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 airports, during the period 2005–2013. Data on airline frequencies and flight shares at the airport level have been obtained from RDC Aviation (Capstats Statistics), representing 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. Moreover, we only include airlines that provide at least one flight per week from the airport under consideration. The unit of observation of our regressions is the airline–airport pair, so that our final sample comprises 4259 observations.

We also consider the variables that might affect flight demand at the airports in our sample. Specifically, we use data on population and GDP per capita obtained from the US census, which refer to the Metropolitan Statistical Area (MSA) in which the airport is located.

An essential feature of our analysis is the distinction drawn between network airlines that operate HS networks and other airlines (usually low-cost airlines) that operate FC configurations. Alaska Airlines, American Airlines, Continental, Delta, Northwest, United, and US Airways are identified as network airlines; and AirTran, Allegiant Air, Cape Air, Frontier, Great Lakes, Jet Blue, Pacific Wings, Republic, Southwest, Spirit, Sun Country, USA3000, and Virgin America are identified as low-cost carriers. All network airlines are integrated in an international alliance (i.e., Oneworld, Star Alliance, and SkyTeam) in the period under study, with the only exception of Alaska Airlines that has codeshare 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 either subsidiaries of a network carrier or independent airlines that have signed contracts with a network carrier.[8]

By definition, hub airports are those airports in which a dominant network carrier exploits the transfer traffic through coordinated banks

[5] Daniel (1995) is the first that recognizes the potential for internalization. However, he supports the idea that carriers behave atomistically due to the competitive pressure exerted by fringe carriers (a result that is confirmed in Daniel and Harback, 2008). Differently, Brueckner (2002) proposes a model that relates internalization of congestion with market power. Mayer and Sinai (2003) demonstrate that, even though delays at hub airports can be longer than those at non-hub gateways, increasing airport concentration does reduce these delays. Rupp (2009), however, reverses Mayer and Sinai's findings, using a different measure of delays. Brueckner and Van Dender (2008) seek a consensus in the internalization debate by showing that some competitive scenarios do lead to self-internalization, while others do not.

[6] Several empirical studies have examined the determinants of airline frequencies at the route level. These studies have generally focused on the effects of either route or airport competition (see, for example, Bilotkach et al., 2010 and 2013, and Fageda, 2014).

[7] It is true that low-cost carriers' passengers may have a lower cost of time (as compared to network carriers' passengers) and that this could be reason for these carriers to incur longer delays. However, our results suggest that there are other factors that overcome this effect and explain the incentives for network carriers to incur longer delays (i.e., the higher yield associated with flight banks; the cost savings from an intense exploitation of economies of traffic density; and the strategic behavior of airlines).

[8] 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.

of arrivals and departures. As such, hub airports usually present two key characteristics: they are big and a network carrier operates a high proportion of the airport's flights.

Hence, our dataset includes the following hub airports: Portland (PDX) and Seattle (SEA) for Alaska Airlines; Dallas (DFW), Miami (MIA), Chicago (ORD), and Saint Louis (STL) for American Airlines;[9] 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.[10]

Southwest has the largest volume of passengers in terms of US domestic traffic and occupies a leading position in several airports included in our sample. Although Southwest passengers might take advantage of a connecting flight, Southwest's network can still be considered an FC. Southwest uses just one aircraft type, it has no regional subsidiaries feeding its main airports, and its 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.

Our analysis assumes that network airlines operate in an HS manner at their hub airports, while the rest of the airlines provide point-to-point connections (i.e., FC networks). This is a simplification since 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 constitute the services of network airlines at their hub airports.

Here, we measure congestion at the airport level. We define the level of congestion as the percentage of originating flights that are delayed by more than fifteen minutes at a given airport.[11] Data regarding delays have been obtained from the US Department of Transportation. Fig. 1 shows the evolution of delayed flights at the airports in our sample. While the data in this figure present a peak in 2007, the percentage of delayed flights was higher than 20% in all the years of the period under consideration with the exception of 2009 and 2012. Thus, a high proportion of flights in the US domestic market are affected by delays over a relatively long period of time.

Table 1 shows some features of the airports included in our sample.[12] 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

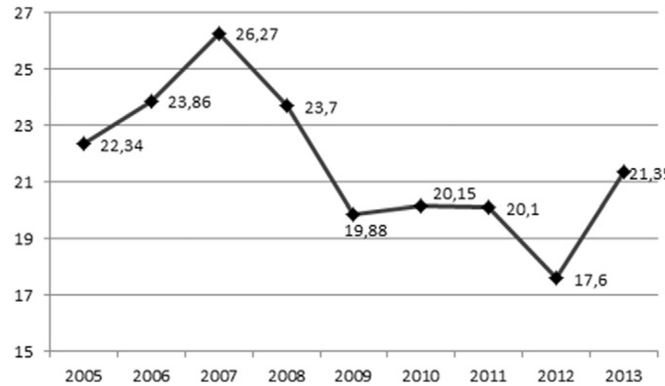

Fig. 1. Evolution of the percentage of delayed flights at airports in our sample.

have relatively large shares, and also 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). In fact, Salt Lake City (SLC), Seattle (SEA), Portland (PDX), and Phoenix (PHX) are the only hub airports with a percentage of delayed flights below 20%.

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 at other airports, including Las Vegas (LAS), San Diego (SAN), and San Antonio (SAT), with a share higher than 40%. Overall, the levels of concentration at the airports dominated by Southwest may be as high as those reported for the hub airports. However, the percentage of delayed flights at Southwest-dominated airports is usually around 20% or less. Therefore, the levels of congestion seem to be generally lower than those registered at hub airports. The non-hub airports at which Southwest is not the clearly dominant airline present, in general, low concentration levels and their congestion levels are similar to those reported at the Southwest-dominated airports. However, Boston (BOS) and New York (LGA) report relatively high percentages of delayed flights.

3. Empirical model

The hypothesis that we seek to test here is whether airlines operating under an HS structure react less to delays than airlines operating under an FC structure. Hence, we estimate the following equation for airline i at airport a in urban area u

$$\begin{aligned} Freq_{i,a,t} = {} & \beta_0 + \beta_1 Delays_{a,t-1} + \beta_2 D^{HS}_{i,a} + \beta_3 D^{HS}_{i,a} x Delays_{a,t-1} \\ & + \beta_4 D^{network\_non\text{-}hub}_{i,a} + \beta_5 D^{network\_non\text{-}hub}_{i,a} x Delays_{a,t-1} \\ & + \beta_6 D^{low\text{-}cost\_non\text{-}hub}_{i,a} + \beta_7 D^{low\text{-}cost\_non\text{-}hub}_{i,a} x Delays_{a,t-1} \\ & + \beta_8 Pop_{u,t-1} + \beta_9 GDPpc_{u,t-1} + \beta_{10} HHI_{a,t-1} + \beta_{11} D^{slot}_a \\ & + \beta_{12} D^{hubs\_smaller\_merged\_airline}_{i,a} + \mu_t + \varepsilon. \end{aligned} \tag{1}$$

The dependent variable ($Freq_{i,a,t}$) is the total number of annual flights that each airline offers at the corresponding airport. The explanatory variables refer to year $t-1$ because airline frequencies at the airport level in period t are influenced by airport and airline features in the previous period.

We consider a measure of airport congestion ($Delays_{a,t-1}$), which is constructed as the percentage of total flights at an airport suffering a

[9] American Airlines eliminated its hub at Saint Louis (STL) in 2010. Hence, our sample includes Saint Louis as a hub airport until 2009.

[10] Several network airlines have instigated a de-hubbing process in the period under consideration. For example, the share of American Airlines at Saint Louis was 57% in 2005 falling to just 12% by 2013, and the share of US Airways at Pittsburg was 68% in 2005 but had fallen to 29% by 2013. Thus, we do not consider these two airports to be hubs although they served this function in a previous period. Note that while the share of Delta in Cincinnati was 92% in 2005, it had fallen to 64% by 2013. Although it seems that Delta is gradually dismantling its hub in Cincinnati, it still maintains a high volume of connection operations. Thus, this airport is considered as being a hub.

[11] Previous empirical studies of the determinants of delays (Mayer and Sinai, 2003; Rupp, 2009; Ater, 2012) 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.

[12] Several merger operations have taken place in the period under consideration. For example, since 2010 the flights of Northwest have been operated by Delta, so that the dominant network carrier at Minneapolis (MSP), Detroit (DTW), and Memphis (MEM) since 2010 has been Delta and not Northwest. Likewise, since 2012 the flights of Continental have been operated by United, so that the dominant network carrier at Cleveland (CLE), Houston (IAH), and Newark (EWR) since 2012 has been United and not Continental. The merger between American Airlines and US Airways came into effect at the end of 2013 but integration is not yet complete and does not affect our analysis.

delay in excess of fifteen minutes. The effect of this variable is, a priori, ambiguous. On the one hand, according to Zou and Hansen (2014), airlines might reduce their frequencies when delays increase because of higher operation costs; on the other hand, they might have incentives to increase frequencies to profit from higher yields and to avoid losing market power.

Furthermore, we consider dummy variables for airlines that operate HS and FC networks. Note that the reference case for all these dummies (observations with zero value) is airline's flights from non-hub airports.

Regarding airlines that operate HS networks, the dummy variable $D_{i,a}^{HS}$ refers to network airline flights from/to their hubs (e.g., American Airlines' flights from/to Miami (MIA)). 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 their exploitation of connecting traffic, which is independent of local demand. Thus, we expect a positive sign for the coefficient associated with $D_{i,a}^{HS}$.

We make a distinction between two different types of flights operated by airlines in FC networks. First, the dummy variable $D_{i,a}^{network\_non\text{-}hub}$ refers to flights of network airlines from/to airports that are a hub of another network airline (i.e., United Airlines' flights from/to Miami (MIA)). Second, the dummy variable $D_{i,a}^{low\text{-}cost\_non\text{-}hub}$ refers to flights of low-cost airlines from/to airports that are a hub of a network airline (i.e., Southwest' flights from/to Miami (MIA)). The expected sign of the coefficients associated with these variables is not clear a priori.

Given that our dependent variable is the frequency at the airline–airport level, we can make the distinction between a network airline that operates at its hub airports (which is considered as a HS carrier) and the same network airline operating at other airports (which is considered as a FC carrier). Hence, our definition of airlines operating HS structures is based on two features: *i*) being a network airline, and *ii*) operating at its hub airports. Consequently, we implicitly consider that non-hub airlines at hub airports (dominated by a hub airline) operate point-to-point services at those airports. For example, Delta concentrates a large share of its total flights at Atlanta (ATL), where it exploits the transfer traffic through coordinated banks of arrivals and departures. By contrast, American Airlines uses Atlanta (ATL) mainly to provide direct services from/to its hub airports.

We also include three variables that are formed from the interaction between the dummy variables for airlines operating HS and FC networks and the measure of congestion ($D_{i,a}^{HS}xDelays_{a,t-1}$, $D_{i,a}^{network\_non\text{-}hub}xDelays_{a,t-1}$, and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}xDelays_{a,t-1}$). The relationship between frequencies and delays for airlines operating HS networks is determined by coefficients β_1 and β_3, while the same relationship for airlines operating FC networks is determined by coefficients β_1 and β_5 on the one hand, and by coefficients β_1 and β_7 on the other hand. Thus, we can test whether airlines react differently to congestion according to the network structure they operate by examining the estimated coefficients β_3, β_5, and β_7. If network airlines react less to delays at their hubs, we would expect $\beta_3 > 0$, $\beta_3 > \beta_5$, and $\beta_3 > \beta_7$. These are the main hypotheses being tested in this study.

Among the explanatory factors, we include two control 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 these variables since airlines should have incentives to increase the number of flights on routes that have as their endpoints airports located in more populated and richer urban areas (i.e., areas with a higher local demand).

The Herfindahl-Hirschman index in terms of flight frequencies at the airport level is also considered an explanatory variable ($HHI_{a,t-1}$). Airlines operating at more concentrated airports typically operate higher frequencies because they have higher yields and are better able to exploit economies of traffic density. This variable may control for the strategic behavior of airlines according to the intensity of competition in the airport. We also include a dummy variable that takes a value of one for slot-constrained airports (D_a^{slot}) as these constraints may affect an airline's frequency choices.[13]

Bilotkach et al. (2013) show that the merger between Delta and Northwest led to a reorganization of route structures in favor of the hubs formerly operated by Delta. Therefore, we include a variable that seeks to control for mergers that took place during the period under consideration ($D_{i,a}^{hubs\_smaller\_merged\_airline}$). This variable takes a value of one for merged airlines operating at the hubs formerly operated by the smaller airline (see footnote 10).

Finally, Eq. (1) also includes time fixed effects (μ_t) to capture shocks common to all airports and airlines during the period under consideration. We use the same year controls in all regressions. The excluded year dummy is 2005 and our results do not change by excluding any other year of the considered period.

4. Estimation and results

Eq. (1) is estimated using the fixed effects estimator, which allows us to control for any omitted time-invariant variable correlated with the variables of interest. A further advantage of the fixed effects model is that it allows us to account for different types of heterogeneity in the data. More specifically, we use airline fixed effects to control for airline heterogeneity. Here, we can identify the different behavior of airlines operating at the same airport. We exploit, as a source of variation in the data, the fact that airlines can operate in the same year at hub and non-hub airports.

A notable 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. Although this could mitigate the bias in the estimation, it is still needed to address the potential endogeneity problem. We deal with this potential bias by using several instruments for the delays variable. First, we use further lags 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 is used here. 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 further than four years are highly non-significant in the first-stage regression of the instrumental variables procedure. Second, we also use as instruments climatic variables of the urban area where the airport is located (temperature and precipitation).[14] These variables may work as appropriate instruments as delays should be correlated with the weather while frequency choices of airlines should be mainly affected by climatic variables through external delays imposed by bad weather.

Tests of instrument appropriateness are reported in the table of results: *i*) the Hansen test, in which the null hypothesis is that the instruments are exogenous, and *ii*) the Kleibergen–Paap LM, in which 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.

Table 2 shows the descriptive statistics of the variables used in the empirical analysis. All the variables show sufficient variability to provide robust estimations. It is important to recall that, although the unit of observation of our analysis is the airline–airport pair, some variables are taken at either the airport or the urban level. (See Table 1.)

Table 3 shows the results of the estimation of Eq. (1) using airline fixed effects. Standard errors are robust to heteroscedasticity and

[13] Only four airports are slot-constrained in the US: Chicago (ORD), New York (JFK), Washington (DCA), and New York (LGA). Among them, Chicago (ORD) and New York (JFK) can be considered hub airports.

[14] Data for climatic variables have been obtained from the web site of the National Oceanic and Atmospheric Administration (NOAA).

Table 1
Characteristics of airports in the sample (mean values in 2005–2013).

	Delayed flights (%)	Departures	HHI	Share dominant airline (%)
Alburquerque (ABQ)	16.5	50,729	0.3	Southwest (54.3)
Atlanta (ATL)	25.4	423,500	0.6	Delta (73.3)
Austin (AUS)	17.2	60,882	0.2	Southwest (40.3)
Hartford (BDL)	19.9	43,728	0.2	US Airways (23.2)/Southwest (22.7)
Nashville (BNA)	20.4	78,370	0.3	Southwest (45.8)
Boston (BOS)	24.5	160,641	0.1	US Airways (19.7)/Delta (17.4)
Baltimore (BWI)	21.3	134,066	0.3	Southwest (56.5)
Cleveland (CLE)	20.8	99,099	0.4	Continental (66.6) in 2005–11/United (73.3) in 2012–13
Charlotte (CLT)	23.4	224,642	0.7	US Airways (85.7)
Columbus (CMH)	21.2	58,940	0.2	Delta (21.4)/Southwest (19.8)
Cincinatti (CVG)	21.8	110,485	0.7	Delta (79.1)
Dallas (DAL)	20.6	62,191	0.8	Southwest (90.2)
Washington (DCA)	21.9	138,096	0.3	US Airways (46.6)
Denver (DEN)	22.4	288,766	0.3	United (47.1)
Dallas (DFW)	24.9	295,620	0.7	American Airlines (83.4)
Detroit (DTW)	25.3	209,909	0.6	Northwest (74.4) in 2005–09/Delta (81.4) in 2010–13
New York (EWR)	32.1	156,175	0.5	Continental (69.9) in 2005–11/United (76.2) in 2012–13
Fort Lauderdale (FLL)	22.6	99,059	0.1	Southwest (23.4)
Houston (HOU)	22.9	72,963	0.8	Southwest (87.1)
Washington (IAD)	24.5	136,697	0.5	United (70.2)
Houston (IAH)	21.9	217,221	0.7	Continental (86.7) in 2005–11/United (87.5) in 2012–13
Indianapolis (IND)	20.1	63,014	0.2	Northwest (21.6) in 2005–09/Delta (26.7) in 2010-13
New York (JFK)	28.7	124,180	0.3	JetBlue (35.0)/Delta (34.9)
Las Vegas (LAS)	21.3	183,366	0.3	Southwest (49.9)
Los Angeles (LAX)	19.3	239,165	0.2	United (28.9)
New York (LGA)	27.2	182,981	0.2	US Airways (29.2)/Delta (27.9)
Kansas (MCI)	20.2	86,363	0.2	Southwest (36.2)
Orlando (MCO)	20.2	149,058	0.2	Southwest (30.2)
Chicago (MDW)	22.7	111,033	0.7	Southwest (81.1)
Memphis (MEM)	20.8	84,778	0.6	Northwest (76.6) in 2005–09/Delta (76.4) in 2010–13
Miami (MIA)	26.7	83,076	0.5	American Airlines (68.6)
Milwaukee (MKE)	22.3	69,267	0.3	Frontier (47.3) in 2005–10/AirTran (21.7) in 2011–13
Minneapolis (MSP)	23.4	200,386	0.6	Northwest (75.4) in 2005–09/Delta (77.5) in 2010–13
New Orleans (MSY)	19.5	51,819	0.2	Southwest (34.5)
Oakland (OAK)	17.4	74,808	0.6	Southwest (76.1)
Chicago (ORD)	29.2	391,806	0.4	American Airlines (39.4)/United (49.6)
Portland (PDX)	15.3	92,987	0.3	Alaska Airlines (40.8)
Philadephia (PHL)	27.5	204,892	0.5	US Airways (68.8)
Phoenix (PHX)	19.2	196,410	0.3	Southwest (41.2)/US Airways (33.3)
Pittsburg (PIT)	22.1	75,874	0.2	US Airways (38.9)
Raleigh-Durham (RDU)	22.1	76,019	0.2	American Airlines (22.3)/Delta (21.1)
Fort Myers (RSW)	19.3	36,973	0.1	Delta (16.5)/AirTran (13.9)
San Diego (SAN)	17.5	99,464	0.2	Southwest (42.3)
San Antonio (SAT)	17.1	55,153	0.2	Southwest (42.5)
Seattle (SEA)	19.7	158,026	0.3	Alaska Airlines (54.5)
San Francisco (SFO)	24.5	154,485	0.3	United (53.4)
Salt Lake City (SLC)	17.2	154,485	0.6	Delta (72.7)
Sacramento (SMF)	17.3	56,477	0.3	Southwest (54.1)
Santa Ana (SNA)	16.9	51,754	0.2	Southwest (34.1)
St. Louis (STL)	20.1	113,701	0.3	American Airlines (30.3)/Southwest (32.5)

Note 1: Since 2010, flights of Northwest are operated by Delta. Thus, the dominant network carrier in MSP, DTW, and MEM is Delta from 2010.
Note 2: Since 2012, flights of Continental are operated by United. Thus, the dominant network carrier in CLE, IAH, and EWR is United from 2012.

clustered by airline to account for any autocorrelation problem. In specification 1, we consider all explanatory variables included in Eq. (1).

In specification 2, we exclude the dummy variables for slot-constrained airports and merged airlines operating at the hubs formerly operated by the smaller airline (i.e., D_a^{slot} and $D_{i,a}^{hubs\_smaller\_merged\_airline}$). These exclusions do not change the results for the rest of variables.

In specification 3, we exclude the dummy variables that identify the airline network structure (i.e., $D_{i,a}^{HS}$, $D_{i,a}^{network\_non\text{-}hub}$, $D_{i,a}^{low\text{-}cost\_non\text{-}hub}$). Note here that the high correlation between these variables and the interaction variables could pose a problem of multicollinearity that might distort the individual identification of regressors. However, the results of these regressions are qualitatively identical to the regressions that include all the variables.

The overall explanatory power of the model is quite high. The impact of the population and income variables on frequencies does not seem to be relevant in our regressions, given that the year fixed effects may capture some of the effect of population and income. The dummy variable for slot constrained airports and the dummy variable for merged airlines operating at the hubs formerly operated by the smaller airline are also non-significant in all regressions.

The coefficient associated with the airport concentration variable is positive and statistically significant. Hence, airline frequencies at the more concentrated airports are higher. Higher yields and a better exploitation of density economies by airlines operating at more concentrated airports account for this result.

As expected, the coefficient of $D_{i,a}^{HS}$ is positive and statistically significant. Naturally, the frequencies of airlines operating HS structures are higher than those of other airlines as they provide both direct and connecting services. Additionally, the coefficients of $D_{i,a}^{network\_non\text{-}hub}$ and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}$ are also positive but not statistically significant.

The coefficient associated with the delays variable is positive but not statistically significant. However, the relationship between frequencies and delays is jointly determined by the coefficient associated with the delays and the interaction variables. In fact, our main interest lies in the interaction variables since our focus is on identifying the different behavior of airlines operating either HS or FC networks.

Table 2
Descriptive statistics of the considered variables.

	Mean	Standard deviation
$Freq_{i,a,t}$ (airline - airport level)	13,623	31,553
$Delays_{a,t-1}$	21.77	4.74
$D_{i,a}^{HS}$	0.045	0.20
$D_{i,a}^{network\_non\text{-}hub}$	0.22	0.41
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}$	0.16	0.37
$Pop_{u,t-1}$	4,707,663	4,536,939
$GDPpc_{u,t-1}$	50,327	8,811
$HHI_{a,t-1}$	0.34	0.18
D_{a}^{slot}	0.08	0.27
$D_{i,a}^{hubs\_smaller\_merged\_airline}$	0.005	0.07

We find that airlines operating HS networks increase their frequencies as the percentage of delayed flights at their hub airports increases. The coefficient associated with the interaction variable $D_{i,a}^{HS}xDelays_{a,t-1}$ is positive and statistically significant. Furthermore, note that the magnitude of the coefficient of this interaction variable is higher than that of the delays variable.

By contrast, the coefficients associated with the interaction variables $D_{i,a}^{network\_non\text{-}hub}xDelays_{a,t-1}$ and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}xDelays_{a,t-1}$ are negative and statistically significant. The magnitude of the coefficients associated with these interaction variables is similar to that of the delays variable.

Given that $D_{i,a}^{network\_non\text{-}hub}xDelays_{a,t-1}$ and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}xDelays_{a,t-1}$ refer to non-hub airlines operating at hub airports, our results indicate that airlines operating at other airlines' hub airports may be more prone to reduce their frequencies than hub airlines in reaction to more frequent delays at such airports.

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 $\beta_3 > 0$, $\beta_3 > \beta_5$, and $\beta_3 > \beta_7$. Hence, our results suggest that airlines operating HS networks have incentives to maintain high frequencies at their hubs even when congestion at these airports increases.

The results of our analysis may reconcile the conflicting results obtained in previous studies examining the impact of delays on airline frequencies (see Pai, 2010; and Zou and Hansen, 2014). The positive relationship between airline frequencies and delays arises when airlines operate HS structures, while the negative relationship characterizes FC configurations.

Our results are in line with those obtained by Daniel and Harback (2008), which show that dominant airlines at many major US hub airports concentrate flights in departure/arrival banks during peak periods, constraining non-hub airlines to cluster their traffic in the uncongested periods. In fact, our aggregate measure of delays could behave 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 they obtain from having dominated departure/arrival banks at their hub airports.

Therefore, network airlines have incentives to keep frequencies high even if this comes at the expense of greater airport congestion at their hub airports. The rationale behind this result would seem to lie in the higher yield associated with flight banks; the cost savings from an intense exploitation of economies of traffic density; and the strategic behavior of airlines that may adopt a preemptive strategy so as to avoid losing market power which involves releasing slots that might be taken over by other competing airlines.

Our results are consistent with the empirical findings in Brueckner (2002), which show that delays are higher in hub airports, and confirm the theoretical results in Fageda and Flores-Fillol (2015), which suggest that congestion typically increases the profitability of HS networks. Finally, our findings explain the non-existent reaction to congestion by the merged Delta-Northwest airline reported in Bilotkach et al. (2013), which is not likely to have been caused by the economic downturn in 2008 but rather represents an active decision on the part of the consolidated airline.

5. Robustness checks

In this section, we report and comment the results of some additional regressions that provide several robustness checks. In Table 4, we show the results using different instruments of the lagged delays variable. In specification 1, we use as instruments three and four lags of the delays variable. Results of this regression are very similar to those

Table 3
Results of estimates — different control variables.

	Dependent variable: airline frequency at the airport level		
	(1) All variables	(2) Excluding D_{a}^{slot} and $D_{i,a}^{hubs\_smaller\_merged\_airline}$	(3) Excluding $D_{i,a}^{HS}$, $D_{i,a}^{network\_non\text{-}hub}$, and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}$
$Delays_{a,t-1}$	793.73 (692.94)	847.12 (620.82)	535.23 (432.60)
$D_{i,a}^{HS}$	52,411.02 (28,233.31)**	50,311.68 (26,593.02)**	–
$D_{i,a}^{network\_non\text{-}hub}$	9199.94 (9289.39)	9868.43 (8318.15)	–
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}$	9396.73 (9629.47)	10,211.33 (8712.19)	–
$D_{i,a}^{HS}xDelays_{a,t-1}$	2432.84 (1085.17)**	2487.90 (1018.31)***	4528.90 (93.10)***
$D_{i,a}^{network\_non\text{-}hub}xDelays_{a,t-1}$	−754.09 (414.87)*	−789.70 (442.32)*	−366.50 (121.85)***
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}xDelays_{a,t-1}$	−646.03 (425.35)*	−687.07 (426.90)*	−238.79 (140.60)*
$Pop_{u,t-1}$	0.00015 (0.0021)	0.00025 (0.00019)	0.000072 (0.00024)
$GDPpc_{u,t-1}$	0.006 (0.08)	0.016 (0.08)	0.036 (0.08)
$HHI_{a,t-1}$	12,824.59 (5998.27)**	12,220.47 (6025.13)**	14,061.31 (6021.54)**
D_{a}^{slot}	2032.97 (3748.12)	–	2178.71 (3591.98)
$D_{i,a}^{hubs\_smaller\_merged\_airline}$	−8223.62 (7192.51)	–	−1358.63 (7988.95)
Time fixed effects	YES	YES	YES
R^2	0.66	0.66	0.65
Test F (joint significance)	3.9e + 06	74,551.73***	25,937.68***
Kleibergen–Paap LM (Ho: eq. underidentified)	14.61***	14.61***	14.61***
Hansen J statistic (Ho: exogenous instruments)	3.09	2.31	2.37
Number observations	4259	4259	4259

Note 1: Estimation made using an instrumental variables procedure with airline fixed effects.
Note 2: Standard errors in parenthesis (robust to heteroscedasticity and clustered by airline).
Note 3: Statistical significance at 1% (***), 5% (**), 10% (*).
Note 4: Instruments of lagged delays are three and four lags and climatic variables (temperature and rain).

Table 4
Results of estimates — different instruments for lagged delays.

	Dependent variable: airline frequency at the airport level	
	(1) Instruments for lagged delays: three and four lags	(2) Instruments for lagged delays: temperature and rain
$Delays_{a,t-1}$	1028.16 (656.12)	−1360.78 (1333.17)
$D_{i,a}^{HS}$	56,003.1 (28,062.93)**	19,399.5 (35,519.76)
$D_{i,a}^{network\_non\text{-}hub}$	12,871.81 (8796.71)	−24,544.94 (19,506.34)
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}$	13,046.25 (9149.47)	−24,142.71 (19,821.74)
$D_{i,a}^{HS}xDelays_{a,t-1}$	2254.52 (1063.18)**	4071.63 (1449.50)***
$D_{i,a}^{network\_non\text{-}hub}xDelays_{a,t-1}$	−936.42 (467.51)**	921.47 (958.19)
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}xDelays_{a,t-1}$	−824.95 (467.01)*	998.25 (911.45)
$Pop_{u,t-1}$	0.00013 (0.0002)	0.00035 (0.00027)
$GDPpc_{u,t-1}$	−0.0021 (0.08)	0.08 (0.08)
$HHI_{a,t-1}$	12,678.12 (5968.03)**	14,170.69 (6352.72)**
D_{a}^{slot}	1559.75 (3770.22)	6381.88 (3975.46)
$D_{i,a}^{hubs\_smaller\_merged\_airline}$	−8504.56 (7186.42)	−5641.72 (7462.69)
Time fixed effects	YES	YES
R^2	0.66	0.63
Test F (joint significance)	2.3e + 06	1.0e + 06***
Kleibergen–Paap LM (Ho: eq. underidentified)	12.94***	12.24***
Hansen J statistic (Ho: exogenous instruments)	2.78	0.73
Number observations	4259	4259

Note 1: Estimation made using an instrumental variables procedure with airline fixed effects.
Note 2: Standard errors in parenthesis (robust to heteroscedasticity and clustered by airline).
Note 3: Statistical significance at 1% (***), 5% (**), 10% (*).

Table 5
Results of estimates — different variables for airlines operating FC networks.

	Dependent variable: airline frequency at the airport level	
	(1) Non-hub airlines at hub airports	(2) Dominant low-cost carriers at non-hub airports
$Delays_{a,t-1}$	787.70 (691.98)	−143.67 (232.22)
$D_{i,a}^{HS}$	52,796.03 (28,634.17)*	38,258.63 (20,191.82)*
$D_{i,a}^{non\text{-}hub}$	9289.97 (9219.24)	–
$D_{i,a}^{low\text{-}cost\_dominant}$	–	59,366.09 (7625.11)***
$D_{i,a}^{HS}xDelays_{a,t-1}$	2437.99 (1088.04)**	3362.34 (1429.53)***
$D_{i,a}^{non\text{-}hub}xDelays_{a,t-1}$	−708.94 (458.59)*	–
$D_{i,a}^{low\text{-}cost\_dominant}xDelays_{a,t-1}$	–	−301.57 (47.71)***
$Pop_{u,t-1}$	0.00015 (0.00021)	−0.0001 (0.0006)
$GDPpc_{u,t-1}$	0.011 (0.07)	0.11 (0.09)
$HHI_{a,t-1}$	12,644.98 (6044.9)**	13,517.77 (5227.85)***
D_{a}^{slot}	1982.73 (3746.73)	–
$D_{i,a}^{hubs\_smaller\_merged\_airline}$	−8344.01 (7155.17)	2102.46 (12,848.73)
Time fixed effects	YES	YES
R^2	0.66	0.5
Test F (joint significance)	1.2e + 06	45.20***
Kleibergen–Paap LM (Ho: eq. underidentified)	14.62***	15.47***
Hansen J statistic (Ho: exogenous instruments)	2.95	1.22
Number observations	4259	4259

Note 1: Estimation made using an instrumental variables procedure with airline fixed effects (specification 1) and airport fixed effects (specification 2).
Note 2: Standard errors in parenthesis (robust to heteroscedasticity and clustered by airline).
Note 3: Statistical significance at 1% (***), 5% (**), 10% (*).
Note 4: Instruments of lagged delays are three and four lags and climatic variables (temperature and rain).

reported in the previous section where we use as instruments three and four lags of the delays variable along with the climatic variables.

In specification 2, we only use the climatic variables as instruments (i.e., rain and temperature of the urban area where the airport is located). In this regression, the coefficient of $D_{i,a}^{HS}$ is positive but not statistically significant while the coefficients of $D_{i,a}^{network\_non\text{-}hub}$ and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}$ are negative and not statistically significant. Regarding the interaction variables, the coefficient of $D_{i,a}^{HS}xDelays_{a,t-1}$ is positive and statistically significant while the coefficients of $D_{i,a}network\_^{non\text{-}hub}xDelays_{a,t-1}$ and $D_{i,a}^{low\text{-}cost\_non\text{-}hub}xDelays_{a,t-1}$ are also positive but not statistically significant. The magnitude of the coefficient of $D_{i,a}^{HS}xDelays_{a,t-1}$ is much higher than those of the other interaction variables. Hence, this regression confirm our main result, i.e., $\beta_3 > 0$, $\beta_3 > \beta_5$, and $\beta_3 > \beta_7$.

Thus, the use of different sets of instruments does not seem to alter our conclusion regarding the relationship between frequencies and delays under different network structures. Having said this, we must be cautious in the interpretation of the results as the reverse causality between frequencies and delays can still be considered a cause for concern.

In Table 5, we show the results using different variables to identify airlines operating FC networks. In specification 1, the interaction variable $D_{i,a}^{non\text{-}hub}xDelays_{a,t-1}$ refers to the flights of non-hub airlines at hub airports (e.g., American Airlines' flights and Southwest's flights from/to Atlanta (ATL)). This regression does not distinguish between network and low-cost carriers in its identification of airlines operating FC configurations. The results of this regression are very similar to those reported in the previous section where we make a distinction between network and low-cost airlines operating in hub airports of other airlines.

In specification 2, we run the regression using airport fixed effects instead of airline fixed effects. Here, we can control for airport heterogeneity, so that the different behavior of airlines operating at different airports can be identified. Hence, $D_{i,a}^{HS}$ is the same as that in the regression with airline specific effects and $D_{i,a}^{low\text{-}cost\_dominant}$ is a dummy variable that takes the value one for dominant airlines operating at non-hub airports. We consider as dominant those airlines that have a share of total flights at the airport greater than 50%. Thus, this regression draws a distinction between network airlines operating at their hub airports (e.g., American Airlines' flights from/to Dallas (DFW)) and low-cost airlines operating at their main airports (e.g., Southwest's flights from/to Dallas (DAL)). Both American Airlines and Southwest concentrate a very high proportion of total flights at Dallas (DFW) and Dallas (DAL), respectively. However, American Airlines exploits the transfer traffic through coordinated banks of arrivals and departures at Dallas (DFW), while the bulk of the activity of Southwest at Dallas (DAL) is based on point-to-point services. With airport fixed effects, we exploit as a source of variation in the data the fact that airports may be dominated by different types of airline (i.e., either network or low-cost airlines).

In this regression, the coefficients of $D_{i,a}^{HS}$ and $D_{i,a}^{low\text{-}cost\_dominant}$ are positive and statistically significant. More importantly, the coefficient of $D_{i,a}^{HS}xDelays_{a,t-1}$ is positive and statistically significant while the coefficient of $D_{i,a}^{low\text{-}cost\_dominant}xDelays_{a,t-1}$ is negative and statistically significant. In contrast to airlines operating HS networks, we find that dominant airlines operating at non-hub airports (i.e., Southwest) clearly reduce their frequencies as delays at these airports increase. Taking into account the results reported in Tables 3 and 5, we can conclude that our main results seem to be driven by both low-cost airlines and network airlines operating in hub airports dominated by a different network airline.

In Table 6, we show the results using different indicators of delays. In specification 1, we use the number of delayed flights, i.e., the number of flights suffering a delay in excess of fifteen minutes. In this regression, the airport concentration variable is not statistically significant while the delays variable is positive and statistically significant. Regarding our variables of main interest, we find that airlines operating HS networks increase their frequencies as the number of delayed flights at their hub airports increases, while airlines operating FC networks in hub airports reduce frequencies as the number of delayed flights in those airports increase.

Table 6
Results of estimates — different measures of delays.

	Dependent variable: airline frequency at the airport level	
	(1) Total delayed flights	(2) Total minutes of delay
$Delays_{a,t-1}$	0.46 (0.14)***	0.0098 (0.0031)***
$D_{i,a}^{HS}$	43,115.92 (9930.48)***	57,237.58 (12,240.06)***
$D_{i,a}^{network\_non\text{-}hub}$	2036.23 (2353.25)	901.45 (2205.08)
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}$	1489.35 (3863.7)	978.25 (3286.11)
$D_{i,a}^{HS} x Delays_{a,t-1}$	1.13 (0.26)***	0.019 (0.006)***
$D_{i,a}^{network\_non\text{-}hub} x Delays_{a,t-1}$	−0.40 (0.13)***	−0.009 (0.003)***
$D_{i,a}^{low\text{-}cost\_non\text{-}hub} x Delays_{a,t-1}$	−0.33 (0.14)***	−0.007 (0.003)**
$Pop_{u,t-1}$	−0.00005 (0.15)	−0.00011 (0.00019)
$GDPpc_{u,t-1}$	0.038 (0.05)	0.05 (0.056)
$HHI_{a,t-1}$	9583.11 (6212.67)	11,658.25 (6462.95)*
D_a^{slot}	−4535.02 (4162.52)	−1482.93 (3854.90)
$D_{i,a}^{hubs\_smaller\_merged\_airline}$	7295.19 (7261.71)	5974.71 (11,100.35)
Time fixed effects	YES	YES
R^2	0.77	0.76
Test F (joint significance)	1.8e + 05	44,954.00***
Kleibergen–Paap LM (Ho: eq. underidentified)	14.73***	15.05***
Hansen J statistic (Ho: exogenous instruments)	2.41	0.40
Number observations	4259	4259

Note 1: Estimation made using an instrumental variables procedure with airline fixed effects.
Note 2: Standard errors in parenthesis (robust to heteroscedasticity and clustered by airline).
Note 3: Statistical significance at 1% (***), 5% (**), 10% (*).
Note 4: Instruments of lagged delays are three and four lags and climatic variables (temperature and rain).
Note 5: Early arrivals are set to zero in the computation of total minutes of delay.

In specification 2, we use total minutes of delay. It should be noted that early arrivals are set to zero in the computation of total minutes of delays. The results of this regression confirm the different behavior of airlines operating HS and FC networks as delays increase.

Finally, Table 7 shows the results of the estimates for different sub-samples depending on the distribution of the concentration variable at the airport level. More precisely, in specifications 1 and 2, we show the results for two different sub-samples excluding observations with values in the lowest and highest quartile of the concentration variable, respectively. These regressions that exclude the tails of the distribution of the concentration variable allow examining the extent to which the level of competition distorts the results on the relationship between frequencies and delays according to the airline network type. The results of these regressions suggest that our main result is not altered using a more homogenous sample in terms of airport competition.

Interestingly, specification 2 (that excludes the most concentrated airports) may be helpful in addressing the potential endogeneity bias. Given that the dependent variable is at the airline–airport level and the delays variable is at the airport level, the endogeneity bias should be more severe for more concentrated airports in which the share of the dominant airline is particularly high.

Furthermore, in specifications 3 and 4, we show the results for two different sub-samples that only include observations with values in the second and third quartile of the concentration variable, respectively. Regressions for the first and fourth quartile are not included here since most of observations in the highest quartile are for hub airports (84% observations) while no observations for hub airports can be found in the lowest quartile. The results of these regressions suggest that the effect that we want to identify is stronger in the third quartile, i.e., when the market power of the hubbing airline (approximated by its share) is higher. This result suggests that airlines operating HS structures may follow a preemptive strategy to avoid losing market power when they keep frequencies high at their hub airports, even if this comes at the expense of greater congestion.

6. Concluding remarks

The importance of connecting traffic at hub airports (compared to that of local traffic) is dependent on the extensive number of potential destinations, which is of obvious benefit to HS networks and, consequently, to the urban areas around hubs. However, the concentration of traffic favored by HS networks has contributed to an increase in airport congestion resulting in delays, cancelations, and missed connections.

Our analysis suggests that airlines operating FC networks reduce frequencies in response to more frequent delays, while airlines operating HS structures increase frequencies. Thus, airlines operating HS networks seem to ignore the social costs (i.e., airport congestion) resulting from their network choice. This explains the fact that network carriers are reluctant to give up slots at their hub airports.

Airport congestion has yet to be adequately tackled from a public policy perspective. This is attributable to various factors including the difficulties encountered in implementing congestion pricing and the high investment costs associated with airport expansions. In addition, while at many large European airports slot constraints are the norm, in the US market only four airports are slot-constrained (O'Hare in Chicago, Ronald Reagan in Washington, and La Guardia and JFK in New York.).[15] Thus, congestion remains a severe problem in the air transportation industry, and it is especially grave in the US.

As a consequence, our model predicts a further reinforcement of the existing hub airports over time. Indeed, we expect the current distribution of hubs to remain stable in the near future as diverting traffic from these airports seems complicated because airlines have no incentives to do so. Although our analysis provides evidence about the airlines' short-term responses to congestion in terms of network structure, long term responses may not be too different given the strong incentives for network airlines to concentrate traffic at their hubs.

Since network airlines do not react to congestion, policy measures promoting direct connections at non-hub airports may have social benefits should problems of congestion become too severe. Policy makers and airport operators might adopt such tools as congestion tolls, capacity investment, and a better marketing of cities in which the non-hub airports are located. Additionally, the rules determining the allocation and use of slots in the US might also be redesigned so as to create incentives for airlines to increase the size of their aircraft and reduce their flight frequencies.

A project for future research is to quantify empirically the externalities associated with hub airports, given that HS networks impose social costs on other airlines and passengers (in terms of congestion) but, at the same time, passengers flying from hub airports benefit from higher frequencies and a greater number of non-stop destinations. It is an open empirical question as to which of these two effects might be more important from a social perspective. Of course, access to disaggregated passenger data would be required to perform this comprehensive welfare analysis of HS networks.

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[15] Brueckner (2009) finds that a slot-distribution regime, where slots are distributed to the carriers and then traded through a clearing house, is equivalent to an efficient regime of differentiated congestion tolls. He recommends that airlines be endowed with clearer property rights over slots to foster more active slot trading.

Table 7
Results of estimates — different subsamples depending on the distribution of the $HHI_{a,t-1}$ variable.

	Dependent variable: airline frequency at the airport level			
	(1) Excluding first quartile	(2) Excluding fourth quartile	(3) Only second quartile	(3) Only third quartile
$Delays_{a,t-1}$	1587.74 (1018.50)	707.64 (256.22)***	1075.09 (356.81)***	1482.94 (899.28)*
$D_{i,a}^{HS}$	64,670.47 (31,118.4)**	18,856.2 (15,674.91)*	56,027.05 (32,531.21)*	28,876.42 (16,367.78)*
$D_{i,a}^{network\_non\text{-}hub}$	21,231.17 (14,811.1)	10,738.24 (3417.47)***	13,452.34 (5962.58)**	28,397.91 (15,936.88)*
$D_{i,a}^{low\text{-}cost\_non\text{-}hub}$	19,289.05 (14,372.87)	12,314.63 (5724.52)**	2793.09 (9519.27)	27,561.08 (15,027.69)*
$D_{i,a}^{HS} xDelays_{a,t-1}$	1857.96 (1040.82)*	2587.70 (1134.09)**	−229.23 (1657.65)	2643.85 (1078.51)***
$D_{i,a}^{network\_non\text{-}hub} xDelays_{a,t-1}$	−1320.99 (778.45)*	−733.63 (253.23)***	−900.67 (320.65)***	−1433.39 (790.72)*
$D_{i,a}^{low\text{-}cost\_non\text{-}hub} xDelays_{a,t-1}$	−1176.24 (681.09)*	−599.93 (312.41)**	−32.31 (527.41)	−1488.08 (812.92)*
$Pop_{u,t-1}$	−0.00014 (0.0002)	0.0002 (0.0001)	0.00018 (0.00015)	−0.000049 (0.00018)
$GDPpc_{u,t-1}$	−0.03 (0.10)	0.012 (0.06)	0.038 (0.09)	−0.068 (0.14)
$HHI_{a,t-1}$	10,760.35 (4455.44)***	9763.44 (10,967.26)	19,307.66 (21,530.61)	−26,792.85 (14,676.72)*
D_{a}^{slot}	2429.83 (5097.94)	3268.80 (2652.85)	−1640.86 (5263.36)	10,476.65 (5529.96)*
$D_{i,a}^{hubs\_smaller\_merged\_airline}$	−8349.76 (7137.61)	−14,504.65 (18,259.74)	–	−18,030.84 (20,645.6)
Time fixed effects	YES	YES	YES	YES
R^2	0.67	0.59	0.41	0.75
Test F (*joint significance*)	1.2e + 06***	8.2e + 05***	34,084.66***	2.4e + 06
Kleibergen–Paap LM (*Ho*: *eq. underidentif.*)	12.97***	13.17***	12.98***	13.76***
Hansen J statistic (*Ho*: exogeneous *instruments*)	3.11	2.29	2.34	2.91
Number observations	3190	3188	1075	1046

Note 1: Estimation made using an instrumental variables procedure with airline fixed effects.
Note 2: Standard errors in parenthesis (robust to heteroscedasticity and clustered by airline).
Note 3: Statistical significance at 1% (***), 5% (**), 10% (*).
Note 4: Instruments of lagged delays are three and four lags and climatic variables (temperature and rain).

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