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AIRPORT CONGESTION AND AIRLINE NETWORK STRUCTURE

XAVIER FAGEDA* AND RICARDO FLORES-FILLOL†

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Abstract

This paper provides a theoretical and empirical analysis of the relationship between airport congestion and airline network structure. We find that the development of hub-and-spoke (HS) networks may have detrimental effects on social welfare in presence of airport congestion. The theoretical analysis shows that, although airline profits are typically higher under HS networks, congestion could create incentives for airlines to adopt fully-connected (FC) networks. However, the welfare analysis leads to the conclusion that airlines may have an inefficient bias towards HS networks. In line with the theoretical analysis, our empirical results show that network airlines are weakly influenced by congestion in their choice of frequencies from/to their hub airports. Consistently with this result, we confirm that delays are higher in hub airports controlling for concentration and airport size.

Keywords: airlines; airport congestion; fully-connected networks, hub-and-spoke networks; network efficiency

JEL Classification Numbers: L13; L2; L93

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1 Introduction

With the deregulation of the US air transportation sector, carriers became free to make strategic choices concerning fares and network structure. The success of hub-and-spoke (HS) structures in the years following the deregulation, which led to a concentration of traffic on the spoke routes, is explained by the savings from operating fewer routes and the exploitation of economies of traffic density from using larger aircraft. However, the concentration of traffic favored by HS networks has contributed to an increase in airport congestion. In congested hubs, a high proportion of flights are affected by delays, cancellations and missed connections that end up affecting both air travelers and airlines. Therefore, congestion is a major concern and a relevant policy issue. A particularity of the US market is that airport slot constraints are not widely used,¹ while this is the norm in many European large airports. Other measures addressed to overcome the problem of congestion are difficult to implement: investing in capacities is very expensive and congestion pricing is complex to put into practice.

Differently to network airlines (which operate HS networks), low-cost carriers operate fully-connected (FC) networks where most air services are point-to-point. The proportion of delayed flights in large US concentrated airports is substantially lower when the dominant airline is a low-cost carrier (in most cases Southwest). As an example, Table 1 shows data on delays at the main airports of American Airlines and Southwest.²

–Insert here Table 1–

Although the share of Southwest may be as high as that of American, the proportion of delayed flights is substantially lower in airports dominated by Southwest. Thus, the analysis of airline network structure is essential to understand the problem of airport congestion.

A more comprehensive preliminary evidence on the relationship between airport congestion and airline network structure is found in Fig. 1, which presents the results of a spline regression that estimates the relationship between the variation of frequencies and delays (in the previous year) using airport-level data, making the distinction between airlines operating in hub airports (i.e., airlines operating HS networks where there is a high proportion of connecting traffic) and airlines offering services in non-hub airports (i.e., airlines operating FC networks where traffic is mostly point-to-point).

–Insert here Fig. 1–

Airlines reduce frequencies as delays increase in non-hub airports. However, the adjustment of frequencies to higher delays is not clear in hub airports. Thus, this spline regression shows that airlines operating in hub airports are less sensitive to airport congestion in their choice of flight frequencies.³

This paper provides a theoretical and empirical analysis of the relationship between airport congestion and airline network structure. We show that the development of HS networks may have detrimental effects on social welfare in presence of airport congestion.

Our theoretical model compares the incentives for airlines to operate either HS or FC networks in presence of congestion. Although airline profits are typically higher under HS networks, congestion could create incentives for airlines to adopt FC networks.⁴ However, the welfare analysis leads to the conclusion that airlines may have an inefficient bias towards HS networks.

Furthermore, we use data of large US airports for the period 2005-2010 to examine how airlines adjust frequencies to congestion both under HS and FC networks. In line with our theoretical analysis, which predicts an inefficient bias towards HS networks, our empirical results show that network airlines are weakly influenced by congestion in their choice of frequencies from/their hub airports. Consistently with this result, we also find that delays are higher in hub airports controlling for concentration and airport size.

Our study brings together two strands of literature on air transportation. First, it is related to the studies on airlines' network choice, which include Brueckner and Zhang (2001), Pels *et al.* (2000), Brueckner (2004), Gillen (2006), Bilotkach (2009), and Flores-Fillol (2009). Most of these papers focus on airlines' choice between FC and HS networks. Our analysis extends the monopoly case (without congestion) studied in Brueckner (2004) by examining network choice in a duopoly market with schedule competition where airport congestion can occur.⁵

Second, it also contributes to the growing literature on airport congestion. The theoretical and empirical studies of airport congestion primarily center around the congestion self-internalization debate. The hypothesis that airlines at concentrated airports may be prone to internalize self-imposed congestion was proposed by Brueckner (2002). Mayer and Sinai (2003) demonstrate that, even though delays at hub airports are longer than at non-hub gateways, increasing airport concentration does lead to lower delays.⁶ Rupp (2009) reversed Mayer and Sinai's findings, using a different measure of delays. More recent evidence in favor of the congestion internalization hypothesis comes from Ater (2012),

Flores-Fillol (2010), and Bilotkach and Pai (2012). On the other hand, Daniel (1995) and Daniel and Harback (2008), despite recognizing the potential for internalization, support the idea that carriers behave atomistically due to the competitive pressure exerted by fringe carriers. Brueckner and Van Dender (2008) try to reach a consensus in the internalization debate showing that some competitive scenarios do lead to self-internalization, while others do not. Our theoretical model complements the analysis of congestion under HS structures in Flores-Fillol (2010) through the analysis of FC structures and the comparison of private and social benefits under both network configurations. Beyond the internalization debate, our empirical application focuses on how airlines adjust frequencies to congestion under HS and FC networks.⁷

The rest of the paper is organized as follows. The theoretical model and the equilibrium analysis is presented in Section 2. The welfare analysis is undertaken in Section 3, while the empirical analysis is executed in Section 4. A brief conclusion closes the paper.

2 The model and the equilibrium analysis

In a rather simple setting, this section presents a model to characterize FC and HS networks, analyzes the equilibrium fares and frequencies, and compares the profitability of each network structure. This model extends the monopoly case studied in Brueckner (2004) by analyzing network choice in a duopoly market and introducing the presence of congestion.

We assume the simplest possible network with three cities (A , B and H), two airlines (1 and 2), and three city-pair markets (AH , BH and AB). Markets AH and BH are served nonstop and AB can be served either directly (when airlines operate a FC network) or indirectly via hub H (when airlines operate a HS network), as shown in Fig. 2.

–Insert here Fig. 2–

Passenger population size in each of the city-pair markets is normalized to unity, and it is assumed that all the passengers undertake travel. Thus, we limit the effect of market power by assuming fully-served markets so that airlines exert no monopoly power over any passenger.⁸ Therefore, the exercise of market power only affects the division of a fixed traffic pool between the carriers through their choices of fares and frequencies.⁹

2.1 Equilibrium analysis of the FC network

In a FC network, both airlines operate flights between each pair of cities, so that nonstop travel occurs in each city-pair market. Utility for a consumer traveling in any city-pair market is given by $c - \text{expected schedule delay} - \text{congestion damage} + \text{travel benefit}$.

Firstly, c is consumption expenditure and equals $y - p_i$, where p_i is airline i 's fare with $i = 1, 2$, and y denotes income, which is assumed to be uniform across consumers without loss of generality.

Secondly, the *expected schedule delay* is modeled as in Brueckner (2004) and Brueckner and Flores-Fillol (2007). Let Z denote the time circumference of the circle and assume a uniform distribution of consumers in terms of preferred departure time along the circle. In this framework, the schedule delay is defined as the difference between the preferred and actual departure times, and the expected schedule delay of airline i equals $Z/4f_i$, where f_i is number of (evenly spaced) flights operated by carrier i , with $i = 1, 2$. Introducing a parameter $\delta > 0$ capturing the disutility per minute of schedule delay, we get the schedule-delay disutility $\delta Z/4f_i$ and, defining $\gamma \equiv \delta Z/4$, we obtain the final expression γ/f_i .¹⁰

Thirdly, *congestion damage* captures the extra time cost per passenger due to congestion and the resulting delays. As in Brueckner and Van Dender (2008) and Flores-Fillol (2010), we collapse the peak and offpeak periods from Brueckner's (2002) analysis into a single period where congestion is always present. In this setup, congestion depends on the overall aircraft movements at each airport, which is given by $2f_1 + 2f_2$ because each airport is connected with the other two airports. Introducing a parameter $\lambda \geq 0$ capturing the disutility of congestion, congestion damage for passengers in each city-pair market is $\lambda(4f_1 + 4f_2)$ because they experience congestion at the origin and destination airports.

Finally, *travel benefit* has two components, as in Brueckner and Flores-Fillol (2007): b , equal to the gain from travel; and a , the airline brand-loyalty variable. Without brand loyalty, the airline with the most attractive frequency/fare combination would attract all the passengers in the market. However, in presence of brand loyalty, consumers are presumed to have a preference for a particular carrier, which means that an airline with an inferior frequency/airfare combination can still attract some passengers. This approach is formalized by specifying a utility gain from using airline 1 rather than airline 2, denoted a , and assuming that this gain is uniformly distributed over the range $[-\alpha/2, \alpha/2]$, so that half the consumers prefer airline 1 (and have $a > 0$) and half prefer airline 2 (and have $a < 0$). Therefore, a varies across consumers. Interestingly, α is a measure of (exogenous)

product differentiation in the sense that a small α indicates similar products and thus small gain from using one airline or the other; whereas a big α allows for significant utility gains depending on passenger's preferred carrier.

The analysis that follows is just presented for carrier 1, and the corresponding expressions for carrier 2 are derived analogously. The utility of a passenger traveling with carrier 1 is

$$u_1 = y - p_1 - \frac{\gamma}{f_1} - \lambda(4f_1 + 4f_2) + b + a. \quad (1)$$

A passenger loyal to 1 (thus with $a > 0$) will fly with her preferred carrier when $y - p_1 - \gamma/f_1 + b + a > y - p_2 - \gamma/f_2 + b$, or equivalently when $a > p_1 - p_2 + \gamma/f_1 - \gamma/f_2 \equiv \hat{a}$.¹¹ Therefore, there is a minimum required brand-loyalty \hat{a} , which depends on fares and frequencies, such that only those passengers with $a > \hat{a}$ will undertake air travel with airline 1. Otherwise, passengers will choose airline 2. Then, carrier 1's traffic is given by $q_1 = \int_{\hat{a}}^{\alpha/2} \frac{1}{\alpha} da$ where $1/\alpha$ gives the density of a .

Carrying out the integration, we obtain the following expression

$$q_1 = \frac{1}{2} - \frac{1}{\alpha}(p_1 - p_2 + \gamma/f_1 - \gamma/f_2), \quad (2)$$

and carrier 2's demand function is identical after interchanging subscripts.

Quite interestingly, the demand function is independent of *passengers' congestion damage* because this term cancels out when comparing utilities. As a consequence, airlines will not take into account the congestion they impose on passengers.

The assumptions on airline costs are the following. Without congestion, as in Brueckner and Flores-Fillol (2007), a *flight's operating cost* on a certain route is given by $\theta + \tau s_1$, where s_1 stands for carrier 1's aircraft size (i.e., the number of seats), θ is a fixed cost independent of aircraft size, and τ is the marginal cost per seat. Under this specification, cost per seat realistically falls with aircraft size, capturing the presence of economies of traffic density (i.e., economies from operating a larger aircraft) that are unequivocal in the airline industry.

Airline's flight frequency (f_1), aircraft size (s_1) and traffic are all related by the equation $s_1 = q_1/f_1$, which says that aircraft size equals airline's total traffic on a route divided by frequency. Therefore, we are assuming that all seats are filled, so that load factor equals 100%.¹² Note that s_1 is an airline choice variable, which is appropriate given that the demands of airlines ultimately determine the nature of aircraft supplied by manufacturers. While s_1 is thus endogenous, its value is determined residually once q_1 and f_1 are known.

Now consider airline congestion costs. Note that the level of congestion on a route is caused by aircraft movements both at the origin and destination airports. As a consequence, airline's congestion cost on a route is given by $\eta(4f_1 + 4f_2)$ with $\eta \geq 0$, and a flight's operating cost on a route is $\theta + \tau s_1 + \eta(4f_1 + 4f_2)$.

Therefore, carrier 1's *total cost* from operating on a route is $f_1[\theta + \tau s_1 + \eta(3f_1 + 3f_2)]$ or equivalently

$$c_1 = \theta f_1 + \tau q_1 + f_1 \eta (4f_1 + 4f_2). \quad (3)$$

Thus, airline 1's profit is $\pi_1 = 3(p_1 q_1 - c_1)$, and it can be rewritten using Eq. (3) as

$$\pi_1 = 3 \left\{ \underbrace{(p_1 - \tau) q_1}_{\text{Margin}} - \underbrace{f_1 [\theta + 4\eta (f_1 + f_2)]}_{\text{Congestion and fixed cost}} \right\}, \quad (4)$$

indicating that variable costs are independent of the number of flights. The corresponding expression for carrier 2 is identical to Eq. (4) after interchanging subscripts.¹³

Airline 1 chooses p_1 and f_1 to maximize Eq. (4), viewing p_2 and f_2 as parametric. After plugging Eq. (2) into Eq. (4) and maximizing, the first-order conditions are

$$\frac{\partial \pi_1}{\partial p_1} = \frac{1}{2} - \frac{1}{\alpha} (2p_1 - p_2 + \gamma/f_1 - \gamma/f_2 - \tau) = 0, \quad (5)$$

$$\frac{\partial \pi_1}{\partial f_1} = \frac{\gamma}{\alpha f_1^2} (p_1 - \tau) - 4\eta (2f_1 + f_2) - \theta = 0. \quad (6)$$

Since carriers are symmetric, the symmetric equilibrium is the natural focus, and this equilibrium is found by setting $p_1 = p_2 = p$ and $f_1 = f_2 = f$.¹⁴ In this case, from Eq. (5) we obtain

$$p = \tau + \alpha/2, \quad (7)$$

revealing that the airfare equals the marginal cost of a seat (τ) plus a markup that depends on the degree of product differentiation ($\alpha/2$). As brand differentiation disappears, the fare converges to the marginal cost, recovering the Bertrand-equilibrium outcome.

Plugging Eq. (7) into Eq. (6), we get the following equilibrium condition for flight frequency

$$\underbrace{12\eta f^3}_{A(f)} = \underbrace{\frac{\gamma}{2} - \theta f^2}_{B(f)}. \quad (8)$$

As in Flores-Fillol (2010), the equilibrium frequency is found graphically, as shown in Fig. 3, where we observe that the f solution occurs at the intersection between a cubic expression ($A(f)$) and a quadratic expression ($B(f)$).

–Insert here Fig. 3–

Looking at Eq. (8) along with Fig. 3, it is easy to carry out a comparative-static analysis for all the parameters in the model. An increase in carriers' congestion cost (η) raises the height of the cubic curve, leading to a decrease in f . The reduction of the equilibrium flight frequency is a natural reaction to more damaging congestion. When the disutility of schedule delay (γ) rises, the intercept of the quadratic expression increases, leading to a higher f . Quite intuitively, carriers respond to a rise in the disutility of schedule delay by increasing flight frequency. An increase in the aircraft fixed cost (θ) leads to a higher f^2 -coefficient and, as a consequence, $B(f)$ becomes more concave and f decreases. As expected, equilibrium frequency falls when the cost of frequency rises.

Finally, looking at travel volumes, we observe that $q_1 = 1/2$ so that each airline carries half of the demand in every city-pair market.

2.2 Equilibrium analysis of the HS network

The analysis of the HS case is analogous to the base case in Flores-Fillol (2010). The main difference with respect to the FC case is that airlines operate flights on only two routes (AH and BH) since route AB is eliminated. Therefore, passengers traveling between cities A and B must make a connecting trip, changing planes at the hub H .

Since congestion depends on the overall aircraft movements at each airport, we need to distinguish between the spoke airports (A and B) and the hub airport (H). On the one hand, the spoke airports only serve one route that connects with the hub, and thus the number of aircraft movements at these two airports is the sum of both carriers' frequency on the mentioned route, i.e., $f_1^h + f_2^h$, where superscript h denotes HS network. On the other hand, the number of aircraft movements at the hub is $2f_1^h + 2f_2^h$ because the hub connects with the two spoke airports, reflecting that congestion is typically a hub-related phenomenon. Thus, congestion damage for local passengers equals $\lambda(3f_1^h + 3f_2^h)$ since they experience congestion at one spoke and at the hub, whereas congestion damage for connecting passengers is $\lambda(4f_1^h + 4f_2^h)$ because they experience congestion at the three airports.

Travel benefit and expected schedule delay are modeled as in the FC case. Finally, consumption expenditure equals $y - p_i^h$ for local passengers and $y - P_i^h$ for connecting passengers, where p_i^h and P_i^h are airline i 's local and connecting fares respectively with $i = 1, 2$. Thus, the utility of a *local* passenger traveling with carrier 1 is

$$u_1^h = y - p_1^h - \frac{\gamma}{f_1^h} - \lambda (3f_1^h + 3f_2^h) + b + a, \quad (9)$$

and, in a similar way, the utility of a *connecting* passenger traveling with carrier 1 is

$$U_1^h = y - P_1^h - \frac{\gamma}{f_1^h} - \lambda (4f_1^h + 4f_2^h) + b - \mu + a, \quad (10)$$

where μ is an extra travel cost term that measures layover time, as in Brueckner (2004). We assume that both airlines generate the same layover time, which enters as a negative shift factor in the utility of connecting passengers since they dislike waiting.

Therefore, we can compute the demand functions as in the FC case, which are given by

$$q_1^h = \frac{1}{2} - \frac{1}{\alpha} (p_1^h - p_2^h + \gamma/f_1^h - \gamma/f_2^h), \quad (11)$$

and

$$Q_1^h = \frac{1}{2} - \frac{1}{\alpha} (P_1^h - P_2^h + \gamma/f_1^h - \gamma/f_2^h), \quad (12)$$

where capital letters denote traffic and fares in market AB . Carrier 2's demand functions are identical after interchanging subscripts.

Shifting attention to cost structure, aircraft size is now $s_1^h = (q_1^h + Q_1^h) / f_1^h$, because we need to take into account airline's total traffic on a route (i.e., local + connecting traffic). Since congestion on a route is caused by aircraft movements both at the hub airport ($2f_1^h + 2f_2^h$) and at the spoke airport ($f_1^h + f_2^h$), airline's congestion cost on a route is given by $\eta (3f_1^h + 3f_2^h)$ with $\eta \geq 0$, and a flight's operating cost on a route is $\theta + \tau s_1^h + \eta (3f_1^h + 3f_2^h)$. Therefore, carrier 1's *total cost* from operating on a route is

$$c_1^h = \theta f_1^h + \tau (q_1^h + Q_1^h) + f_1 \eta (3f_1^h + 3f_2^h). \quad (13)$$

Thus, airline 1's profit is $\pi_1^h = 2p_1^h q_1^h + P_1^h Q_1^h - 2c_1^h$, and it can be rewritten using Eq. (13) as

$$\pi_1^h = \underbrace{2(p_1^h - \tau) q_1^h}_{\text{Local margin}} + \underbrace{(P_1^h - 2\tau) Q_1^h}_{\text{Connecting margin}} - \underbrace{2f_1^h [\theta + 3\eta (f_1^h + f_2^h)]}_{\text{Congestion and fixed cost}}. \quad (14)$$

Now airline 1 chooses p_1^h , P_1^h , and f_1^h to maximize Eq. (14), viewing p_2^h , P_2^h , and f_2^h as parametric. After plugging Eqs. (11) and (12) into Eq. (14) and maximizing, the first-order conditions are

$$\frac{\partial \pi_1^h}{\partial p_1^h} = \frac{1}{2} - \frac{1}{\alpha} (2p_1^h - p_2^h + \gamma/f_1^h - \gamma/f_2^h - \tau) = 0, \quad (15)$$

$$\frac{\partial \pi_1^h}{\partial P_1^h} = \frac{1}{2} - \frac{1}{\alpha} (2P_1^h - P_2^h + \gamma/f_1^h - \gamma/f_2^h - 2\tau) = 0, \quad (16)$$

$$\frac{\partial \pi_1^h}{\partial f_1^h} = \frac{\gamma}{\alpha (f_1^h)^2} (2p_1^h + P_1^h - 4\tau) - 6\eta (2f_1^h + f_2^h) - 2\theta = 0. \quad (17)$$

Looking at the symmetric equilibrium, i.e., setting $p_1^h = p_2^h = p^h$, $P_1^h = P_2^h = P^h$, and $f_1^h = f_2^h = f^h$,¹⁵ Eqs. (15) and (16) yield

$$p^h = \tau + \alpha/2 \text{ and } P^h = 2\tau + \alpha/2. \quad (18)$$

The local airfare is as the FC equilibrium fare (see Eq. (7)), and the connecting fare is similar but takes into account the fact that two routes are needed to serve this market. The same results are obtained in Flores-Fillol (2009 and 2010) in a similar setup.

It is important to note that, while fares p_1^h and P_1^h are set independently, they must satisfy non-arbitrage conditions. These conditions are of two types. The first type is written $P_1^h > p_1^h$ and prevents a local passenger from purchasing an interline ticket (i.e., an AB ticket) and then get off at the hub airport. The second type is given by $P_1^h < 2p_1^h$ and ensures that an AB passenger will not be able to travel cheaper by purchasing two separate tickets (on routes AH and BH). The fulfillment of these conditions can be trivially observed from inspection of Eq. (18).

Plugging the equilibrium values in Eq. (18) into Eq. (17), we get the following equilibrium condition for flight frequency

$$\underbrace{6\eta (f^h)^3}_{A^h(f)} = \underbrace{\frac{\gamma}{2} - \frac{2\theta}{3} (f^h)^2}_{B^h(f)}. \quad (19)$$

We have again a cubic expression ($A^h(f)$) and a quadratic expression ($B^h(f)$), and thus the equilibrium frequency f^h is generated by a diagram analogous to Fig. 3. The comparative-static analysis is as in the FC case and each airline carries half of the demand in every city-pair market, i.e., $q_1^h = Q_1^h = 1/2$. Which is really interesting is to compare FC and HS network configurations, and to analyze the choice of network type.

2.3 Comparison of equilibria and airline network choice

From Eqs. (8) and (19), it is clear that both the f^2 -coefficient of the quadratic curve and the height of the cubic curve in the positive quadrant are greater in the FC case, as shown in Fig. 4.

–Insert here Fig. 4–

$A(f)$ is higher than $A^h(f)$ in the positive quadrant and $B(f)$ is more concave than $B^h(f)$ (and both of them have the same intercept $\gamma/2$). Therefore, the result in the following proposition can be established.

Proposition 1 *Flight frequency is higher in the HS network than in the FC network, with $f^h > f$.*

Frequencies are higher under HS networks because there is more traffic on each of the two active routes AH and BH . This finding extends the duopoly result reported in Flores-Fillol (2009) to a setting with airport congestion and confirms the link between frequency and network structure. After the deregulation, with airlines free to compete on airfares, softer competition on frequency was expected but exactly the opposite occurred on many routes, due to the the adoption of HS networks and the concentration of traffic on the spoke routes.

Since carriers are symmetric, flight frequency (which differs between FC and HS configurations) does not affect the equilibrium airfare in markets AH and BH and,¹⁶ as a consequence, $p = p^h$. More interestingly, airlines charge higher airfares in market AB under HS configurations (i.e., $P^h > p$), which is explained by the use of two routes to serve this connecting market.

In equilibrium, the total number of flights operated by an airline under FC networks is given by $3f$ since three routes are active. Analogously, the total number of flights operated by an airline under HS networks is $2f^h$.

Assumption 1 *We assume that HS operations reduce the total number of flights, i.e., $2f^h < 3f$.*

As pointed out in Brueckner (2004), HS networks are meant to save airline costs through the operation of fewer routes and, as a consequence, this seems a natural expectation. Note that the equilibrium aircraft size for an airline is $s = q_1/f = 1/(2f)$ under FC networks,

and $s^h = (q_1^h + Q_1^h) / f_1^h = 1/f^h$ in the case of HS networks. Therefore, under Assumption 1, $s < s^h$ is observed, an implication of the model that appears to be realistic and that is in line with Brueckner (2004) and Flores-Fillol (2009). HS configurations endow the passengers with a higher flight frequency and allow airlines to make cost savings coming from the presence of economies of traffic density because aircraft size is larger and cost per seat decreases with aircraft size (as it has been argued before).

To study airlines' network choice, we need to compare equilibrium profits under both network structures. Computing this profit differential is not trivial because there is not an equilibrium closed-form solution for flight frequency under either network configuration. However, this comparison can be done recasting the optimization problem as a two-stage problem, where fares are chosen first conditional on flight frequency, and flight frequency is then chosen in a second stage. Substituting Eq. (7) into Eq. (4), after simplifying and applying symmetry, we obtain

$$\pi_1(f) = \frac{3\alpha}{4} - 3\theta f - 24\eta f^2, \quad (20)$$

where the 3 factor in the first term of the expression denotes the number of city-pair markets served by the airline; the 3 factor in the second term indicates the number of routes in which the airline operates; and the 24 factor in the third term shows that each of the 3 routes operated by the airline is affected by 8 aircraft movements (i.e., 4 aircraft movements of each airline).

Similarly, substituting Eq. (18) into Eq. (14), after simplifying and applying symmetry, we obtain

$$\pi_1^h(f^h) = \frac{3\alpha}{4} - 2\theta f^h - 12\eta (f^h)^2, \quad (21)$$

where the 3 and the 2 factors in the first and the second terms of the expression denote that the airline serves 3 city-pair markets but only 2 routes; and the 12 factor in the third term shows that each of the 2 routes operated by an airline is affected by 6 aircraft movements (i.e., 3 aircraft movements of each airline: 2 at the hub airport and 1 at the spoke airport).

Therefore, the HS-FC profit differential $\Delta = \pi_1^h(f^h) - \pi_1(f)$ can be easily computed from Eqs. (20) and (21) and is given by

$$\Delta = \theta(3f - 2f^h) + 12\eta[2f^2 - (f^h)^2], \quad (22)$$

where the first term, which is positive, captures the aircraft fixed cost advantage of HS networks from operating only 2 routes; and the second term, which can be either positive or

negative, captures the congestion cost advantage that can favor either network structure. The following proposition discusses the sign of Δ .

Proposition 2 *In absence of congestion (i.e., $\lambda = \eta = 0$), airline profits are higher under HS networks (i.e., $\Delta > 0$). In presence of congestion, airline profits are higher under HS networks (i.e., $\Delta > 0$) when $f^h \leq 2^{1/2}f = 1.4f$, whereas the sign of the profit differential is ambiguous for $f^h > 2^{1/2}f$.*

From Proposition 1 and Assumption 1, we know that $f < f^h < 3f/2$. Although FC networks imply twice the aircraft movements of HS networks, the congestion cost can be higher under HS configurations when f^h approaches its upper bound. The corollary that follows is directly derived from Proposition 2.

Corollary 1 *Congestion could create incentives for airlines to adopt FC network configurations.*

This result could explain the initial success of HS networks after the deregulation, and how congestion could act as a brake on hubbing strategies.¹⁷

3 Social optimum and congestion tolls

Having explained the properties of the equilibrium, we now shift our attention to the welfare analysis where a social planner dictates flight frequency. Then we can derive the congestion tolls that are required to achieve efficiency. Finally, we will compare social welfare under FC and HS structures and we will assess the equilibrium network choice, which is the ultimate purpose of this section.

3.1 Welfare analysis of the FC network

Since the fare paid is just a transfer between consumers and airlines, and markets are fully served (i.e., total traffic is fixed), the planner's goal is to minimize costs, which are given by

$$3 \left\{ \underbrace{\frac{1}{2} \left(\frac{\gamma}{f_1} + \frac{\gamma}{f_2} \right)}_{\text{Schedule delay cost}} + \underbrace{4\lambda(f_1 + f_2)}_{\text{Congestion costs for passengers}} + \underbrace{(f_1 + f_2)[\theta + \eta(4f_1 + 4f_2)]}_{\text{Fixed and congestion costs for airlines}} + \underbrace{\tau}_{\text{Seat cost}} \right\}. \quad (23)$$

To interpret Eq. (23), recall that total traffic in each market (i.e., markets AH , BH and AB) is equal to unity. On the passengers side, the *schedule delay cost* caused by each airline acquires a factor $3/2$, because there are three markets and half of the unitary population in each market is loyal to each airline. The *congestion cost for passengers* has a factor 12 that accounts for all aircraft movements in the three markets (4 corresponding to each market).

On the airlines side, each carrier bears the *fixed cost* and the *congestion cost* of operating three routes ($3\theta f_i$ and $3f_i\eta(4f_1 + 4f_2)$ with $i = 1, 2$), and the *seat cost* of serving three city-pair markets.

The condition for optimal choice of f_1 is

$$\frac{\gamma}{2f_1^2} - \theta - 4\lambda - 8\eta(f_1 + f_2) = 0, \quad (24)$$

and, after applying symmetry, we obtain the following social-optimum condition

$$\underbrace{16\eta f^3}_{C(f)} = \underbrace{\frac{\gamma}{2} - (\theta + 4\lambda) f^2}_{D(f)}. \quad (25)$$

Eqs. (8) and (25) are easily compared. Note that the social-optimum cubic function is higher than the equilibrium one (i.e., $A(f) < C(f)$ for $f > 0$); and that the f^2 -coefficient in the quadratic function is larger in the social-optimum condition for $\lambda > 0$, as depicted in Fig. 5. Superscript SO denotes socially-optimal values.

–Insert here Fig. 5–

Therefore, equilibrium frequencies are excessive compared with the optimum (i.e., $f > f^{SO}$). On the other hand, we also observe that the equilibrium aircraft size is inefficiently small (i.e., $s < s^{SO}$) since markets are fully served and all seats are filled (recall that $s_1 = q_1/f_1$). Interestingly, in absence of congestion (i.e., $\eta = \lambda = 0$) the inefficiency disappears and $f = f^{SO} = (\frac{\gamma}{2\theta})^{1/2}$ and $s = s^{SO} = (\frac{\theta}{2\gamma})^{1/2}$.

Proposition 3 *Under congested FC networks, there is an overprovision of flight frequency and aircraft size is suboptimal. In absence of congestion, both frequency and aircraft size are efficient.*

As pointed out in Flores-Fillol (2010), when there is congestion airlines operate too many flights using overly small aircraft, and a socially preferred outcome would require

less frequent flights and larger aircraft. In fact, the source of the inefficient choice of flight frequency can be seen by comparing the first-order conditions corresponding to the equilibrium analysis and the social-optimum analysis. The marginal *social* congestion cost from operating an extra flight on each route $4\lambda + 16\eta f$ (after imposing symmetry in Eq. (24)); and the marginal congestion costs that are taken into account by airlines are $12\eta f$ (after imposing symmetry in Eq. (6)). Therefore, the difference between these two expressions is $4\lambda + 4\eta f$, which captures the part of social congestion costs that are not internalized by each airline. More precisely, $4\eta f$ represents the congestion inflicted on the other carrier, and 4λ is the congestion experienced by *all* passengers (including the carrier's own passengers) on each of the three routes.

Thus, the per-flight congestion toll that is needed to reach the social optimum is $4\lambda + 4\eta f$ evaluated at the social optimum, i.e.,

$$T = 4\lambda + 4\eta f^{SO}. \quad (26)$$

Note that the marginal congestion damage (*MCD*) from an extra flight *on a route* is given by $4\lambda + 4\eta f_1 + 4\eta f_2$ (see Eq. (23)); and thus each carrier is charged a toll equal to the marginal congestion damage evaluated at the social optimum (MCD^{SO}) after subtracting carrier's own internalized congestion. The inefficiency in flight frequency (and thus in aircraft size) arises because airlines only internalize their own congestion, neglecting the higher operating costs imposed on other airlines as well as the congestion costs imposed on all passengers, including their own.

The fact that airlines fail to internalize the congestion inflicted on other carriers is well documented in the literature,¹⁸ and the failure to internalize passenger congestion is a contribution of Flores-Fillol (2010).¹⁹

3.2 Welfare analysis of the HS network

Proceeding in the same way, the cost expression under HS networks is

$$\underbrace{\frac{3}{2} \left(\frac{\gamma}{f_1^h} + \frac{\gamma}{f_2^h} \right)}_{\text{Schedule delay cost}} + \underbrace{10\lambda (f_1^h + f_2^h)}_{\text{Congestion costs for passengers}} + \underbrace{\mu}_{\text{Layover time cost}} + \underbrace{2(f_1^h + f_2^h) [\theta + \eta(3f_1^h + 3f_2^h)]}_{\text{Fixed and congestion costs for airlines}} + \underbrace{4\tau}_{\text{Seat cost}}. \quad (27)$$

The *congestion cost for passengers* has now a factor 10 that accounts for all aircraft movements in the three markets (3 corresponding to each local market, and 4 corresponding

to market AB), and there is also the layover time cost borne by connecting passengers. Each carrier bears the *fixed cost* and the *congestion cost* of operating two routes ($2\theta f_i^h$ and $2f_i^h\eta(3f_1^h + 3f_2^h)$ with $i = 1, 2$). Finally, the *seat cost* acquires a factor 4 because it incorporates the cost of serving all local passengers on markets AH and BH (who make use of one route) and all connecting passengers (who make use of two routes).

The condition for optimal choice of f_1^h is

$$\frac{3\gamma}{2(f_1^h)^2} - 2\theta - 10\lambda - 12\eta(f_1^h + f_2^h) = 0, \quad (28)$$

and, after applying symmetry, we obtain the following social-optimum condition

$$\underbrace{8\eta(f^h)^3}_{C^h(f)} = \underbrace{\frac{\gamma}{2} - \frac{2(\theta + 5\lambda)}{3}(f^h)^2}_{D^h(f)}. \quad (29)$$

Again, the comparison between the expressions in Eqs. (19) and (29) can be represented by a diagram analogous to the one in Fig. 5, where we observe that equilibrium frequencies are excessive (i.e., $f > f^{SO}$) and aircraft size is inefficiently small (i.e., $s < s^{SO}$).²⁰ As in the previous case, in absence of congestion, the inefficiency disappears and $f = f^{SO} = \left(\frac{3\gamma}{4\theta}\right)^{1/2}$ and $s = s^{SO} = \left(\frac{4\theta}{3\gamma}\right)^{1/2}$.²¹

Proposition 4 *Under congested HS networks, there is an overprovision of flight frequency and aircraft size is suboptimal. In absence of congestion, both frequency and aircraft size are efficient.*

The marginal *social* congestion cost from operating an extra flight on both of the segments equals $10\lambda + 24\eta f^h$ (after imposing symmetry in Eq. (28)); and the marginal congestion costs that are taken into account by airlines are $18\eta f^h$ (after imposing symmetry in Eq. (17)). Therefore, the difference between these two expressions is $10\lambda + 6\eta f^h$, which captures the part of social congestion costs that are not internalized by each airline. More precisely, $6\eta f^h$ represents the congestion inflicted on the other carrier on both routes, and 10λ is the congestion experienced by *all* passengers (including the carrier's own passengers).

In this situation, taking into account that there are two routes in the network, the toll per flight will be exactly half of the expression $10\lambda + 6\eta f$ evaluated at the social optimum, i.e.,

$$T^h = 5\lambda + 3\eta f^{hSO}. \quad (30)$$

Note that the marginal congestion damage (MCD) from an extra flight *on a route* is given by $5\lambda + 3\eta f_1 + 3\eta f_2$ (see Eq. (27)); and thus each carrier is charged a toll equal to the marginal congestion damage evaluated at the social optimum (MCD^{SO}) after subtracting carrier's own internalized congestion. The inefficiency in flight frequency (and thus in aircraft size) arises because airlines only internalize their own congestion, neglecting the higher operating costs imposed on other airlines as well as the congestion costs imposed on all passengers, including their own.

Brueckner (2004) studies network choice and network efficiency in the monopoly case (without congestion) and concludes that frequencies are suboptimal (i.e., underprovision of flight frequencies). He recognizes that this result is closely linked to the assumed monopoly market structure and suggests that an oligopoly version of the model with schedule competition could lead to the opposite outcome. This is precisely what we find in our analysis (and is summarized in Propositions 3 and 4).

Looking at Eqs. (26) and (30), we observe that congestion under HS networks is unequivocally worse for passengers (first term of the expressions), and that it is also worse for airlines for $3f^{hSO} \geq 4f^{SO}$ (second term of the expressions).²² Thus, when the latter inequality holds, we can conclude that the overall congestion damage is higher under HS networks, and thus $T^h > T$. When congestion is worse for airlines under FC networks, then $3f^{hSO} < 4f^{SO}$. In this case, $T^h > T$ requires $\lambda > \eta(4f^{SO} - 3f^{hSO})$, meaning that the overall congestion damage is higher under HS configurations when the advantage for airlines does not compensate for the disadvantage for passengers. This argument is developed in the next subsection that focuses on network choice efficiency.

3.3 Network efficiency

From the aforementioned analysis, we conclude that the presence of congestion generates excessive frequency, independently of the network type. When there is congestion, airlines operate too many flights using overly small aircraft (regional jets or even turboprops), and less frequent flights and larger aircraft would be socially preferred.

A final exercise is to compare the equilibrium and the socially-optimal network choices. To carry out this exercise, we need to compute a HS-FC welfare differential $\Gamma = W^h - W$, which is tantamount to computing Eq. (27) – Eq. (23) and yields

$$\Gamma = 2\Delta + k, \tag{31}$$

with $k = 3\gamma(1/f - 1/f^h) - \tau - \mu + 4\lambda(6f - 5f^h)$. The first term in k is positive and shows the advantage of HS networks in terms of schedule delay given that it yields a larger flight frequency. However, k also comprises two negative terms, which are cost elements related to HS connecting passengers: an extra seat cost because these passengers make use of two routes (whereas AB passengers just make use of one route under FC networks), and a layover time cost since these passengers change planes at the hub H . Finally, the last term of the expression, which captures the different impact of HS and FC networks in passengers congestion cost, can be either positive or negative depending on the relative value of f and f^h .

With $k = 0$, the sign of Γ is the same as the sign of Δ and therefore the airlines' preferred network configuration coincides with the socially optimal choice. However, with $k \neq 0$, airlines' network choices may be inefficient. In absence of congestion (i.e., $\lambda = \eta = 0$) then $\Delta > 0$, as pointed out in Proposition 2. In this case, a conflict between private and public interests can only arise when $k < 0$, meaning that the extra seat and layover time costs associated to HS structures are important enough as compared to the HS schedule delay advantage, i.e., $\tau + \mu > 3\gamma(1/f - 1/f^h)$. In presence of airport congestion, studying the sign of Γ requires to analyze simultaneously the sign of Δ and k .

If $f^h \leq 6f/5 = 1.2f$ then $4\lambda(6f - 5f^h) > 0$ and $\Delta > 0$.²³ In this case, there can be a private-public conflict when $k < 0$, i.e., in presence of important extra seat and layover time costs associated to HS structures, as compared to the HS advantage in terms of schedule delay and passengers congestion cost, i.e., $\tau + \mu > 3\gamma(1/f - 1/f^h) + 4\lambda(6f - 5f^h)$.

When $f^h \in (1.2f, 1.4f]$ then $4\lambda(6f - 5f^h) < 0$ and $\Delta > 0$. In this case, there can be a private-public conflict when $k < 0$, i.e., in presence of important extra seat, layover time, and passengers congestion costs associated to HS structures, as compared to the HS advantage in terms of schedule delay, i.e., $\tau + \mu - 4\lambda(6f - 5f^h) > 3\gamma(1/f - 1/f^h)$.

The difference between these two cases is found on the effect of passengers' congestion disutility: it is larger under FC networks for $f^h \leq 1.2f$, whereas it becomes larger under HS networks as f^h exceeds this threshold value because there is an increase in the probability of flight delays, cancellations, and missed connections in the hub airport.

Finally, if $f^h > 1.4f$ then $4\lambda(6f - 5f^h) < 0$ still holds but the sign of Δ is ambiguous. Thus, airlines network choice may exhibit an inefficient bias either toward the HS network or toward the FC network. In a highly congested environment where both airlines' and passengers' marginal congestion damage (η and λ) are large, then $\Delta < 0$ and $k < 0$, so

that there is no private-public conflict and the FC is preferred. However, if airlines' fixed cost (θ) is sufficiently high as compared to airlines' congestion damage (η), then $\Delta > 0$ and $k < 0$ could be observed, yielding an airlines' inefficient bias toward HS networks. The proposition that follows summarizes these results.

Proposition 5 *In absence of congestion, airlines network choice may exhibit an inefficient bias toward the HS network when the extra seat and layover time costs associated to HS structures overcome to the advantage in terms of schedule delay. In presence of congestion, this result is reinforced for $f^h > 1.2f$ (requiring a high airline fixed cost when $f^h > 1.4f$) and it also remains true for $f^h \leq 1.2f$ when passengers' congestion damage is not very high.*

Therefore, airport congestion can yield an inefficient outcome where airlines decide to adopt HS network configurations, whereas the optimal social network would recommend a FC structure. This result extends and complements the monopoly result in Brueckner (2004), which also finds an inefficient bias toward the HS network for $f^h < 3f/2$. The section that follows tries to analyze empirically these results.

4 An empirical application

The equilibrium analysis in Section 2 shows 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. The welfare analysis in Section 3 leads to the conclusion that there is an overprovision of flight frequency under HS and FC networks in presence of congestion, and airlines may have an inefficient bias towards HS configurations. In this section, we want to examine empirically (i) how airlines adjust frequencies to congestion both under HS and FC networks, and (ii) whether delays are higher in airports dominated by network airlines (i.e., airlines providing services in HS configurations).

The results of the empirical analysis are consistent with what it is found in the theoretical model: (i) airlines react less to congestion when they operate HS configurations (as compared to FC networks), and (ii) delays are higher in airports dominated by network airlines (controlling for airport size and concentration level).

We have data of the 51 largest US airports during the period 2005-2010, which include the most congested airports in the country. Airline frequencies are expected to be high on routes that have one of these airports as an endpoint. Our analysis assumes that network airlines operate in a HS manner at their hub airports, while the rest of airlines provide point-to-point connections.²⁴ Data on airline frequencies and flight shares at the airport level have been obtained from RDC Aviation (Capstats statistics). Since we focus on US domestic traffic, intercontinental flights are excluded from the analysis.

Network airlines are understood to be those carriers that belonged to an international alliance (i.e., Oneworld, Star Alliance, and SkyTeam) in the considered period, i.e., American Airlines, Continental, Delta, Northwest, United, and US Airways. Today, the amount of connecting traffic that can be channeled by an airline not involved in an international alliance is necessarily modest. We consider the following hub airports: Dallas (DFW), Miami (MIA), and Chicago (ORD) for American Airlines; Cleveland (CLE), Houston (IAH), and New York (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 (PHX), and Phoenix (PHX) for US Airways.

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 schedules are not clustered in coordinated banks of arrivals and departures. In this vein, Boguslaski *et al.* (2004) show that Southwest's bulk of 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 more than fifteen minutes in a given airport. Data of delays have been obtained from the US Department of Transportation.²⁵ Table 2 shows some features of the airports included in our sample.

–Insert here Table 2–

Regarding hub airports, the share of the dominant airline in terms of total airport departures is normally above 60%, except for some cases (New York (JFK), Chicago (ORD), and Phoenix (PHX)) where two airlines have a relatively large share. In the considered period, the percentage of delayed flights in hub airports is well above 20%, and it is close

to 30% in the more congested airports (New York (EWR and JFK), Chicago (ORD), and Philadelphia (PHL)). Salt Lake City (SLC) and Phoenix (PHX) are the only hub airports having a percentage of delayed flights slightly below 20%.

A high number of non-hub airports are dominated by Southwest. In some of these airports, the share of Southwest is above 75%, like Dallas (DAL), Houston (HOU), Chicago (MDW), and Oakland (OAK). Thus, the levels of concentration in non-hub airports dominated by Southwest may also be very high. The percentage of delayed flights in Southwest-dominated airports is usually above 20%, although it seems that the levels of congestion are generally lower than in hub airports. The non-hub airports where Southwest is not the dominant airline generally show low concentration and congestion levels. However, New York (LGA), which is a slot constrained airport, is also very congested.

4.1 The relationship between frequencies and delays

The spline regression displayed in Fig. 1 already shows some preliminary evidence (without any restriction) on the relationship between airport congestion and airline network structure. It suggests that airlines operating in hub airports are less sensitive to airport congestion in their choice of flight frequencies. However, we should distinguish the different airlines operating at each airport and control for demand to come to a definite conclusion. Thus, we estimate the following equation for the airline i at airport a from urban area u

$$\begin{aligned}
 Freq_{i,a,t} = & \beta_0 + \beta_1 Pop_{u,t-1} + \beta_2 GDPpc_{u,t-1} + \beta_3 Delays_{a,t-1} + \beta_4 D_{i,a}^{hub} + \beta_5 D_{i,a}^{hub} x Delays_{a,t-1} \\
 & + \beta_6 D_t^{2006} + \beta_7 D_t^{2007} + \beta_8 D_t^{2008} + \beta_9 D_t^{2009} + \beta_{10} D_t^{2010} + \varepsilon.
 \end{aligned}
 \tag{32}$$

The dependent variable ($Freq_{i,a,t}$) is the total number of annual flights that each airline offers in the corresponding airport. Data of the explanatory variables are for the previous year because airline frequencies at the airport level in period t should be influenced by airport and airline features in period $t - 1$. Among the explanatory variables, we include variables related to local demand: population ($Pop_{u,t-1}$), GDP per capita ($GDPpc_{u,t-1}$), and time dummies for each year of the considered period, being 2005 the excluded year. Data on population and GDP per capita, which has been obtained from the US census, refer to the Metropolitan Statistical Area (MSA) where the airport is located.

We can expect a positive sign of the coefficients associated to 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, demand of

airline services should be higher in airports located in more populated and richer urban areas. Furthermore, the economic recession shows its first effects on demand for air transportation in 2008, although it must be taken into account that airlines schedule frequencies some months in advance. Thus, the year dummies may identify the impact of the economic recession on the demand and, hence, on airline frequencies.

Along with variables related to local demand, we consider a measure of airport congestion ($Delays_{a,t-1}$), which is constructed as the percentage of total flights in the airport with a delay exceeding fifteen minutes. Furthermore, we consider a dummy variable ($D_{i,a}^{hub}$) that takes the value one for network airlines operating in their hub airports and zero otherwise. Finally, we include a variable that results from the interaction between the dummy variable for network airlines operating in their hubs and the measure of congestion ($D_{i,a}^{hub} \times Delays_{a,t-1}$).

Controlling for local demand, frequencies of network airlines in their hub airports (i.e., airlines operating HS networks) should be higher than frequencies of other airlines in those hub airports and than frequencies of any airline operating in non-hub airports (i.e., airlines operating FC networks). The reason is the exploitation of connecting traffic, which is independent from local demand. Thus, we expect a positive sign in the coefficient associated to $D_{i,a}^{hub}$.

The relationship between frequencies and delays is determined by the coefficient associated to the delays variable (β_3). Furthermore, the slope of the relationship frequencies-delays for network airlines operating in their hubs (i.e., airlines operating HS networks) will also be influenced by the coefficient associated to the interaction variable between delays and the dummy for network airlines at hub airports (β_5). Overall, airline frequencies should fall when delays rise because of the costs associated to congestion. Hence, we expect $\beta_3 < 0$. However, if network airlines at their hubs react less to delays than the rest of airlines, we should expect $\beta_5 > 0$. This result would be consistent with the theoretical model where we find an inefficient bias towards HS networks in presence of congestion.

The estimation is made using Ordinary Least Squares (OLS) and airport fixed effects (within estimator) for different subsamples.²⁶ An advantage of the fixed-effects model is that it allows controlling for any omitted variable, which is correlated with the variables of interest and does not change over time. However, a shortcoming of the fixed effects model is that it may be less informative than other estimation techniques because the within variation of data may be low and time-invariant variables are not identified. This implies

that the dummy for hub airports and its interaction with the delays variable, which are two important variables in our analysis, must be excluded from the regression.

The OLS estimation of Eq. (32) is made for the full sample and for a subsample that just considers concentrated airports to take into account the internalization hypothesis. According to this hypothesis, airlines only internalize their own congestion, neglecting the higher operating costs imposed on other airlines as well as the congestion costs imposed on all passengers. Therefore, delays should have a higher impact on frequencies in more concentrated airports (regardless of the network configuration they operate) because the dominating airline should respond to the congestion costs generated by its own flights.

The estimation of Eq. (32) with airport fixed effects is made for a subsample that considers hub airports and another one that considers non-hub airports.²⁷ If airlines operating under HS networks react less to congestion than airlines operating FC structures, then the delays variable should have a stronger (negative) influence on frequencies in the subsample that considers non-hub airports.

Standard errors are robust to heterocedasticity and are clustered by time to account for any problem of serial autocorrelation. Since there could be a simultaneous determination of frequencies and delays, we deal with this potential endogeneity bias by using the first lag of the delays variable. Delays at the airport in period $t - 1$ should not be conditioned upon frequencies in period t . Note also that the frequency variable is at the airline-airport level, while the delays variable is at the airport level.

Another econometric issue that must be mentioned is the high correlation between the variables $D_{i,a}^{hub}$ and $D_{i,a}^{hub} \times Delays_{a,t-1}$, which may pose a multicollinearity problem that could distort the individual identification of these variables. However, additional regressions excluding either of the two variables show that the sign and the statistical significance of both variables is not altered.²⁸

–Insert here Table 3–

Table 3 depicts some descriptive statistics of the variables used in the empirical analysis. From this table, it is clear that congestion is a general problem in the US largest airports since the mean percentage of delayed flights is about 23%. However, there is a wide dispersion across the airports of the sample because the minimum value is 13% and the maximum is about 38%. The rest of variables also show a high enough variability to provide robust estimations. Note that we consider as concentrated those airports having

a mean Herfindahl-Hirschman Index (HHI) higher than the sample mean, which is 0.33. The concentration index is measured through the share of airlines in the airports in terms of total departures.

Table 4 shows the results of the estimation of Eq. (32) for different subsamples using OLS and airport fixed effects. Table 5 reports the elasticities obtained from the estimated coefficients evaluated at sample means in relation to $Delays_{a,t-1}$ and $D_{i,a}^{hub}$. The overall explanatory power of the model is notably high. Furthermore, the elasticities obtained for the main variables are also remarkable.

–Insert here Tables 4 and 5–

We confirm that airlines offer higher frequencies in airports where the urban area can potentially involve a higher demand for air travel. The coefficient associated to the population variable is always positive, although it is statistically significant only in the OLS regression that considers the full sample.

The GDP per capita variable does not show a statistically-significant positive effect on airline frequencies, while the coefficient associated to the 2010 dummy variable (after the global recession) is always negative and statistically significant.

As expected, the coefficient of the dummy for hub airports is positive and statistically significant in the regressions that can be identified. Hence, network airlines in their hub airports provide more frequencies than the rest of airlines in those hub airports, but also than any airline (even dominant airlines) in non-hub airports. This finding confirms the result in Proposition 1 and is explained by the fact that HS network configurations are characterized by the exploitation of connecting services and the concentration of traffic on the routes connecting different endpoints with the hub airport.

Overall, we find that airlines operating under HS networks are less influenced by airport congestion in their choice of frequencies. In the OLS regressions, the coefficient associated with the delays variable is negative and statistically significant both in the full sample and in the sample with concentrated airports. However, the effect of delays on frequencies is mitigated in the case of network airlines operating in their hub airports because the coefficient associated with the interaction between the dummy variable for network airlines operating in their hubs and the measure of congestion is positive and statistically significant (both in the full sample and in the sample with concentrated airports). In terms of elasticities, a 10 percent increase in airport delays implies a decrease of about 3 percent

in airline frequencies. This negative relationship is partially compensated when airlines operate HS networks as the (positive) elasticity obtained from the interaction variable is about 1-3 percent. Furthermore, in the regressions with airport fixed effects, the coefficient associated with the delays variable is negative and statistically significant for non-hub airports, while it is positive (although not statistically significant) for hub airports. The differences in terms of elasticities are very high.

Shifting attention to concentrated airports (airports with a mean concentration index higher than the sample mean), we find weak evidence in favor of the internalization hypothesis. Airlines are slightly more sensitive to delays in concentrated airports because the elasticity obtained from the estimated coefficient of the delays variable (which is always negative) is a little higher. However, the positive elasticity of the interaction variable is particularly high on concentrated airports. Therefore, the results for airlines operating HS networks are not favorable to the internalization hypothesis. In any case, the aim of the analysis is not to provide direct tests on the internalization hypothesis, although we have to take into account the extent to which our results are affected by the levels of concentration at the considered airports. As we have seen in our theoretical model where own congestion is always internalized, congestion is unequivocally worse for passengers and may also be worse for airlines under HS networks (as compared to FC networks). Therefore, independently of the internalization phenomenon, HS networks may be socially detrimental.

In short, we find that airlines operating HS networks are less influenced by congestion in their choice of frequencies. Recall that airlines may exploit network effects under HS networks: higher frequencies enhance demand and a higher demand implies savings in terms of economies of traffic density. Furthermore, they save fixed costs by operating fewer routes than under a FC network, as can be seen from inspection of Eq. (22).

As pointed out in Flores-Fillol (2010), network size in HS configurations may contribute to explain this behavior. On the one hand, by adding a new route to an existing HS network, carriers gain access to one local market and to n connecting markets and, hence, they increase flight frequency. However, on the other hand, there is also an additional aircraft movement at the hub airport that increases congestion, affecting both carriers and passengers. It seems that the first effect partially compensates the second one for the airlines in our sample.

4.2 Hub airports and delays

Results of regressions of Eq. (32) provide evidence that airlines operating a HS network react less to delays. To examine the consequences of this behavior on passengers, we run an additional regression at the airport level. Controlling for the number of departures and concentration, we want to test whether delays are higher in hub airports. Thus, we estimate the following equation at airport a

$$Delays_{a,t} = \beta_0 + \beta_1 Freq_{a,t-1} + \beta_2 D_a^{hub} + \beta HHI_{a,t-1} + \beta_4 D_t^{2007} + \beta_5 D_t^{2008} + \beta_6 D_t^{2009} + \beta_7 D_t^{2010} + \varepsilon. \quad (33)$$

The dependent variable is our measure of airport congestion, which is the percentage of total flights in the airport with a delay exceeding fifteen minutes. As explanatory variables, we consider the total number of annual flights in the airport, a dummy variable that takes the value one for hub airports where the dominant airline adopts a HS network, and the HHI in terms of airline frequencies. Finally, we include time dummies for each year of the considered period, being 2006 the excluded year. Recall that the explanatory variables are lagged one year and that no data is available for frequencies in 2004. Thus, the first year of the considered period is lost in the estimation of Eq. (33).

Quite naturally, we should expect a positive relationship between frequencies (which are a measure of airport size) and delays. The possible simultaneous determination of delays and frequencies is taken into account by considering one year lag of the frequencies variable.²⁹

As we have mentioned above, the empirical literature on airport congestion has focused on testing the internalization hypothesis. A positive evidence of it would be a negative relationship between delays and the concentration index. As in the case of the frequencies variable, we also consider one year lag of the concentration variable.

Furthermore, we expect a positive relationship between delays and the hub airport variable. For a given level of frequencies and competition at the airport, delays should be higher in hub airports. In line with the previous results, delays should be higher in hub airports because airlines operating under HS are less influenced by congestion in their choice of frequencies

The estimation is made using OLS. The use of fixed effects implies losing one time invariant variable (i.e., the dummy for hub airports), which makes the rest of explanatory variables statistically non-significant. It seems that the airport fixed effects capture all the

relevant relationships in our context.

Table 6 reports the results of the estimates of Eq. (33). We confirm that delays are higher in larger airports because the frequency variable is positive and statistically significant. The concentration variable is negative but it is not statistically significant, so that we do not find clear evidence of internalization. The time dummies are negative and statistically significant from 2008 onwards. The fall in demand due to the economic downturn in 2009 can explain this result.

–Insert here Table 6–

Finally, the hub variable is positive and statistically significant as expected. Controlling for the number of frequencies and concentration, we find evidence that delays are higher in airports where airlines are operating under a HS configuration. From our results, we could also infer that the internalization hypothesis is weaker when we distinguish between hub and non-hub airports. It seems that airlines operating HS networks do not fully internalize congestion even when their share of frequencies in the corresponding hub airport is very high. The explanation is found in the aforementioned network benefits that airlines may obtain from operating under HS networks.

5 Concluding remarks

Network carriers tend to concentrate traffic at few airports. Under HS networks, airlines may exploit network effects: higher frequencies enhance demand and a higher demand implies savings in terms of economies of traffic density. Furthermore they save costs by operating fewer routes than under a FC network. This concentration of traffic exacerbates congestion problems, which cause substantial costs for passengers and airlines.

Airport congestion has not been adequately tackled from a public policy perspective. This may be explained by different factors such as the difficulties in implementing congestion pricing or the high investments costs associated to airport expansions. As a consequence, congestion still remains a severe problem in the air transportation industry, which becomes especially serious in the US where only four airports are slot-constrained.

From a social point of view, our analysis suggests that policy measures promoting direct connections away from hubs may have social benefits. Policy makers and airport operators could use tools such as airport charges (both the level and the relation with the weight

of the aircraft), investment in capacities, and marketing of the cities where the airports are located. From our results, we can also infer that the rules determining the allocation and use of slots in the US should be re-designed so as to create incentives for airlines to increase aircraft size and reduce flight frequency.

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Notes

¹Only four US airports are slot-constrained: O’Hare at Chicago, Ronald Reagan at Washington, and La Guardia and JFK at New York.

²Table 2 provides more extensive data by considering the 51 largest US airports during the period 2005-2010.

³An advantage of the spline regression is that it does not impose any restriction or shape in the functional form of the considered relationship. However, we should distinguish the different airlines operating at each airport and control for demand to come to a definite conclusion.

⁴In a different setting without congestion, Fageda and Flores-Fillol (2012a and 2012b) study the surge of new point-to-point connections in thin markets, which seems to be related to the success of two major innovations in the provision of air services: the regional jet technology and the low-cost business model.

⁵Other studies of frequency choice and scheduling competition include works by Brueckner (2004), Brueckner and Flores-Fillol (2007), Flores-Fillol (2010). Empirical analysis of the determinants of aircraft size and flight frequency choice in the US airline industry has been offered by Pai (2010). Bilotkach *et al.* (2010) focuses primarily on the relationship between the frequency choice and distance and offers an analysis of the frequency choice by the airlines on a set of European markets.

⁶Santos and Robin (2010) replicate the analysis of Mayer and Sinai (2003) using European data. Their results are favorable to the internalization hypothesis but they find mixed evidence in the relationship between airlines’ destinations at the airport and delays.

⁷Other empirical papers assess the effects of delays for airlines and passengers. For example, Forbes (2008) uses data of routes of La Guardia airport (one of the four slot constrained airports in the US) to study price responses to flight delays, finding an average price reduction per additional minute of flight delay of \$1.42 for direct passengers and of \$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 have an upward impact on prices and a negative impact on demand. From their results, a 10 percent decrease in delays would imply a benefit of \$1.50-\$2.50 for passenger, while the gains for airlines of reducing delays are about three times higher. From a different perspective, Morrison and Whinston (2007) compare the welfare effects of traditional congestion tolls and the optimal congestion that would take into account the internalization, finding that there are not substantial gains from applying the optimal congestion tolls.

⁸We follow the approach in Flores-Fillol (2010). Partially-served markets introduce tractability complications derived from the presence of market power. In such a case, it is difficult to have unambiguous effects because a reduction in a carrier’s flight volume mitigates airport congestion but raises fares (through a standard market-power effect). As a result, airline choices involve both the exploitation of market power and the desire to limit congestion. Therefore, for the sake of simplicity and to have clear results, we rule out market power by assuming fully-served markets.

⁹In a related model without congestion and network structure, Brueckner and Flores-Fillol (2007) allow for partially-served markets by considering the possibility of having *low-type passengers*, who are characterized by a low valuation of travel and may not undertake air travel. In a different setting without congestion, Flores-Fillol (2009) compares FC and HS networks allowing for partially-served markets, and

finds that HS networks arise when costs are sufficiently low, and that flight frequency can become excessive under HS configurations.

¹⁰Therefore consumers compare fares (p_1 and p_2) and expected schedule delay (γ/f_1 and γ/f_2) of both airlines. While this approach may not be fully accurate for individual consumers, it appears to capture the choice setting of a corporate travel department, which must sign an exclusive contract with a particular airline for transporting its employees. The travel department cares about the average schedule delay for the company employees, while also seeking low fares. It signs an exclusive contract with the airline providing the best combination of these features. Alternatively, the model could apply to individual business travelers, who cannot predict their travel times and thus purchase refundable full-fare tickets, which allow them to board the next flight upon arriving at the airport. In either case, the precise departure times of individual flights are not relevant, accounting for the simplicity of the overall approach.

¹¹Analogously, the utility of a passenger traveling with carrier 2 is $u_2 = y - p_2 - \frac{\gamma}{f_2} - \lambda(4f_1 + 4f_2) + b - a$, with $a < 0$ for passengers loyal to carrier 2 and $a > 0$ for passengers loyal to carrier 1.

¹²As in Fageda and Flores-Fillol (2012a), the 100% load factor assumption could be relaxed by considering $l_1 s_1 = q_1/f_1$, where $l_1 \in [0, 1]$ stands for load factor; and $l_1 s_1$ is interpreted as the number of passengers per flight, which depends both on the load factor and the aircraft size. However, this distinction is not needed for the purposes of this analysis and therefore we do not include it to keep the setting as simple as possible. In any case, high load factors are a prerequisite for profitable operations, and the industry average load factor is around 75% (data from IATA, see www.iata.org).

¹³As suggested before, when maximizing profits, carriers do not take into account the congestion inflicted on passengers since demand functions are independent of passengers' congestion damage.

¹⁴The second-order conditions $\partial^2 \pi_1 / \partial p_1^2, \partial^2 \pi_1 / \partial f_1^2 < 0$ are satisfied by inspection. The remaining positivity condition on the Hessian determinant, which is assumed to hold, requires $p_1 - \tau > \frac{\gamma}{4f_1} - \frac{4\alpha\eta f_1^3}{\gamma}$, i.e., the margins in each of the markets operated by an airline have to be sufficiently large.

¹⁵The second-order conditions $\partial^2 \pi_1^h / \partial (p_1^h)^2, \partial^2 \pi_1^h / \partial (P_1^h)^2, \partial^2 \pi_1^h / \partial (f_1^h)^2 < 0$ are satisfied by inspection. The remaining positivity condition on the Hessian determinant, which is assumed to hold, requires $2(p_1^h - \tau) + (P_1^h - 2\tau) > 3\left(\frac{\gamma}{4f_1^h} - \frac{2\alpha\eta(f_1^h)^3}{\gamma}\right)$, i.e., the sum of margins in the three markets operated by an airline has to be sufficiently large.

¹⁶Note that the first-order condition for p_1 is the same both under FC and under HS.

¹⁷As commented in footnote 4, Fageda and Flores-Fillol (2012a and 2012b) study the surge of new point-to-point connections in thin markets in a different setting without congestion.

¹⁸See Brueckner (2002 and 2005), Mayer and Sinai (2003), and Brueckner and Van Dender (2008).

¹⁹Therefore, the rule pointed out in Brueckner and Van Dender (2008) suggesting that each airline is charged MCD^{SO} times its airport flight share (which equals 1/2 in the symmetric equilibrium) does not apply to our setting because airlines are also charged by the congestion imposed on all passengers. Levying atomistic tolls would imply charging MCD^{SO} to each airline since these kind of tolls ignore carriers' own-congestion internalization.

²⁰Recall that, under HS configurations, $s_1 = (q_1 + Q_1)/f_1$ because both local and connecting passengers travel on routes AH and BH .

²¹It is easy to observe that, in absence of congestion, $f^h > f$ and $s^h > s$.

²²By comparing Eqs. (25) and (29), we can easily observe that $f^{hSO} > f^{SO}$, but both $3f^{hSO} > 4f^{SO}$ and $3f^{hSO} < 4f^{SO}$ are possible.

²³Proposition 2 shows that $f^h \leq 1.4f$ is a sufficient condition ensuring $\Delta > 0$, whereas the sign of Δ is ambiguous for $f^h > 1.4f$.

²⁴This is a simplification because all airlines may offer connecting services in any airport when their frequencies are sufficiently high. However, we think this is sensible assumption given that the bulk of HS operations in the US domestic market are network airlines' services connecting their hub airports.

²⁵There are previous empirical literature on the determinants of delays (Mayer and Sinai, 2003; Rupp, 2009; Santos and Robin, 2010) that 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 frequency choices of airlines at the airport level, such a disaggregated analysis is not needed.

²⁶The Hausman test rejects the use of random effects, which are likely to be correlated with the explanatory variables. Furthermore, results of regressions that use variables in first differences are not satisfactory because of the very low explanatory power of the model (most of the independent variables are not statistically significant).

²⁷The Chow test shows the existence of a structural break between these two subsamples.

²⁸The results of these additional regressions are available upon request from the authors.

²⁹Previous papers examining the determinants of delays use data at the flight level, ignoring airport size (with the exception of Brueckner, 2002). However, the disaggregated analysis has some advantages because it allows analyzing the airlines behavior at a very detailed level, and some technical refinements like the inclusion of airport fixed effects can be considered.

Figures and Tables

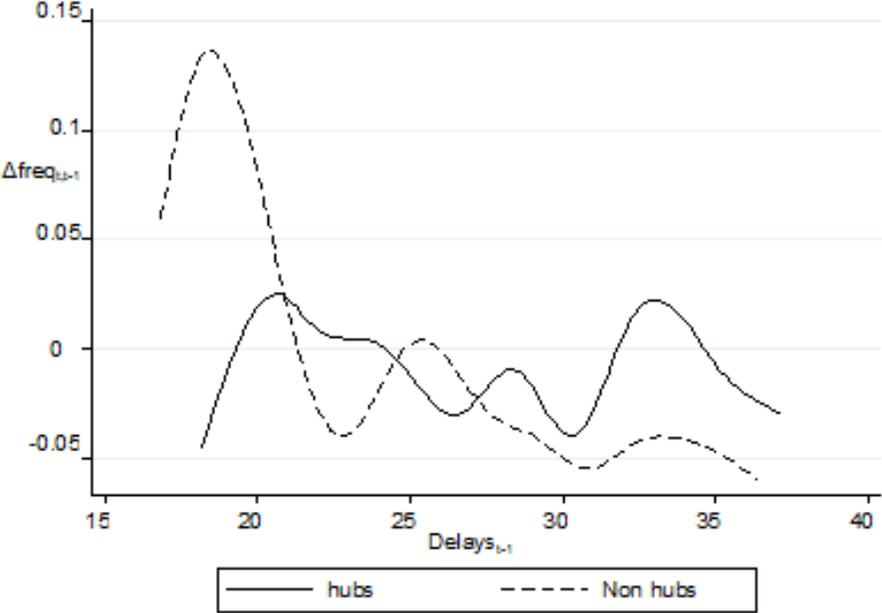


Fig. 1: Median-spline between frequencies and delays (airport level data)

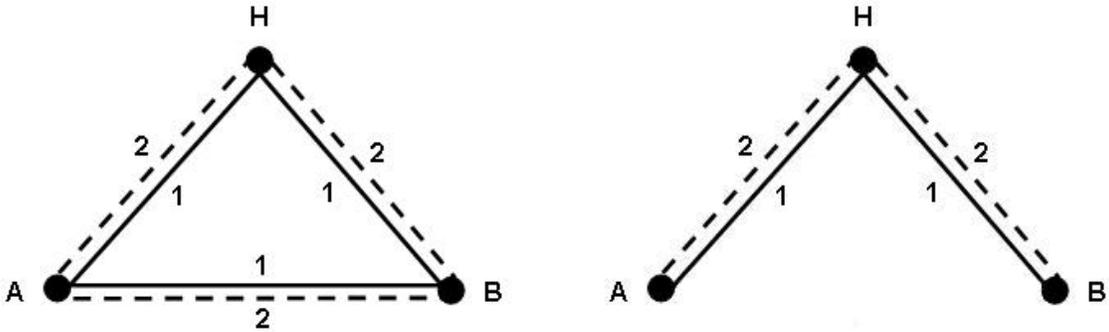


Fig. 2: The FC and HS networks

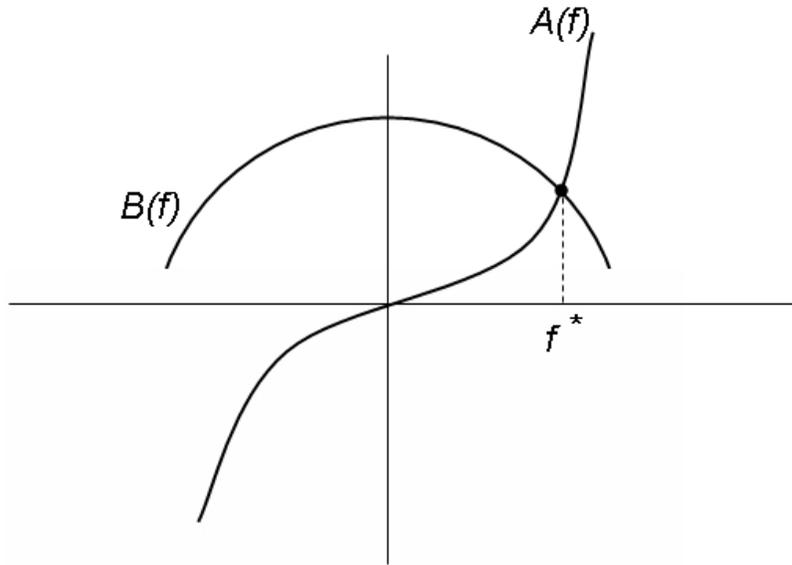


Fig. 3: The f solution

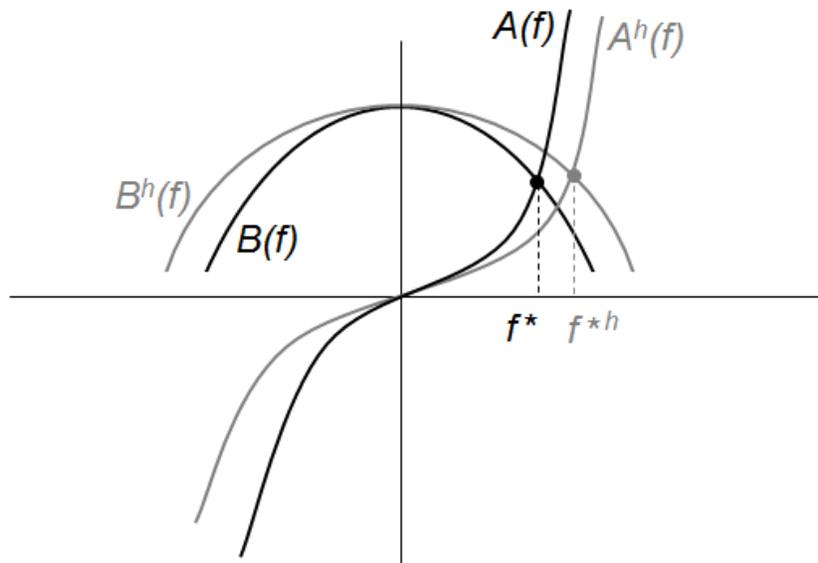


Fig. 4: Comparing f^* and f^{*h}

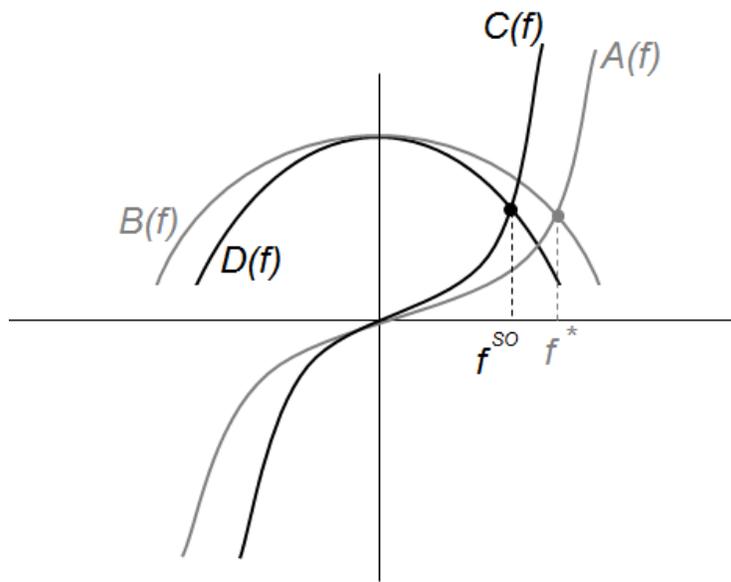


Fig. 5: Overprovision of frequency

Table 1: Delays at main airports of American Airlines and Southwest (mean values 2005-2010)

American Airlines			
Main Airports	Delayed flights (%)	Departures	Share (%)
Chicago (ORD) ¹	29.8	407,678	39.2
Dallas (DFW)	26.1	310,938	82.9
Miami (MIA)	28.3	87,713	64.3
Southwest			
Main Airports	Delayed flights (%)	Departures	Share (%)
Phoenix (PHX) ²	19.9	206,203	43.4
Baltimore (BWI)	21.8	144,633	55.2
Chicago (MDW)	23.3	117,328	78.0

Source: The figures in the first column are taken from the US Department of Transportation. Departures and flight-share data are from RDC Aviation.

Note 1: Chicago (ORD) is also a hub of United, which has a share of 49.9%.

Note 2: Phoenix (PHX) is also a main airport for US Airways, which has a share of 27.3%.

Table 2a: Airports in the sample (mean values in 2005-2010)

	Delayed flights (%)	Departures	HHI	Share dominant airline (%)
Albuquerque (ABQ)	16.8	59,341	0.3	Southwest (55.2)
Atlanta (ATL)	27.6	446,547	0.6	Delta (71.4)
Austin (BDL)	18.0	67,655	0.2	Southwest (40.8)
Hartford (BDL)	20.8	50,567	0.2	Southwest (23.4)
Nashville (BNA)	21.4	88,870	0.3	Southwest (46.3)
Boston (BOS)	25.8	172,342	0.1	US Airways (20.7)
Baltimore (BWI)	21.8	144,633	0.3	Southwest (55.2)
Cleveland (CLE)	20.8	110,792	0.4	Continental (63.3)
Charlotte (CLT)	25.2	225,141	0.7	US Airways (84.6)
Columbus (CMH)	22.5	66,130	0.2	Southwest (20.6)
Cincinnati (CVG)	22.8	140,244	0.7	Delta (86.0)
Dallas (DAL)	21.1	71,201	0.8	Southwest (90.2)
Washington (DCA)	23.3	142,909	0.3	US Airways (44.1)
Denver (DEN)	23.5	298,541	0.3	United (48.4)
Dallas (DFW)	26.1	310,938	0.7	American Airlines (82.9)
Detroit (DTW)	27.7	224,153	0.6	Northwest (74.4)
New York (EWR)	32.2	166,891	0.5	Continental (69.5)
Fort Lauderdale (FLL)	23.4	110,333	0.1	Southwest (24.2)
Houston (HOU)	23.4	79,917	0.8	Southwest (87.6)
Washington (IAD)	25.4	152,355	0.5	United (66.3)
Houston (IAH)	21.8	236,590	0.8	Continental (86.4)
Indianapolis (IND)	21.1	71,444	0.1	Northwest (21.6)
New York (JFK)	31.4	132,704	0.3	Jet Blue (35.7)/Delta (33.8)
Las Vegas (LAS)	21.7	197,007	0.3	Southwest (49.6)
Los Angeles (LAX)	19.6	254,715	0.2	United (29.9)
New York (LGA)	29.2	194,798	0.2	US Airways (33.1)
Kansas (MCI)	20.0	99,691	0.2	Southwest (35.5)

Table 2b: Airports in the sample (mean values in 2005-2010)

	Delays	Departures	HHI	Share dominant airline
Orlando (MCO)	20.7	164,616	0.2	Southwest (30.8)
Chicago (MDW)	23.3	117,328	0.5	Southwest (78.0)
Memphis (MEM)	21.9	101,050	0.6	Northwest (76.6)
Miami (MIA)	28.3	87,713	0.4	American airlines (64.3)
Milwaukee (MKE)	23.8	80,406	0.3	Frontier (47.3)
Minneapolis (MSP)	25.8	213,777	0.6	Northwest (75.4)
New Orleans (MSY)	20.9	55,998	0.2	Southwest (34.1)
Oakland (OAK)	17.8	88,861	0.6	Southwest (75.0)
Chicago (ORD)	29.8	407,678	0.4	American Airlines (39.2)/United (49.9)
West Palm Beach (PBI)	22.9	35,983	0.2	Delta (20.6)
Portland (PDX)	16.0	103,304	0.3	Alaska airlines (40.2)
Philadelphia (PHL)	28.8	220,472	0.5	US Airways (65.4)
Phoenix (PHX)	19.9	206,203	0.3	Southwest (43.4)/US Airways (27.3)
Pittsburg (PIT)	23.9	89,160	0.3	US Airways (43.7)
Raleigh-Durham (RDU)	23.2	85,184	0.2	American Airlines (24.3)
Fort Myers (RSW)	20.4	48,775	0.1	Delta (15.0)
San Diego (SAN)	17.8	115,216	0.2	Southwest (42.3)
San Antonio (SAT)	17.8	63,123	0.2	Southwest (42.5)
Seattle (SEA)	21.2	173,493	0.3	Alaska Airlines (52.3)
San Francisco (SFO)	24.9	154,106	0.3	United (53.5)
Salt Lake City (SLC)	18.2	155,003	0.5	Delta (70.4)
Sacramento (SMF)	17.6	70,241	0.3	Southwest (54.9)
Santa Ana (SNA)	17.4	58,518	0.2	Southwest (30.2)
St. Louis (STL)	20.9	130,148	0.3	American Airlines (39.6)

Note 1: Airline share data of airports dominated by either Delta or Northwest refer to the period 2005-2009.

Table 3: Descriptive statistics

	Mean	Standard deviation	Min	Max
$Freq_{i,a,t}$	14,521.28	32,927.01	2	341,833
$Pop_{u,t-1}$	4,624,362	4,491,739	539,097	1.91e+07
$GDPpc_{u,t-1}$	28,915	4,252	21,367	41,929
$Delays_{a,t-1}$	23.38	5.10	13.44	38
$D_{i,a}^{hub}$	0.03	0.19	0	1
$D_{i,a}^{hub} \times Delays_{a,t-1}$	1.05	5.27	0	38
$HHI_{a,t-1}$	0.33	0.19	0.1	0.9

Table 4: Estimates of airline frequencies at the airport level - OLS and airport fixed effects

	All airports		Concentrated airports		Hub airports		Non-hub airports	
	OLS (1)		OLS (2)		Airport fixed effects (3)		Airport fixed effects (4)	
$Pop_{u,t-1}$	0.00025 (0.00005)***		0.00019 (0.00013)		0.0013 (0.0018)		0.0005 (0.0006)	
$GDPpc_{u,t-1}$	0.02 (0.03)		-0.08 (0.05)		0.23 (0.29)		-0.33 (0.18)*	
$Delays_{a,t-1}$	-177.16 (59.17)**		-298.34 (114.33)**		43.41 (58.47)		-162.15 (71.16)**	
$D_{i,a}^{hub}$	92,159.07 (12,168.78)***		63,398.20 (10,749.29)***		—		—	
$D_{i,a}^{hub} \times Delays_{a,t-1}$	1,561.93 (500.77)**		3,046.62 (460.35)***		—		—	
D_t^{2006}	1,681.23 (173.26)***		532.38 (163.01)***		-578.54 (536.30)		2,131.39 (232.04)***	
D_t^{2007}	1,824.21 (256.33)***		1,114.01 (456.78)**		-3.02 (843.74)		2,934.58 (368.53)***	
D_t^{2008}	1,377.81 (381.13)***		248.58 (656.93)		-1,114.82 (1,223.63)		3,243.20 (583.95)***	
D_t^{2009}	273.05 (182.04)		-872.61 (268.41)**		-2,334.57 (15,195.78)		2,069.81(562.45)***	
D_t^{2010}	-1,382.77 (103.73)***		-2,165.77 (305.98)***		-2,706.44 (1,242.85)**		-1,282.84 (547.44)**	
$Constant$	11,471.15 (476.67)***		16,959.47 (1,455.40)***		6,676.31 (12,954.45)		20,076.48 (5,263.08)***	
R^2	0.63		0.73		0.04		0.12	
$Test F$ (joint significance)	45.48***		41.01***		4.84***		17.73***	
N	2,821		1,176		1,050		1,771	

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

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

Table 5: Elasticities of main variables evaluated at sample mean

	All airports OLS (1)	Concentrated airports OLS (2)	Hub airports Airport fixed effects (3)	Non-hub airports Airport fixed effects (4)
$Delays_{a,t-1}$	-0.28 (0.09)***	-0.36 (0.20)*	0.05 (0.07)	-0.32 (0.14)**
$D_{i,a}^{hub}$	0.24 (0.03)***	0.26 (0.11)**	—	—
$D_{i,a}^{hub} \times Delays_{a,t-1}$	0.11 (0.03)***	0.32 (0.11)***	—	—

Table 6: Estimates of delays at the airport level - OLS

	Coefficients	Elasticities evaluated at sample mean
$Freq_{a,t-1}$	0.000014 (3.28e-06)***	0.09 (0.02)***
D_a^{hub}	2.75 (0.46)***	0.04 (0.007)***
$HHI_{a,t-1}$	-0.80 (1.06)	-0.013 (0.01)
D_t^{2007}	2.30 (0.12)***	0.02 (0.001)***
D_t^{2008}	-0.36 (0.14)***	-0.003 (0.001)***
D_t^{2009}	-4.04 (0.12)***	-0.005 (0.001)***
D_t^{2010}	-3.70 (0.11)***	-0.03 (0.0009)***
<i>Constant</i>	21.11 (0.26)***	—
R^2	0.44	—
<i>Test F (joint significance)</i>	28.52***	—
N	255	—

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

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