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Scheduled service versus personal transportation: The role of distance

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ABSTRACT

This paper presents a theoretical and empirical analysis of the relationship between frequency of scheduled transportation services and their substitutability with personal transportation (using distance as a proxy). We study the interaction between a monopoly firm providing a high-speed scheduled service and private transportation (i.e., car). Interestingly, the carrier chooses to increase the frequency of service on longer routes *when competing with personal transportation* because by providing higher frequency (at extra cost) it can also charge higher fares which can boost its profits. However, in line with the results of earlier studies, frequency decreases for longer flights *when driving is not a viable option*. An empirical application of our analysis to the European airline industry confirms the predictions of our theoretical model.

1. Introduction

A problem faced by companies providing scheduled transportation (airlines, railway companies, etc.) is that it is impossible to achieve the level of mobility offered by the use of a private vehicle. Customers traveling by car do not have to bear a schedule delay cost inherent to the limited choice of departure times that characterizes scheduled services. However, providers of scheduled transportation can make their product more attractive when competing with consumers' personal vehicles by offering high-frequency, high-speed services. There are also cases in which driving is not a relevant alternative (when the distance between the endpoints is particularly long), and in this case a scheduled carrier has to make its service attractive with respect to the option of not traveling at all. These two problems may have different solutions; however, no differentiation between them has been offered in the literature.

This paper fills this void by examining fare and frequency choices of a monopoly provider of scheduled transportation services. We compare the case where the customer's next best available alternative is driving with the scenario where driving is not a relevant option (i.e., it is a dominated alternative). The model yields testable predictions regarding frequency–distance relationships, which we put to the test using data from the European airline industry (where services are provided by a single carrier on over 60% of airport-pair markets).

In the theoretical part, we model a carrier (which we will consider to be an airline, although the analysis is easily applicable to high-speed rail as well) choosing fares and frequency of services, given that it enjoys an exogenous advantage in terms of higher speed of service than the private vehicle. This part builds on Brueckner (2004), Brueckner and Flores-Fillol (2007) and Bilotkach (2009). Brueckner (2004) considers a monopoly airline's network choice, incorporating decisions concerning frequency in the model. Brueckner and Flores-Fillol (2007) use this framework to analyze fare and frequency choices in duopoly markets. Finally, Bilotkach (2009) introduces a valuation of time similar to the one we use here in a model of airlines' network choice.

We find that the monopolist's choice crucially depends on whether driving is a dominated option or not. The carrier will reduce the frequency of service for longer trips when driving is dominated but, more interestingly, the relationship between frequency and distance may reverse when driving is not dominated and carriers compete with personal transportation.

Our result is explained by a trade-off between two forces. First, the provider of scheduled transportation services will always incur an extra cost when increasing frequency. Indeed, higher frequency implies additional fixed costs and reduces the opportunity of exploiting

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density economies which, in the case of airlines, arise from the use of bigger aircraft at high load factors. Second, an increase in distance may boost the demand for high-speed scheduled transportation services on short-haul routes where the use of personal vehicles is a relevant option for travelers. This is because an increase in distance makes the high-speed transportation mode more competitive and so providers of scheduled transportation services are able to increase frequency and charge higher fares.

On short-haul routes, our theoretical model shows that the positive effect of distance on frequency derived from charging higher fares outweighs the negative effect derived from incurring extra costs. This explains the main result of our analysis: the positive relationship between frequency and distance on routes where personal transportation is a relevant option. However, on long-haul routes where driving is a dominated option, an increase in distance does not necessarily imply an increase in the demand for scheduled services. Hence, we can expect a negative relationship between frequency and distance since the provider of scheduled services tries to minimize costs (and avoid potential travelers staying at home). Finally, from the perspective of the social optimum, we find that a monopoly carrier provides lower frequency of service than is socially optimal and the number of passengers making use of the scheduled transportation services is inefficiently low (as is usual for models of this kind).

Our model relates to the issue of intermodal competition and choice of transport mode. In this vein, Combes and Linnemer (2000) consider a model à la Hotelling in which two transportation modes compete (car and airplane) when a new infrastructure is built. More recently, Cantos-Sánchez et al. (2009) study alternative regulatory regimes in a model of intermodal competition and suggest an empirical application to the Spanish market. The issue of mode substitution and its effects has also been discussed, for example by Bel (1997), González-Savignat (2004), Janic (2003) and López-Pita and Robusté (2004). Some studies on choice of transport mode conclude that commuters mostly consider frequency of service (and more generally convenience of service) as one of the factors determining their elasticity (Voith, 1997 and Asensio, 2002); or the impact of urban transit projects (Baum-Snow and Kahn, 2000). Since with longer distances scheduled services become more attractive than personal transportation, due to their higher speed, we study how the monopolist's choice changes as the substitutability between the two transportation options increases.

We test the predictions of our theoretical model concerning the relationship between the length of haul and frequency using data on annual frequencies at the airline-route level. Our sample includes about 900 routes that link the ten largest airports in Europe with other European destinations (EU27+Switzerland and Norway) in the period 2006–2007. The empirical application examines the relationship between airlines' frequency choices and distance controlling for demand shifters at the route level, the attractiveness of air transport with respect to cars, the intensity of competition and airline attributes. A spline regression that shows the relationship between frequency and distance in our dataset makes it advisable to differentiate between routes shorter and longer than around 500 km (311 miles). Interestingly, the empirical application shows that airlines' frequency increases with distance for short-haul routes. In contrast, frequency decreases with distance for long-haul routes. Thus, the predictions of the theoretical model are confirmed. As expected, frequency increases with demand (captured by several variables) and with better airport access. We also find that airlines compete aggressively in frequency of service, low-cost carriers provide lower quality products, and airport presence strongly influences the number of flights that airlines offer on the routes served.

Previous empirical work has analyzed the determinants of airlines' flight frequency. Borenstein and Netz (1999) and Salvanes et al. (2005) find that airlines cluster the departure times of flights when competition increases in their studies for the US and Norway, respectively. Our empirical application is more closely related to the studies by Pai (in press) and Wei and Hansen (2007). Pai (in press) estimates the determinants of flight frequency in the US airline market, observing a decreasing relationship between frequency and distance. From a different perspective, Wei and Hansen (2007) develop an application for three game-theoretic models of airline choices, obtaining that frequency on long-haul routes is less than on short-haul routes. These findings are in line with our results when driving is a dominated option. Thus, although these two previous studies adequately explain the relationship between frequency and distance on long-haul routes, our results suggest that the applicability of their findings to short-haul markets is limited.[3]

To sum up, the main contribution of this paper is to point out that the relationship between frequency choices and distance depends crucially on the presence of personal transportation, a finding identified theoretically and tested empirically for the European airline industry. Thus, the distance between endpoints in city-pair markets constitutes a potentially important factor to be considered when analyzing scheduled transportation services.

The plan of the paper is as follows. Section 2 presents the model and the equilibrium and compares the equilibrium outcome with the social optimum. An empirical application to the European airline market is provided in Section 3 and a brief conclusion closes the paper. All the proofs are provided in the Appendix.

2. The model

Our model is based on indirect utilities of heterogeneous travelers choosing between scheduled services and personal transport. We consider an air carrier as the provider of scheduled services, for the purpose of exposition, but other modes of transportation (in particular, the high-speed train) can easily fit into our framework.

The model combines elements of Brueckner's (2004) monopoly scheduling model along with a differentiation of consumers by their value of time similar to the one suggested in Bilotkach (2009). In the model, utility for a consumer *traveling by air* is given by *Consumption – Schedule delay disutility + Value of available time*. *Consumption* is $y - p_{\text{air}}$ where y is the common level of income and p_{air} is the airline's fare.

Letting H denote the time circumference of the circle, consumer utility then depends on *expected schedule delay* (defined as the difference between the preferred and actual departure times) which equals $H/4f$, where f is number of (evenly spaced) flights operated by the airline. The *Schedule delay disutility* is equal to a disutility parameter $\delta > 0$ times the expected schedule delay expression from above, thus equaling $\delta H/4f = \gamma/f$, where $\gamma \equiv \delta H/4$. We assume that all passengers value frequency equally and thus the parameter γ is common for all of them. Passenger heterogeneity arises here through travelers' value of time, as it is explained below.

Finally, the available time at the destination is computed as the difference between passenger's total trip time (T) and the actual traveling time which depends on the distance between the origin and the destination (d) and the plane's speed (V), thus equaling $T - d/V$. We assume a large enough T so that $T > d/V$. Thus, taking into account the traveler's specific value of time α, the *Value of available time* at the destination equals $\alpha(T - d/V)$, where α is assumed to be uniformly distributed over the range [0,1]. Hence, utility from air travel is

$$u_{\text{air}} = y - p_{\text{air}} - \gamma / f + \alpha[T - d / V]. \quad (1)$$

However, consumers can also make use of an alternative surface transport mode (i.e., car) obtaining a utility of *Consumption + Value of*

[3] Additionally, unlike the US airline industry, European airline markets have been relatively under-researched (due predominantly to the lack of sufficient data).

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available time since there is no schedule delay in this case. Therefore utility from driving is

$$u_{\mathrm{car}} = y - cd + \alpha[T - d/(\beta V)], \tag{2}$$

where cd is the cost of the trip that increases with distance, β captures the airline/car speed differential and $\beta \in (0,1/2)$, i.e., we assume that traveling by car is at least twice as slow as air travel, and T is large enough so that $T > d/(\beta V)$.[4]

Observe that, since air travel is faster than travel by private vehicle, the $u_{\mathrm{air}} - u_{\mathrm{car}}$ differential is greater the higher the consumer's value of time (α). In other words, both u_{air} and u_{car} increase with α, but u_{air} is steeper than u_{car}. This basically ensures that the higher a consumer's value of time, the more likely she is to fly rather than drive, other things being equal.

Additionally, we allow for partially-served markets because consumers can also choose not to travel and stay at home, obtaining a utility of $u_{\mathrm{o}} = y$. Then, disregarding the trivial cases (either where nobody travels or where everyone uses the same mode of transport), we can state the following: a consumer will undertake air travel when $u_{\mathrm{air}} > \max\{u_{\mathrm{car}}, u_{\mathrm{o}}\}$. The inequality $u_{\mathrm{air}} > u_{\mathrm{car}}$ requires $\alpha > \tilde{\alpha}$ with

$$\tilde{\alpha} = \frac{(p_{\mathrm{air}} - cd + \gamma/f)\beta V}{d(1-\beta)}; \tag{3}$$

and the inequality $u_{\mathrm{air}} > u_{\mathrm{o}}$ holds for $\alpha > \overline{\alpha}$ with

$$\overline{\alpha} = \frac{p_{\mathrm{air}} + \gamma/f}{T - d/V}. \tag{4}$$

Finally, a consumer will drive when $u_{\mathrm{car}} > \max\{u_{\mathrm{air}}, u_{\mathrm{o}}\}$, where $u_{\mathrm{car}} > u_{\mathrm{air}}$ requires $\alpha < \tilde{\alpha}$ and $u_{\mathrm{car}} > u_{\mathrm{o}}$ requires $\alpha > \hat{\alpha}$ with

$$\hat{\alpha} = \frac{cd}{T - d/(\beta V)}. \tag{5}$$

Consumers with sufficiently high value of time will undertake air travel and consumers with sufficiently low time value will stay at home. Consequently, we are left with two possible scenarios depending on whether driving is a dominated alternative or not: the *case with drivers* where $0 < \hat{\alpha} < \tilde{\alpha} < 1$ (Scenario 1); and the *situation where there are no drivers* with $0 < \tilde{\alpha} < \hat{\alpha} < 1$ (Scenario 2). These two scenarios are represented in Figs. 1 and 2 below, where we observe that u_{air} is steeper than u_{car} because $\beta \in (0,1/2)$; also, the figures show that passengers with higher value of time (i.e., larger α) are more likely to travel by air.

The case with drivers (Scenario 1) requires $\hat{\alpha} < \tilde{\alpha}$ and, from this inequality we obtain $\left(\frac{p_{\mathrm{air}}V}{\beta} + cTV^2 + \frac{\gamma V}{\beta f}\right)d - TV^2\left(p_{\mathrm{air}} + \frac{\gamma}{f}\right) < cd^2V$. Then, it can be shown that this condition requires $d < d^*$, so we conclude that Scenario 1 is only relevant for short distances, meaning that driving is considered a viable alternative by some consumers only for sufficiently short-haul trips. Lemma 1 below summarizes this result (a detailed proof is provided in Appendix A).

Lemma 1. *Given the indirect utilities specified above, there is a single cut-off distance d^* such that Scenario 1 (with drivers) is observed for $d < d^*$ (short-haul city-pair markets); while Scenario 2 (without drivers) emerges for $d > d^*$ (long-haul city-pair markets).*

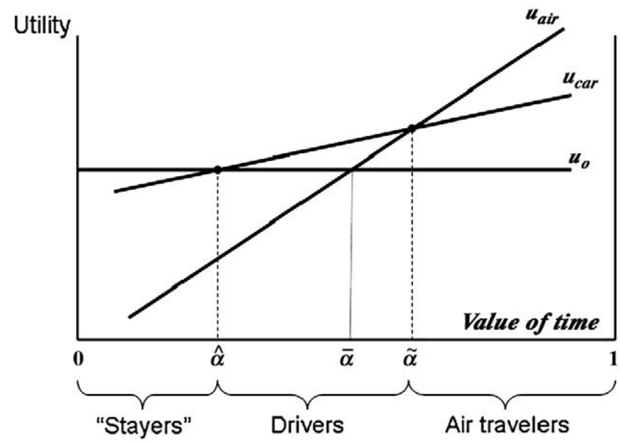

Fig. 1. Utilities in Scenario 1.

Looking at our data for the European airline markets examined in the empirical application in Section 3, this cut-off distance d^* is evaluated at around 500 km (311 miles).

For each of the two scenarios, the analysis that follows derives the demand functions, specifies the airline's cost structure, and describes the profit functions. Afterwards, both the equilibrium and the social optimum are analyzed in each scenario.

2.1. Scenario 1: driving is not a dominated alternative

Under Scenario 1, a traveler will fly when $\alpha > \tilde{\alpha}$. Otherwise, the consumer will use private transportation or stay at home. Then, using Eq. (3), the airline's demand is given by

$$q_{\mathrm{air}} = \int_{\tilde{\alpha}}^{1} d\alpha = 1 - \tilde{\alpha} = 1 - \frac{(p_{\mathrm{air}} - cd + \gamma/f)\beta V}{d(1-\beta)}. \tag{6}$$

To characterize the equilibrium in fares and frequencies,[5] we need to specify the carrier's cost structure. A *flight's operating cost* is given by $\theta(d) + \tau s$ where s stands for aircraft size (i.e., the number of seats). The parameter τ is the marginal cost per seat of serving the passenger on the ground and in the air. Finally, the function $\theta(d)$ stands for the cost of frequency (or cost per departure) that captures the aircraft fixed cost which includes landing and navigation fees, renting gates, airport maintenance and the cost of fuel. We assume that $\theta(d)$ is continuously differentiable with respect to $d > 0$ and that $\theta'(d) > 0$ because fuel consumption increases with distance.

As in Brueckner (2004), it is assumed that all seats are filled, so that load factor equals 100% and therefore $s = q_{\mathrm{air}}/f$, i.e., aircraft size can be determined residually dividing the airline's total traffic on a route by the number of flights. Note that cost per seat, which can be written $\theta(d)/s + \tau$, visibly decreases with s capturing the presence of economies of traffic density (i.e., economies from operating a larger aircraft holding the load factor constant) which are unequivocal in the airline industry.[6] In other words, having a larger traffic density on a certain route reduces the impact on the cost associated with higher frequency.

Therefore, the airline's total cost from operating on a route is $f[\theta(d) + \tau s]$ or equivalently

$$c = \theta(d)f + \tau q_{\mathrm{air}}. \tag{7}$$

[4] Note that V and βV just capture airline's and car's speed respectively. The fact that personal transportation is more flexible and may be more convenient (and even take less time) is captured through the schedule delay element (that only affects airlines). While schedule delay is not included in the empirical application, we incorporate in the econometric specification elements such as road quality and the distance between air travel and personal transportation. Also note that cars are much slower than new high-speed trains, which have been designed to reach a speed above 250 km/h.

[5] On the other hand, a traveler will prefer to drive instead of stay at home (i.e., not travel at all) for $\alpha > \hat{\alpha}$; and thus, $q_{\mathrm{car}} = \int_{\hat{\alpha}}^{\tilde{\alpha}} d\alpha = \tilde{\alpha} - \hat{\alpha}$ and $q_{\mathrm{o}} = \int_{0}^{\hat{\alpha}} d\alpha = \hat{\alpha}$. The demand for the three possible consumer options is determined by the choices made by the airline. However, the focus of the paper is the airline's frequency choice.

[6] Empirical studies confirming presence of economies of traffic density in the airline industry include Caves et al. (1984), Brueckner and Spiller (1994) and Berry et al. (2006).

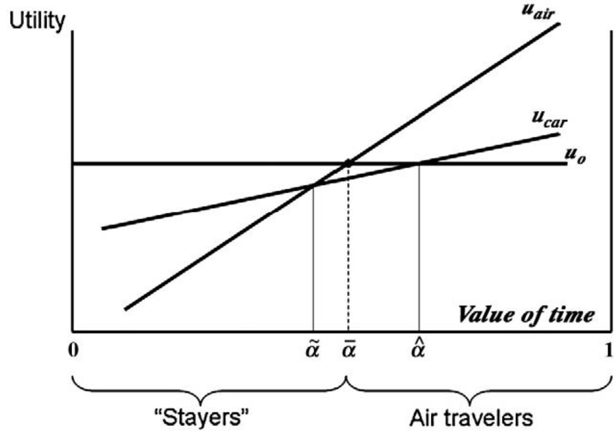

Fig. 2. Utilities in Scenario 2.

This cost function has two elements (i.e., cost per departure and cost of seats), which allow us to isolate the expenses associated to two important instruments for airlines: flight frequency and aircraft size.[7]

Thus the airline's profit is $\pi_{air} = p_{air}q_{air} - c$, which can be rewritten using Eq. (7) as

$$\pi_{air} = (p_{air} - \tau)q_{air} - \theta(d)f, \tag{8}$$

indicating that average variable costs are independent of the number of flights.

After plugging Eq. (6) into Eq (8) and maximizing, the first-order condition for the fare is

$$\frac{\partial \pi_{air}}{\partial p_{air}} = 1 - \frac{\beta V}{d(1-\beta)}(2p_{air} - cd + \gamma/f - \tau) = 0, \tag{9}$$

and, from this condition, it is easy to obtain the following expression

$$p_{air} = \frac{1}{2}\left(cd + \tau - \gamma/f + \frac{d(1-\beta)}{\beta V}\right), \tag{10}$$

so that fares increase with variable costs and with distance, and they decrease with schedule delay and with the speed of personal transportation (βV).

On the other hand, the first-order condition for frequency is given by

$$\frac{\partial \pi_{air}}{\partial f} = \frac{(p_{air} - \tau)\gamma\beta V}{d(1-\beta)f^2} - \theta(d) = 0, \tag{11}$$

or equivalently by

$$f = \left(\frac{(p_{air} - \tau)\gamma\beta V}{\theta(d)d(1-\beta)}\right)^{1/2}, \tag{12}$$

indicating that frequency increases with passengers' disutility of delay, carrier's margin ($p_{air} - \tau$) and the speed of personal transportation, and decreases with the cost of frequency and distance.

The second-order conditions $\partial^2\pi_{air}/\partial^2 p_{air}$, $\partial^2\pi_{air}/\partial f^2 < 0$ are satisfied by inspection and the remaining positivity condition on the Hessian determinant is discussed below. By combining the two first-order conditions, we obtain the following equilibrium condition

$$\underbrace{\frac{2\theta(d)d(1-\beta)}{\gamma\beta V}f^3}_{Cf^*} = \underbrace{\left(cd - \tau + \frac{d(1-\beta)}{\beta V}\right)f - \gamma}_{Lf^*}. \tag{13}$$

The equilibrium frequency is shown graphically in Fig. 3, as in Brueckner (2004) and Brueckner and Flores-Fillol (2007), where we observe that the f solution occurs at an intersection between a cubic expression (Cf^*) and a linear expression (Lf^*) whose vertical intercept is negative. The slope of Lf^* must be positive for the solution to be positive and thus we assume that τ is small enough for this to be the case. We observe that there are two possible positive solutions, but only the second one satisfies the second-order condition.[8]

Looking at Eq. (13) together with Fig. 3, we can carry out a comparative statics analysis for all the parameters in the model. Although some effects do not seem trivial from inspection of Eq. (13), the lemma below ascertains the overall effect by analyzing the sign of the total differential of the equilibrium frequency with respect to each parameter.

Lemma 2. *In Scenario 1, the equilibrium frequency falls with an increase in the marginal cost per seat (τ). Frequency also decreases with the speed of both plane (V) and car (β) if $\tau > cd$. However, it rises with the cost of driving (c) and the disutility of delay (γ) for small values of β.*

Looking at the effect of distance on the equilibrium flight frequency, although the effect is in general indeterminate, we observe that $\frac{df^*}{dd} > 0$ can hold at least for sufficiently low distances.

As expected, when the cost of driving (c) rises, the equilibrium frequency also increases because the car becomes a worse option and more passengers choose air travel. There is also a positive relationship between γ and f^* when β is small since carriers increase frequency as passengers' disutility of delay increases. When the marginal cost per seat (τ) increases, frequency falls since air travel becomes a less competitive option.

Note that β is the airline/car speed differential and that when β increases the car's speed increases relative to that of the airplane, and driving becomes a more attractive option for travel (for $\tau > cd$, so that the cost per seat is higher than the cost of driving). Thus, more passengers prefer personal transportation and flight frequency falls. Finally, the effect of plane's speed (V) seems to be somewhat counterintuitive since frequency falls when V rises (again for $\tau > cd$). Yet, higher speed of the aircraft means that the traveler reaches her final destination faster, compensating for the disutility of schedule delay.

Looking at the effect of distance on equilibrium frequency, our result suggests that the airline may choose to increase the frequency of service as distance increases. This result appears counterintuitive at first. Indeed, with longer distance driving becomes a less attractive substitute for flying, as the ratio of remaining time for the driver to remaining time for the flyer $\frac{T - d/(\beta V)}{T - d/V}$ shrinks with distance. Then, as distance increases, the airline will have less incentive to increase the quality of its product, and can simply charge the customers more as demand grows by itself. In fact, the first-order condition for f (see Eq. (12)) tells us exactly that: with higher distance, other things being equal, our carrier can afford to reduce the frequency (and save money). Thus, distance has a *negative direct effect* on frequency.

The answer to this puzzle lies in the first-order condition for p_{air} which shows a *positive indirect effect* of distance on frequency through

[7] For instance, when demand increases, a carrier may decide to increase frequency or, alternatively, to use larger aircraft. On the one hand, by increasing frequency, airlines provide a "higher-quality" product and decrease their schedule delay, but they incur an extra cost of departure. On the other hand, by increasing aircraft size, they reduce the cost per passenger because of the presence of economies of traffic density.

[8] Positivity of the Hessian determinant requires $p_{air} - \tau > \frac{\gamma}{4f}$. Observe that for the second intersection to be relevant, the slope of Cf^* must exceed the slope of Lf^*, i.e., $\frac{6\theta(d)d(1-\beta)}{\gamma\beta V}f^2 > cd - \tau + \frac{d(1-\beta)}{\beta V}$. Using the first-order conditions for p_{air} and f, this expression reduces to $p_{air} - \tau > \frac{\gamma}{4f}$, which is exactly the condition required by the positivity of the Hessian determinant.

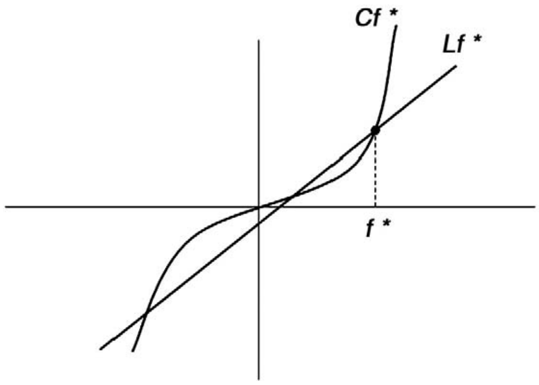

Fig. 3. The f^* solution.

fares (see Eq. (10)) since $p_{\text{air}}\left(\substack{d\\+}\right)$ and $f\left(\substack{p_{\text{air}}\\+}\right)$. The lemma above suggests that the *indirect effect* may prevail.

Air travel is perceived as a better option than driving as distance increases because it is faster and reduces travel time and, as a consequence, our monopoly carrier faces a higher demand as distance increases. Since there is a positive relationship between p_{air} and f, when facing a higher demand (as distance increases) our monopolist can boost profits by increasing flight frequency. Thus, in addition to the marginal cost associated with higher frequency, the airline can obtain the marginal benefit in terms of the higher price it will be able to charge (in addition to the price increase due to longer distance already present in Eq. (10)). What Lemma 2 says, then, is that the airline will increase its service quality (frequency) when the marginal benefit from doing so outweighs the marginal cost; moreover, the set of parameter values where this will happen will be non-empty.

2.2. *Scenario 2: driving is a dominated alternative*

The case without drivers is not nearly as exciting: we observe the empirically confirmed decreasing relationship between frequency and distance. Under Scenario 2, a traveler will fly when $\alpha > \overline{\alpha}$ and stay home otherwise. From Eq. (4), demand for air travel is given by

$$q_{\text{air}} = \int_{\overline{\alpha}}^{1} d\alpha = 1 - \overline{\alpha} = 1 - \frac{p_{\text{air}} + \gamma / f}{T - d / V}, \tag{14}$$

and costs and profits are as in Scenario 1 (see Eqs. (7) and (8)). After plugging Eq. (14) into the profit function and maximizing, the first-order conditions for fares and frequencies are

$$\begin{aligned} \frac{\partial \pi_{\text{air}}}{\partial p_{\text{air}}} &= 1 - \frac{1}{T - d / V}(2p_{\text{air}} + \gamma / f - \tau) = 0, \\ \frac{\partial \pi_{\text{air}}}{\partial f} &= \frac{(p_{\text{air}} - \tau)\gamma}{(T - d / V)f^2} - \theta(d) = 0 \end{aligned} \tag{15}$$

From the fare first-order condition, we obtain

$$p_{\text{air}} = \frac{1}{2}(T - \gamma / f - d / V + \tau), \tag{16}$$

which shows that fares rise with passengers' total time, variable costs and aircraft's speed, and fall with schedule delay and distance. Comparing Eqs. (10) and (16), we observe that p_{air} increases with distance in Scenario 1, but the sign of this effect changes in Scenario 2. This is explained by the different kinds of competition existing in the two scenarios. On the one hand, when competing against driving, flying becomes more attractive as distance increases and thus the airline can increase fares. On the other hand, when competing against staying at home, flying becomes less attractive for longer distances and the airline tries to compensate this negative effect by lowering fares.

From the first-order condition for frequency, we get

$$f = \left(\frac{(p_{\text{air}} - \tau)\gamma V}{\theta(d)(TV - d)}\right)^{1/2}, \tag{17}$$

showing that frequency increases with passengers' disutility of delay, carrier's margin ($p_{\text{air}} - \tau$) and airline's speed, whereas it decreases with passengers' total time and the cost of frequency. Differently from Scenario 1, the effect of distance on f is unclear.

By combining the two first-order conditions, we obtain the following equilibrium condition

$$\underbrace{\frac{2\theta(d)(TV - d)}{\gamma} f^3}_{Cf^*} = \underbrace{(TV - d - \tau V)f - \gamma V}_{Lf^*}. \tag{18}$$

As in Scenario 1, the f solution occurs at an intersection of Cf^* and Lf^* whose vertical intercept is negative. It is sufficient to assume a large T to have a positive sloping Lf^* so that there are positive values for f^*. As in Scenario 1, there are two possible positive solutions, but only the second one satisfies the second-order condition.[9]

The comparative statics effects are summarized in the lemma below.

Lemma 3. *In Scenario 2, equilibrium flight frequency falls with an increase in the marginal cost per seat (τ). However, frequency rises with the disutility of delay (γ), the plane's speed (V) and passengers' total time (T).*

Finally, looking at the effect of distance, we observe that $\frac{df^*}{dd} < 0$, i.e., equilibrium flight frequency decreases with distance.

As under Scenario 1, we observe a positive effect of γ on f^*, and a negative effect of τ on f^*. When passengers' total time (T) rises, more passengers are willing to undertake air travel since the utility of flying increases and, as a consequence, the equilibrium frequency increases. Finally, when the plane's speed increases (V), we observe the same effect as with T, i.e., the valuation of air travel increases and thus the equilibrium frequency rises.

Looking at the effect of distance, from the first-order conditions we observe that the *direct effect on frequency is unclear* (see Eq. (17)) and there is a *negative indirect effect* through fares (see Eq. (16)) since $p_{\text{air}}\left(\substack{d\\-}\right)$ and $f\left(\substack{p_{\text{air}}\\+}\right)$. The above lemma states that the indirect effect outweighs the direct one.

Combining the results from Lemmas 1–3, we deduce that the equilibrium frequency can increase with distance when driving is not a dominated option (i.e., Scenario 1), whereas it decreases with distance when driving is disregarded by consumers as a relevant mode of transport (i.e., Scenario 2), as stated in the proposition that follows.

Proposition 1. *From Lemmas 1–3 we conclude that equilibrium frequency*

i. *may increase with distance for $d < d^*$;*
ii. *decreases with distance for $d > d^*$.*

Hence, when driving is a dominated alternative (i.e., $d > d^*$), flight frequency decreases with distance, confirming the results in Wei and Hansen (2007) and Pai (in press). More interestingly, when driving is not a dominated alternative (i.e., $d < d^*$), air travel is perceived as a better option than driving as distance increases because it is faster and reduces travel time. Then airlines increase service quality with distance by offering higher frequency at a higher fare.

As we suggested above, our result is due to a trade-off between two forces. On the one hand, increasing frequency always implies an

[9] The second-order conditions $\partial^2\pi_{\text{air}}/\partial p_{\text{air}}^2$, $\partial^2 \pi_{\text{air}}/\partial f^2 < 0$ are satisfied by inspection and the remaining positivity condition on the Hessian determinant is the same as in Scenario 1, i.e., $p_{\text{air}} - \tau > \frac{\gamma}{4f}$. Again as in Scenario 1, for the second intersection to be relevant, the slope of Cf^* must exceed the slope of Lf^*; and this condition exactly reduces to $p_{\text{air}} - \tau > \frac{\gamma}{4f}$.

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extra cost for the provider of scheduled transportation services in terms of higher fixed costs and lower benefits from density economies which, in the case of airlines, arise from using bigger aircraft at high load factors. On the other hand, an increase in distance may boost the demand for high-speed scheduled transportation services on short-haul routes where the use of private vehicles is a relevant option for travelers. This is because an increase in distance makes the high-speed transportation mode more competitive and so providers of scheduled transportation services are able to increase frequency and charge higher fares. Thus, the relationship between frequency choices and distance depends crucially on the presence of personal transportation.

2.3. The social optimum

Having analyzed the monopoly airline's choice, our attention now shifts to welfare analysis in which a social planner decides flight frequency and traffic so as to maximize social surplus, which is computed as the sum of total utility and airline profit. More precisely, the planner chooses the air-travel/driving margin (α^*) and the driving/staying margin (α^{**}). We need to differentiate between the two scenarios.

Scenario 1: driving is not a dominated alternative

Total utility for passengers undertaking air travel is $U_{air} = \int_{\alpha^*}^{1}[y - p_{air} - \gamma/f + \alpha(T - d/V)]d\alpha$, and carrying out the integration we obtain

$$U_{air} = (y - p_{air} - \gamma/f)(1 - \alpha^*) + \frac{T - d/V}{2}\left(1 - \alpha^{*2}\right). \tag{19}$$

Total utility for driving passengers is $U_{car} = \int_{\alpha^{**}}^{\alpha^*}[y - cd + \alpha(T - d/(\beta V))]d\alpha$, and integrating across drivers we obtain

$$U_{car} = (y - cd)(\alpha^* - \alpha^{**}) + \frac{T - d/(\beta V)}{2}\left(\alpha^{*2} - \alpha^{**2}\right). \tag{20}$$

Finally, total utility for "stayers" is[10]

$$U_o = \int_0^{\alpha^{**}} y d\alpha = y\alpha^{**}. \tag{21}$$

From Eq. (8), airline's total profit equals $\pi_{air} = (p_{air} - \tau)\int_{\alpha^*}^{1} d\alpha - \theta(d)f$ and after integrating across flyers it becomes

$$\pi_{air} = (p_{air} - \tau)(1 - \alpha^*) - \theta(d)f. \tag{22}$$

The total welfare function is computed by adding utilities and profits, i.e., $W = U_{air} + U_{car} + U_o + \pi_{air}$.[11] This expression, after substituting Eqs. (19), (20), (21) and (22), becomes

$$W = y - (\gamma/f + \tau)(1 - \alpha^*) - \theta(d)f + \frac{T - d/V}{2}\left(1 - \alpha^{*2}\right) + \frac{T - d/(\beta V)}{2}\left(\alpha^{*2} - \alpha^{**2}\right) - cd(\alpha^* - \alpha^{**}). \tag{23}$$

[10] It is important to notice the difference between the previous expressions u_{air}, u_{car} and u_o with respect to U_{air}, U_{car} and U_o. The former were used to denote indirect utility of a separate consumer from using one of the available alternatives, while the latter indicate aggregate utility for a class of consumers (i.e., air travelers, drivers and stayers).

[11] This analysis implicitly assumes that the "gasoline market" is perfectly competitive. If the "gasoline market" is either imperfectly competitive or regulated so that the price is kept above cost, then (at least part of) the cost drivers incur is somebody's profit. In the case in which all the cost of driving represents the profit of "gasoline companies" (i.e., $\pi_{car} = cd\int_{\alpha^{**}}^{\alpha^*} d\alpha$), the welfare function that the social planner is to maximize has to incorporate this new element, so that it becomes $W = U_{air} + U_{car} + U_o + \pi_{air} + \pi_{car}$. In fact, taking into account a positive profit for "gasoline firms" makes driving a better travel option from the viewpoint of the social planner. In this framework, the socially desired number of flyers and "stayers" decreases, the number of drivers increases, and equilibrium frequency can be both suboptimal or excessive depending on the value of cd. More information on this particular case is available from the authors upon request.

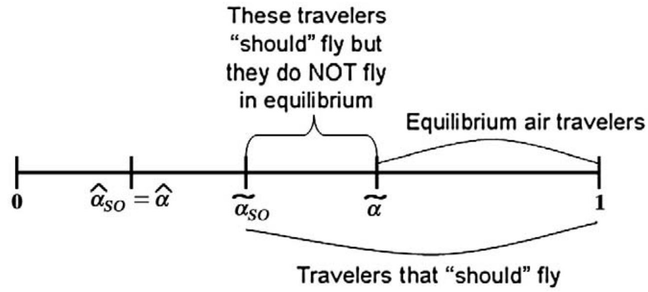

Fig. 4. Suboptimal air traffic.

The planner chooses α^* and α^{**}, which determine the optimal air and road traffic, along with flight frequencies to maximize Eq. (23). Observe that airfares do not appear in the expression because they are transfers between airlines and air travelers.

From the first-order condition for frequency we obtain

$$f^2 = \frac{\gamma(1 - \alpha^*)}{\theta(d)}, \tag{24}$$

which indicates that the optimal frequency increases with the disutility of delay and with the proportion of air travelers, whereas it decreases with the cost of frequency.

The first-order condition for choice of α^* yields

$$\alpha^* = \frac{(\tau - cd + \gamma/f)\beta V}{d(1 - \beta)} \equiv \tilde{\alpha}_{so}, \tag{25}$$

and, by comparing Eq. (3) with Eq. (25) it is easy to check that $\tilde{\alpha} > \tilde{\alpha}_{so}$ since $p_{air} > \tau$ (because otherwise the airline would have negative profits). Therefore, air traffic is suboptimal and there are too many drivers in equilibrium, as shown in Fig. 4.

The first-order condition for choice of α^{**} yields

$$\alpha^{**} = \frac{cd}{T - d/(\beta V)} \equiv \hat{\alpha}_{so}, \tag{26}$$

so that $\hat{\alpha} = \hat{\alpha}_{so}$ and thus the amount of "stayers" is socially optimal (see Fig. 4).

From Eqs. (24) and (25), we obtain the following expression

$$\underbrace{\frac{\theta(d)d(1 - \beta)}{\gamma\beta V}f^3}_{Cf^{SO}} = \underbrace{\left(cd - \tau + \frac{d(1 - \beta)}{\beta V}\right)f - \gamma}_{Lf^* = Lf^{SO}}. \tag{27}$$

The social optimum and equilibrium are easily compared because the RHS is identical and the only difference in the LHS is the absence of the 2 factor multiplying the expression. Fig. 5 below compares the equilibrium and the social optimum frequency.

As a result, the socially optimal flight frequency is higher than the equilibrium frequency, as shown in the figure above. The results are summarized in the lemma that follows.

Lemma 4. *Under Scenario 1, both the equilibrium flight frequency and air traffic are suboptimal (i.e., $f^* < f^{so}$ and $\tilde{\alpha}_{so} < \tilde{\alpha}$).*

Therefore, in the eyes of the social planner, more drivers should undertake air travel. To achieve this, the airline should increase flight frequency. This result is consistent with those in Brueckner (2004), Brueckner and Flores-Fillol (2007) and Flores-Fillol (2009). As pointed out in Flores-Fillol (2009), the underprovision of frequency is the natural result in monopolistic situations and even under competition when carriers operate point-to-point networks.[12]

[12] Flores-Fillol (2009) claims that the apparent overprovison of flight frequency in the current unregulated context, requires us to consider airline competition where carriers operate in hub-and-spoke networks and markets are partially served.

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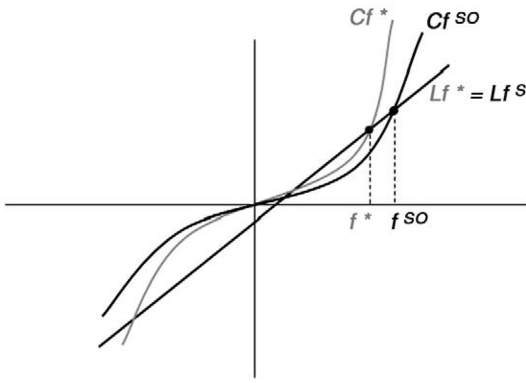

Fig. 5. Underprovision of flight frequency.

Scenario 2 driving is a dominated alternative.

Proceeding in a similar way as in Scenario 1, we have $U_{air} = (y - p_{air} - \gamma/f)(1-\alpha^*) + \frac{T-d/V}{2}(1-\alpha^{*2})$, $U_o = y\alpha^*$ and $\pi_{air} = (p_{air} - \tau)(1-\alpha^*) - \theta(d)f$ where α^* now denotes the social planner's choice of the air-travel/driving margin. Computing $W = U_{air} + U_o + \pi_{air}$, we obtain

$$W = y - (\gamma/f + \tau)(1-\alpha^*) - \theta(d)f + \frac{T-d/V}{2}(1-\alpha^{*2}). \tag{28}$$

From the planner's first-order conditions for f and α^*, we obtain $f^2 = \frac{\gamma(1-\alpha^*)}{\theta(d)}$ which is the same condition as in Scenario 1 (see Eq. (24)); and

$$\alpha^* = \frac{\tau + \gamma/f}{T - d/V} \equiv \overline{\alpha}_{so}, \tag{29}$$

and, by comparing Eq. (4) with Eq. (29) it is easy to check that $\overline{\alpha}_{so} < \overline{\alpha}$ since $p_{air} > \tau$. Therefore, air traffic is again suboptimal and the number of "stayers" is no longer efficient in Scenario 2, since some of them should undertake air travel to achieve the social optimum. Finally, from Eqs. (24) and (29), we obtain the following expression

$$\underbrace{\frac{\theta(d)(TV-d)}{\gamma}f^3}_{Cf^{SO}} = \underbrace{(TV - d - V\tau)f - \gamma V}_{Lf^* = Lf^{SO}}. \tag{30}$$

As in Scenario 1, the social optimum and equilibrium are easily compared because the RHS is identical and the only difference in the LHS is the absence of the 2 factor multiplying the expression. As a result, there is also an underprovision of flight frequency in absence of drivers as summarized in the lemma below.

Lemma 5. *Under Scenario 2, both the equilibrium flight frequency and air traffic are suboptimal (i.e., $f^* < f^{SO}$ and $\overline{\alpha}_{SO} < \overline{\alpha}$).*

Indeed, to carry the extra passengers needed to obtain efficiency, our carrier should increase frequency, as in Scenario 1. To sum up, the social optimum analysis performed under the two scenarios considered suggests that higher flight frequency should be provided by the carrier so that more passengers make use of air travel.

3. Empirical application

This section offers an empirical test of the model's predictions, using the data on frequency choices by airlines in the deregulated EU market. Specifically, we use airline-route-level frequencies on European routes over the period from May 2006 until April 2007.[13]

Our sample includes markets served from the ten busiest airports in Europe to all European destinations (EU27 + Switzerland and Norway) with direct flights.[14] Since our data refer to flights departing from these ten large airports, our sample includes, for example, the route from Rome–Fiumicino to Berlin–Tegel but does not include the route from Berlin–Tegel to Rome–Fiumicino. Since airlines' frequencies are exactly or nearly identical in both directions, treating airlines' services on a given route as directional would not add more information, but can yield incorrect standard errors.

Table 1 includes some characteristics of origin airports included in our dataset (ten largest European gateways in terms of total passenger traffic). Our sample includes a total of 887 routes. Some differences across airports should be noted. Amsterdam and Barcelona serve the most European destinations, and London-Heathrow and Paris–Orly the fewest. Note that the three largest airports in terms of total traffic (London–Heathrow, Paris–CDG and Frankfurt) do not necessarily have the highest amount of frequencies to European destinations. Capacity constraints may explain the fact that low-cost carriers do not operate in London–Heathrow, but have a significant share in airports like Barcelona, Amsterdam, Paris–Orly and especially London–Gatwick. For the rest of airports, the role of low-cost carriers is modest. The position of the dominant airline seems to be especially strong in the case of Air France (Paris–CDG, Paris–Orly) and Lufthansa (Frankfurt, Munich), although the dominant airline also controls about half of total operations in the rest of airports. In all the cases, the average number of route competitors is lower than 3 and it is lower than 2 in London airports, Paris–Orly and Amsterdam. Average route distance is about 1000 km, a figure that varies depending on the geographical location of each airport (except in London–Gatwick which is very high).

Table 2 shows some preliminary evidence of airlines' frequency and aircraft size choices as a function of route distance. For all airlines in our sample, frequencies are substantially higher on short-haul routes than on long-haul ones. Differences in average frequencies between short-haul and long-haul routes are statistically significant when considering all airlines, hubbing airlines at the origin airport, and low-cost carriers. In contrast, planes are bigger on long-haul routes although differences from a statistical point of view are modest. Low-cost airlines are the exception, as they typically use the same type of aircraft on most of their routes. The analysis must take into account other variables that influence airline choices, but it seems that airlines are required to offer high frequencies on short-haul routes. In contrast, they may exploit density economies on long-haul routes from the use of bigger planes at high load factors.[15]

Our theoretical model predicts the possibility of increasing frequency with length of haul for routes on which potential customers may consider driving as a viable alternative to flying. Fig. 6 shows the spline that estimates the relationship between distance and frequency in our dataset without imposing any restriction or shape on the functional form of this relationship.

Results of the spline suggest that the frequency–distance relationship changes at a haul length of about 500 km (311 miles). Specifically, this figure suggests a higher frequency on longer routes for distances less than 500 km; the direction of the relationship is reversed for routes longer than 500 km (note that, for the sake of clarity, we depict the spline only for distances less than 1000 km). However, since Fig. 6

[13] We define routes as air services between two different airports, so that one city-pair market (e.g., London–Milan) may include several routes.

[14] Data on airline frequencies comes from the Official Airlines Guide (OAG Data market analysis publication). We exclude observations for airlines that offer fewer than 52 frequencies per year on a particular route: operations with less than one flight per week should not be considered as scheduled.

[15] Note also that aircraft costs correspond to three stages: takeoff, inflight time and landing. With regard to the size of the aircraft scale diseconomies arise in takeoff and landing, while scale economies arise at the cruise speed. This explains why aircraft that minimize costs are smaller on short-haul than on long-haul routes.

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Table 1
Data characteristics of origin airports.

Airport	Total frequency	# Destin.	Dominant airline	Share dominant airline[a](%)	Share LCC[a](%)	Av. distance[b]	Av. # competitors[b]
Madrid	186,464	94	Iberia	53.34	6.33	1133.06	2.88
Paris-CDG	176,520	99	Air France-KLM	59.97	7.02	886.81	2.08
Munich	167,101	98	Lufthansa	64.75	18.67	928.23	2.69
Frankfurt	163,655	97	Lufthansa	67.57	5.25	1026.93	2.13
Amsterdam	152,449	106	Air France-KLM	53.04	15.45	917.53	1.97
London-LHR	148,805	57	British Airways	45.83	0.16	1002.52	1.88
Barcelona	143,063	102	Iberia	40.26	17.49	1083.66	2.47
Rome-FCO	127,178	80	Alitalia	46.63	8.50	897.74	2.64
Paris-Orly	95,624	72	Air France-KLM	65.91	14.43	782.40	1.40
London-LGW[c]	74,232	82	British Airways	44.93	41.12	1365.72	1.93

[a] Share in terms of departures at the origin airport to European destinations (destinations within EU27+Switzerland and Norway).
[b] Data at the route level.
[c] In London–LGW, Easyjet has a share of 28.21%.

Table 2
T-test for mean differences in frequency and aircraft size choices of airlines.

	Average frequency			Average seats per flight		
Routes	All airlines	Hubbing airlines	LCC	All airlines	Hubbing airlines	LCC
<500 km (1) # obs.	1477.95	1962.04	656.47	116.93	100.63	160.58
	(1491.03)	(1648.43)	(615.99)	(53.28)	(37.35)	(45.53)
	365	176	57	365	175	57
>500 km (2) # obs.	769.64	1127.79	380.52	152.25	165.47	166.61
	(760.38)	(924.27)	(353.31)	(470.31)	(834.22)	(50.36)
	1163	367	343	1163	367	343
T statistic mean diff. (1) − (2)	11.98***	8.08***	4.81***	−1.43*	−1.20	−0.84

Notes: 1. Data at the route level; 2. Hubbing airlines at origin airport; 3. Significance at 1% (***), 10% (*).

presents a rough picture, we must control for several route features and airline specific factors to come to a definite conclusion.

An obvious but important feature of the theoretical model is that there is a positive relationship between flight frequency and demand for air services. The empirical application is based on examining determinants of airlines's frequency choices. Thus, to be consistent with our theoretical model, we have to include distance together with the usual *regional variables* (*population*, *income*, etc.) as explanatory variables to capture relevant air demand shifters at the route level. Lemmas 2 and 3 in the theoretical model state that frequency decreases with the airline/car speed differential (β), while it increases with the disutility of delay (γ). Note that the disutility of delay should be more important on short-haul routes in which personal transportation is a relevant option (i.e., driving is not a dominated alternative).

Even though distance between endpoints is a relevant measure of the attractiveness of air transport with respect to cars, it is clearly not the only one: the *distance from the city-center to each airport* and the

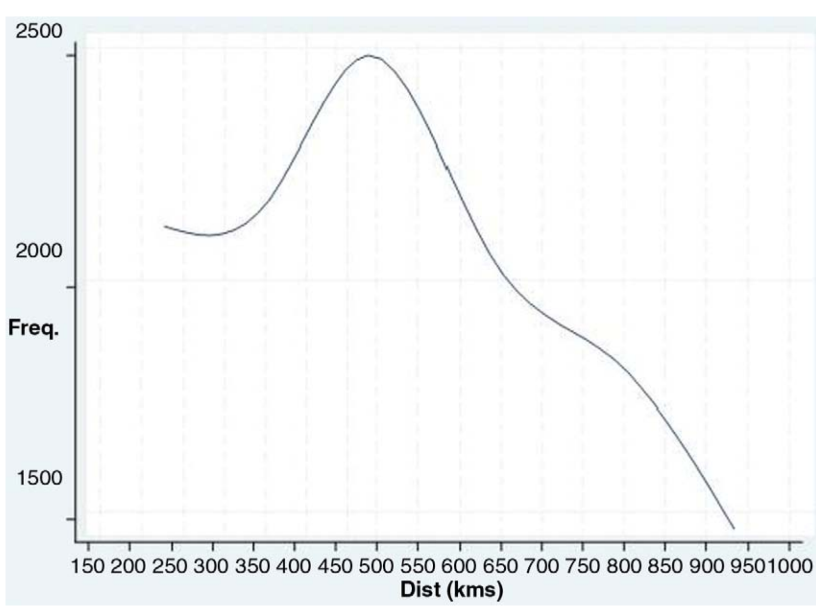

Fig. 6. Spline of total frequency with respect to distance.

quality of surface road network can also play a major role; additionally, some endpoints may be located on *islands*.[16]

In the estimation of our empirical model, we exclude routes where at least one of the endpoints is located on an *island*, since these routes do not have direct roadways between the endpoints. The focus of our analysis is in the interaction between airlines and cars, so that we prefer to exclude from our empirical analysis routes that have islands as one of the endpoints. In this regard, we exclude flights from London–Heathrow and London–Gatwick to the continent. We also exclude flights that have any island as the destination.[17]

Furthermore, the theoretical model also predicts a negative relationship between frequency and the marginal cost per seat (τ); and in the empirical application we include some *airline attributes* (i.e., *airport presence*, *exploitation of connecting traffic*) that may influence the marginal cost per seat of carriers or, alternatively, their marginal revenue given the marginal cost per seat (Borenstein, 1989; Berry et al., 2006).

Beyond the theoretical model, the *intensity of airline competition* is also taken into account as an explanatory variable since, other things being equal, the specific demand for an airline is influenced both by service quality of other airlines operating on the same route and of surface transportation modes. Note that our theoretical model considers a monopoly provider of scheduled transportation services, while our empirical analysis uses a sample of routes with different market structures. However, a large proportion of the routes in our sample have a high level of concentration. In fact, 54% of routes are monopoly routes and the concentration index (HHI) is higher than 0.80 in an additional 6% of routes, so the monopoly seems to be the best-fitting market structure for about 60% of the routes included in our sample.

Eventually, the following equation will be estimated

$$\begin{aligned}\text{Frequency}_{ijk} = {} & \alpha + \beta_1\text{Distance}_{ij} + \beta_2\text{Distance}_{ij} * D_{ij}^{\text{kms}} + \beta_3\text{Airport\_access}_{ij} \\ & + \beta_4\text{Road\_quality}_{ij} + \beta_5\text{Population}_{ij} + \beta_6\text{GDPC}_{ij} + \beta_7 D_{ij}^{\text{capital}} \\ & + \beta_8\text{Tourism}_{ij} + \beta_9\text{HHI}_{ij} + \beta_{10} D_k^{\text{LCC}} + \beta_{11} D_k^{\text{hub}} \\ & + \beta_{12}\text{Destination}_k + \beta_{13} D_{ij}^{\text{HST}} + \varepsilon_{ijk},\end{aligned} \tag{31}$$

Where the dependent variable is annual frequencies of airline k from airport i to airport j (Frequency_{ijk}). We consider the following variables as exogenous explanatory variables of airlines' frequency choices: [18]

1. Distance_{ij}: Number of kilometers flown from airport i to airport j.[19] We also consider the interaction between distance and an indicator variable for routes shorter than certain length ($\text{Distance}_{ij} * D_{ij}^{\text{kms}}$). Generally, the relationship between distance and frequency should be negative, but that relationship may switch to positive on short-haul routes. Thus, we expect a negative sign for the coefficient on the distance variable, but a positive one on the above described distance–short-haul routes interaction variable.
2. $\text{Airport\_access}_{ij}$: Sum of distance from the city center to each airport of the route. We used Google Maps (http://maps.google.com/) to compute these distances. In most cases, the identity of the relevant cities were self-evident. For airports located in the proximity of more than one city, we calculated the distance from the airport to the closest city with more than 100,000 inhabitants. Other things equal, airlines' frequency should be lower on routes in which airports are located farther from the city-center, since air transport would lose attractiveness.
3. Road_quality_{ij}: Proportion of kilometers of the road trip that can be made using highways (taking the fastest route combination). This variable has been constructed using the tool provided by Via Michelin (http://www.viamichelin.com). We expect that competition from cars will be the stronger, the higher the quality of roads. Thus, we should expect a positive sign of the coefficient associated with this variable.
4. Population_{ij}: Weighted average of population at the origin and destination regions of the route (NUTS 2 level). Airline frequencies should be higher on routes that link more populated regions due to higher demand for air travel.
5. GDPC_{ij}: Weighted average of Gross Domestic Product per capita at the origin and destination regions of the route (NUTS 2 level). Weights are based on population. Airline frequencies should be higher on routes that link richer regions due to higher demand for air travel.
6. D_{ij}^{capital}: Dummy variable that takes value 1 when one of the route endpoints is located in the political capital of the corresponding country. Employees of public administrations may require air services to carry out their professional duties.
7. Tourism_{ij}: Weighted average of the percentage of employment in hotels and restaurants at the origin and destination regions of the route (NUTS 2 level). Airline frequencies should be higher on routes where tourist activity is more intense due to the higher demand for air services.
8. HHI_{ij}: Herfindahl–Hirschman index in terms of airline frequencies at the airport-pair level. Since airlines compete in fares and frequencies, they should increase frequencies when competition from other carriers is tougher.
9. D_k^{LCC}: Dummy variable that takes value 1 for low-cost carriers. We define as low-cost carriers those airlines that do not use a business fare class on any route and have only economy class cabins. At least in Europe, the route network of low-cost carriers is based on point-to-point services. Therefore, their frequencies should be lower than those of other airlines that may be operating hub-and-spoke networks.
10. D_k^{hub}: Dummy variable that takes value 1 for hubbing airlines that use the origin airport (one of the ten largest airports in Europe in our sample) as the spoke of its hub (e.g., Lufthansa's flights from Charles de Gaulle to Frankfurt). These airlines should have a high number of frequencies to feed their hubs. Note that the influence on frequencies of hubbing airlines in the origin airports is captured by the variable Destination_k (see below).
11. Destination_k: The total number of non-stop destinations served by the airline from the origin airport, as an indicator of hubbing activities of the airline in this airport, i.e., airport presence. Given the importance of this element, we have tried an additional variable to define the presence of the airline at the origin airport: the market share of the airline in terms of total departures from the origin airport (Airportshare_k). We present the results using Destination_k as explanatory variable, but the results are very similar regardless of the indicator of airport presence used.[20] Note that the frequency that an airline sets at the route level should be high when its presence in the origin airport is strong. Airport dominance allows an airline to have control of the slots and facilities at the terminal building (gates, check-in counters, etc.)

[16] The attractiveness of air transport in relation to cars may be also related to differences in mandatory security time at airports. Unfortunately, we do not have data available to capture this effect.

[17] Our total sample of routes includes 1528 observations. This sample is reduced to 1033 observations when we exclude routes that have islands as endpoints. Finally, we are left with 1023 observations since we do not have available data for road quality on certain routes that involve 10 observations.

[18] Data for population, GDP and tourism specialization at the NUTS 2 level (the statistical unit used by Eurostat to delimit regions) have been provided by Cambridge Econometrics (European Regional Database publication).

[19] We use air transport distance instead of road distance since our main focus is on the choices made by airlines.

[20] Results of the estimates when using the variable Airportshare_k as indicator of airport presence are available from the authors upon request.

that are needed to offer high frequencies. This has been well documented in the literature since the seminal work of Borenstein (1989). In addition to this, a high amount of operations in a large airport by an airline usually indicates the use of that airport to exploit connecting traffic.

12. D_{ij}^{HST}: Dummy variable that takes value 1 for routes on which airlines compete with high-speed train services. Following the definition used by the International Union of Railways (Union Internationale des Chemins de Fer — UIC), we consider high-speed train lines to be those lines with trains able to reach a speed above 250 km/h. Airline frequencies should be higher when they compete with high-speed trains since this is a major attribute of competition between these two transportation modes to attract travelers.[21]

Our empirical strategy involves estimating specification Eq. (31) for all routes using several distance thresholds for the distance-short-haul route dummy interaction variable. Taking into account that the spline suggests a distance threshold around 500 km, we have chosen the following distance thresholds: i) 475 km, ii) 500 km, iii) 525 km, iv) 550 km. At the same time, the coefficient of the distance-short-haul route interaction variable only measures whether and how the slope of the distance–frequency relationship differs between the short-haul route and the entire sample. Therefore, even if we observe the expected positive sign of this coefficient, we cannot immediately conclude that the distance–frequency relationship is positive for short-haul routes (the relationship might still be negative, being less strong). Thus, besides doing our estimation for the entire sample, we have also estimated some additional specifications of Eq. (31) both for the short-haul routes (routes shorter than 475, 500, 525, 550 km) and for the long-haul routes (routes longer than 475, 500, 525, 550 km). This allows us to examine the relationship between frequencies and distances depending on whether driving is a dominated alternative or not, along with providing a sensitivity test for the 500 km cut-off suggested by the spline.

Table 3 provides descriptive statistics for the continuous and discrete variables used in the empirical analysis. Most of the variables appear to have enough variability to capture the relevant differences across the routes in our sample. However, that variability is relatively modest when looking at the variables of tourism intensity and road quality.

Table 4 shows results of estimation of Eq. (31) for all routes, while Tables 5 and 6 present the results for short-haul and long-haul routes, respectively. We estimate our equation using the Zero Truncated Poisson (ZTP) technique. This technique allows us to exploit the form of the dependent variable which takes positive integer values. However, since the number of counts is high, we do not expect substantial differences in our results when using either OLS or ZTP.[22] Unfortunately, we do not have enough observations to include the city-pair fixed effects to account for heterogeneity not captured by the variables used in the empirical analysis.

The overall explanatory power of the estimated models is reasonably good. Regarding flight frequency and distance, we find a negative relationship between them when considering all routes. The coefficient of the variable that interacts distance with the dummy for short-haul routes takes on a positive value and is statistically significant when considering routes shorter than 500, 525, and 550 km. This interaction variable is, however, not statistically significant for routes shorter than 475 km. This may be explained by the fact that, as we lower the cut-off distance for the short-haul routes, the variability in the distance-short-haul route interaction variable decreases, making it more difficult to obtain a precise estimate of the corresponding coefficient.

Table 3
Descriptive statistics (# obs. = 1033).

	Continuous variables			
	Mean	Std. deviation	Min.	Max.
Frequency (annual airline flights at the route)	999.18	1111.45	52	13441
Distance (km)	903.01	512.08	137	2947
Population (000 inhabitants)	5878.44	2496.89	2170	11134
GDPC — pps (index: EU25 = 100)	132.42	21.52	85	194
HHI (concentration index)	0.66	0.26	0.06	1
Destination (# destinations airline at origin airport)	26.87	27.01	1	70
Tourism (% employment in hotels and restaurants)	0.051	0.007	0.031	0.071
Airport access (sum of distance from the city center to each airport of the route)	46.24	15.61	21.5	140.7
Road quality (proportion of highway km)	0.95	0.08	0.37	0.99
	Discrete variables			
	Total obs.	# obs. with value 1	# obs. with value 0	
D^{capital}	1033	372	661	
D^{LCC}	1033	242	791	
D^{hub}	1033	119	914	
D^{HST}	1033	28	1005	

Notes: 1. We exclude routes located on islands in this computation; 2. Data on road quality is not available for ten observations.

Looking at Table 4, the coefficients of both distance and distance-short-haul route interaction dummy suggest that the slope of the frequency–distance relationship for short-haul routes in our sample is close to 0. However, the results reported in Tables 5 and 6, clearly show that this relationship is positive on short-haul routes (shorter than 475, 500, 525, 550 km), and negative on longer-haul routes (longer than 475, 500, 525, 550 km).

In terms of elasticities, regarding routes shorter than 500 km, a 10% increase in route distance implies an increase of about 7% in frequency. Interestingly, 7% of the average frequency for routes shorter than 500 km amounts to 103 flights, meaning that a 10% increase in distance adds about two flights per week, other things being equal. For routes longer than 500 km, a 10% increase in route distance implies a decrease of about 5% in airline frequency. Note that 5% of the average frequency for routes longer than 500 km constitutes 38 extra flights per year (i.e., about 3 extra flights per month).

Thus, we provide empirical evidence in support of the hypothesis stated in our theoretical framework. On the one hand, airline frequency decreases with distance on long-haul routes. On the other hand, airline frequency increases with route distance on short-haul routes. The distance threshold in which this relationship is reversed seems to be somewhere around 500 km, although our empirical analysis is not able to identify this cut-off point precisely.

As expected, the airlines reduce frequencies when the airports of the route are further away from the city center. Indeed, the coefficient of the variable of airport access takes a negative value and is statistically significant in several of the specifications estimated. The coefficient of the variable of road quality is statistically significant and has the expected positive coefficient only when considering routes longer than 550 km. Note that the European cities which are relatively close to each other are usually connected by highways, while the variability of road quality may be higher for cities located farther away from each other.

Looking at demand shifters at the route level, population has a positive influence on airline frequency, as expected, although its statistical significance is modest when considering only the short-haul routes. Interestingly, Gross Domestic Product per capita has a

[21] Note that we do not include the variable for high-speed train services when just considering long-haul routes. In our dataset, very few of long-haul routes have high-speed train as an available alternative.

[22] Results of the estimates when using the OLS technique are available from the authors upon request.

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Table 4
Frequency$_{ijk}$ equation estimates — all routes (ZTP).

	Specif. (1): Distance$_{ij}$* D_{ij}^{475}	Specif. (2): Distance$_{ij}$* D_{ij}^{500}	Specif. (3): Distance$_{ij}$* D_{ij}^{525}	Specif. (4): Distance$_{ij}$* D_{ij}^{550}
Distance$_{ij}$	−0.00075	−0.00054	−0.00056	−0.00054
	(0.00009)***	(0.00006)***	(0.00006)***	(0.00006)***
Distance$_{ij}$*D_{ij}^{kms}	−0.00034	0.00049	0.00038	0.00042
	(0.00022)	(0.00021)**	(0.00019)**	(0.00018)**
Airport_access$_{ij}$	−0.0029	−0.0031	−0.0032	−0.0032
	(0.0016)*	(0.0016)**	(0.0016)**	(0.0016)**
Road_quality$_{ij}$	0.23	0.27	0.26	0.28
	(0.30)	(0.32)	(0.32)	(0.29)
Population$_{ij}$	0.000051	0.000047	0.000047	0.000047
	(0.000013)***	(0.000013)***	(0.000013)***	(0.000012)***
GDPC$_{ij}$	0.0030	0.0035	0.0037	0.0037
	(0.0014)**	(0.0014)**	(0.0013)***	(0.0013)***
$D_{ij}^{capital}$	0.09	0.06	0.07	0.08
	(0.08)	(0.08)	(0.09)	(0.08)
Tourism$_{ij}$	12.77	10.39	10.90	10.96
	(4.78)***	(4.59)**	(4.59)**	(4.48)**
HHI$_{ij}$	−0.53	−0.58	−0.57	−0.57
	(0.11)***	(0.11)***	(0.11)***	(0.10)***
D_k^{LCC}	−0.39	−0.38	−0.38	−0.37
	(0.09)***	(0.09)***	(0.09)***	(0.09)***
D_k^{hub}	0.91	0.91	0.91	0.91
	(0.12)***	(0.12)***	(0.12)***	(0.12)***
Destination$_k$	0.016	0.016	0.016	0.016
	(0.0014)***	(0.0014)***	(0.0014)***	(0.0014)***
D_{ij}^{HST}	0.28	0.21	0.23	0.23
	(0.14)**	(0.14)	(0:14)*	(0.14)*
Intercept	5.81	5.61	5.62	5.55
	(0.35)***	(0.35)***	(0.35)***	(0.35)***
N	1023	1023	1023	1023
Pseudo − R^2	0.50	0.50	0.50	0.50
L – pseudolikelihood	−220,827.61	−219, 184.38	−220, 247.51	−219, 611.89
Test F (joint sign.)	801.74***	867.80***	852.71***	846.60***

Notes: 1. Standard errors in parenthesis (robust to heteroscedasticity); 2. Significance at 1% (***), 5% (**), 10% (*); 3. The coefficient of D_{ij}^{HST} is statistically significant at the 15% level in specif. (2).

statistically significant positive influence on airline frequencies on long-haul routes but is not generally a relevant factor on the short-haul routes. Moreover, tourism specialization at the destination has a positive influence on airline frequencies, particularly on short-haul routes. Finally, the role of the city as a political capital does not seem to influence the airlines' choice of frequency.

The coefficient of the variable measuring competition intensity is statistically significant in all the specifications except for the sub-sample of routes longer than 550 km. Hence, airline frequencies decrease with the level of route concentration, although this effect is not as important for the very long-haul routes. As expected, airlines compete strongly in frequencies, so the monopolization of a route allows an airline to operate fewer flights, other things equal.

Concerning airline attributes, the coefficient of the variable used to capture presence at the origin airport has a positive sign and is statistically significant in all the specifications. The coefficient of the dummy variable for airlines that use the origin airport as spoke is also clearly significant in all specifications. Finally, the coefficient of the dummy variable for low-cost carriers is negative and is statistically significant in all the specifications as well.

The results for variables for intensity of competition and airline attributes are consistent with those obtained by Carlsson (2004). Indeed, this study analyzes the effect of market structure on flight frequency for a sample of European city-pair markets, finding that former flag carriers provide more flights than other airlines, and that market concentration has a negative influence on flight frequency. In this vein, Schipper et al. (2002) find that bilateral airline liberalization in Europe led to a higher frequency in city-pair markets for the period 1988–1992.

Note that some air routes in our sample are also affected by competition from high-speed trains. This is particularly the case for routes

Table 5
Frequency$_{ijk}$ equation estimates — short-haul routes (ZTP).

	Specif. (1): <475 km	Specif. (2): <500 km	Specif. (3): <525 km	Specif. (4): <550 km
Distance$_{ij}$	0.0012	0.0017	0.0013	0.0010
	(0.0006)*	(0.00006)***	(0.0005)***	(0.0004)***
Airport_access$_{ij}$	−0.0012	−0.0036	−0.005	−0.004
	(0.003)	(0.0031)	(0.0027)**	(0.0026)*
Road_quality$_{ij}$	−1.37	−0.64	−0.93	−1.35
	(1.20)	(1.56)	(1.43)	(0.86)
Population$_{ij}$	0.000012	0.000039	0.000037	0.000041
	(0.000022)	(0.000021)*	(0.000021)*	(0.000020)**
GDPC$_{ij}$	0.0041	0.0005	0.0009	0.0011
	(0.0021)**	(0.0019)	(0.0019)	(0.0019)
$D_{ij}^{capital}$	−0.06	0.22	0.19	0.19
	(0.15)	(0.14)	(0.14)	(0.14)
Tourism$_{ij}$	5.33	14.24	13.38	13.55
	(6.74)	(7.66)*	(7.45)*	(6.78)**
HHI$_{ij}$	−0.78	−0.77	−0.75	−0.85
	(0.21)***	(0.20)***	(0.20)***	(0.19)***
D_k^{LCC}	−0.53	−0.43	−0.40	−0.44
	(0.21)**	(0.20)**	(0.19)**	(0.19)**
D_k^{hub}	0.80	1.03	1.05	1.02
	(0.15)***	(0.17)***	(0.18)***	(0.19)***
Destination$_k$	0.017	0.017	0.018	0.017
	(0.0018)***	(0.0020)***	(0.0019)***	(0.0019)***
D_{ij}^{HST}	0.23	0.15	0.19	0.18
	(0.15)	(0.14)	(0.14)	(0.13)
Intercept	7.04	6.07	6.53	7.05
	(1.46)***	(1.63)***	(1.48)***	(1.18)***
N	228	269	295	316
Pseudo − R^2	0.38	0.46	0.46	0.45
L − pseudolikelihood	−61, 473.84	−88,520.69	−95,070.91	−100, 173.88
Test F (joint sign.)	852.71***	243.05***	227.84***	232.57***

Notes: 1. Standard errors in parenthesis (robust to heteroscedasticity); 2. Significance at 1% (***), 5% (**), 10% (*); 3. The coefficient of D_{ij}^{HST} is statistically significant at the 12% level in specif. (1).

that have Paris as origin airport. The interaction between air services and high-speed trains is beyond the scope of this paper. However, this interaction is fully consistent with the empirical predictions of our

Table 6
Frequency$_{ijk}$ equation estimates — long-haul routes (ZTP).

	Specif. (1): >475 km	Specif. (2): >500 km	Specif. (3): >525 km	Specif. (4): >550 km
Distance$_{ij}$	−0.00088	−0.00062	−0.00064	−0.00062
	(0.00010)***	(0.000058)***	(0.00006)***	(0.00006)***
Airport_access$_{ij}$	−0.0041	−0.0035	−0.0025	−0.0026
	(0.0017)**	(0.0018)**	(0.0019)	(0.0020)
Road_quality$_{ij}$	0.24	0.34	0.34	0.62
	(0.30)	(0.29)	(0.29)	(0.26)**
Population$_{ij}$	0.000053	0.000026	0.000029	0.000030
	(0.000016)***	(0.000013)**	(0.000013)**	(0.000013)**
GDPC$_{ij}$	0.0040	0.008	0.0077	0.0072
	(0.0018)**	(0.0014)***	(0.0015)***	(0.0015)***
$D_{ij}^{capital}$	0.19	0.028	0.017	0.039
	(0.10)*	(0.07)	(0.07)	(0.07)
Tourism$_{ij}$	15.83	6.79	7.05	6.34
	(5.71)***	(5.06)	(5.19)	(5.15)
HHI$_{ij}$	−0.30	−0.26	−0.25	−0.18
	(0.12)**	(0.11)***	(0.11)**	(0.12)
D_k^{LCC}	−0.38	−0.43	−0.44	−0.40
	(0.11)***	(0.09)***	(0.09)***	(0.09)***
D_k^{hub}	0.95	0.80	0.78	0.82
	(0.15)***	(0.07)***	(0.08)***	(0.08)***
Destination$_k$	0.016	0.014	0.014	0.014
	(0.0018)***	(0.0011)***	(0.0011)***	(0.0012)***
Intercept	5.53	5.32	5.30	5.04
	(0.37)***	(0.36)***	(0.37)***	(0.37)***
N	795	754	728	707
Pseudo − R^2	0.53	0.50	0.50	0.50
L-pseudolikelihood	−152, 808.04	−116,757.65	−113,274.45	−107,923
Test F (joint sign.)	551.31***	846.44***	792.00***	759.37***

Notes: 1. Standard errors in parenthesis (robust to heteroscedasticity); 2. Significance at 1% (***), 5% (**), 10% (*).

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theoretical model. Airlines are required to provide higher quality products to prevent travelers from using other transport modes (i.e., cars and trains on certain routes). In this regard, the coefficient on the dummy variable for high-speed trains takes a positive value and is statistically significant in several of the specifications for the entire sample. However, it is not statistically significant for the sub-sample including routes shorter than 500, 525 and 550 km, and it is only marginally significant for routes shorter than 475 km. Thus, we find mixed evidence of the influence of high-speed trains on airlines' frequency choice. Note that airlines react to new high-speed services by adjusting aircraft size and maintaining flight frequency. For example, the reaction of Iberia to the new high-speed train service on the route Madrid–Barcelona (the densest route in our sample) was to reduce aircraft size but maintain high frequencies. Moreover, an accurate analysis of competition between airplanes and trains should take into account the situation before and after the start of high-speed train services since these new services typically cause a reduction in the number of airlines offering services on the route.

To sum up, we have shown the same result both theoretically and empirically: airline frequency choices are dependent upon competition from private vehicles. Airlines always incur extra costs when adding flights on a route since economies of traffic density require the use of big aircraft at high load factors and each additional flight is associated with additional fixed costs. However, the demand for air services rises with distance on routes where airlines compete with personal transportation since the latter is a slower transportation mode and, in this case, airlines can increase frequency and charge higher fares as they become more competitive.

In this regard, our empirical analysis shows that airlines increase frequency as distance increases on routes shorter than about 500 km. Nevertheless, for routes longer than about 500 km, on which driving is a dominated alternative, airlines decrease frequency as distance increases. In the latter scenario, the demand for air services may not increase when the origin and destination airports are more remote because some potential travelers may prefer to stay at home, and airlines prefer to save costs by exploiting density economies.

4. Concluding remarks

The main contribution of this paper is to underscore that presence of the personal transportation option crucially affects frequency choice by a provider of scheduled transportation services. We have shown this to be true, using distance as a proxy for the substitutability between higher-speed scheduled services and private vehicles; our findings are identified theoretically and tested empirically for the European airline industry. Analysts and policy-makers should consider this factor when analyzing investment in transportation infrastructures and regulation of scheduled services.

A large proportion of air traffic involves short-haul routes where airlines must provide high flight frequency to compete with cars. Our social optimum analysis shows that there is an underprovision of flight frequency supposing that airports are not congested, implying an overuse of personal transportation that may create problems such as pollution, noise and road congestion.

Investing in road infrastructures may place strong pressure on public budgets. In fact, the US Department of Transportation predicts a required expenditure of $225 billion (which represents over 1.5% of the current US GDP) annually for the next 50 years to upgrade the existing road network. In this vein, a major goal in the transportation policy of the European Commission is to alleviate road congestion by promoting the use of scheduled transportation services.[23] Since road and airport infrastructures are connected, we suggest that policy makers could take into account capacity at national airports as an instrument available to reduce road congestion. Similarly, high-speed train lines providing a high frequency of service may also be useful in alleviating road congestion.

While our empirical application relates to the airline industry (a competitive industry for which relevant data are readily available), our analysis has policy implications for any transport market with private transportation and scheduled services like inter-city and intra-city surface transportation. Furthermore, the logic of the model goes beyond the transportation sector since a similar setup could be used to analyze the behavior of a firm in situations where better alternatives in certain dimensions are either present or absent. When these alternatives are present, the firm may be required to find other ways to improve its position in the market even when this implies a higher cost; when they are absent, the main concern of the firm will be related to the customers using its services.

A natural extension of our theoretical model would be to introduce competition across scheduled carriers to capture the interaction among airlines. Additionally, the emerging intermodal competition in Europe between airlines and high-speed trains should be examined thoroughly. Although we find mixed evidence of competition between air transport and high-speed trains, this interaction needs further analysis since airlines typically react to new high-speed services by adjusting the aircraft size and maintaining the flight frequency.

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Appendix A. Proofs

Proof of Lemma 1. The case with drivers (Scenario 1) requires $0<\hat{\alpha}<\tilde{\alpha}<1$. From the inequality $\hat{\alpha}<\tilde{\alpha}$ and after some computations we get:

$$\underbrace{\left(\frac{p_{\mathrm{air}}V}{\beta} + cTV^2 + \frac{\gamma V}{\beta f}\right)d - TV^2\left(p_{\mathrm{air}} + \frac{\gamma}{f}\right)}_{Ld} < \underbrace{cd^2V}_{Qd}, \tag{A1}$$

that is represented in the Fig. A1 below

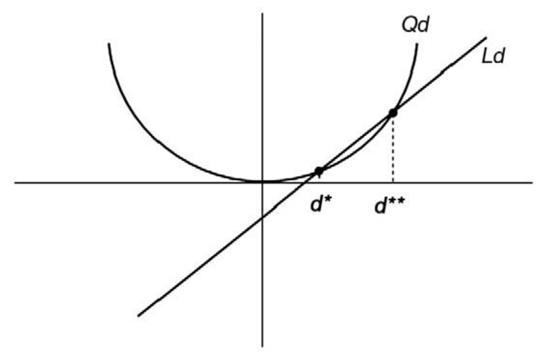

Fig. A1.

[23] See the Report of the US Department of Transportation (2007), and the White Paper "European Transport Policy for 2010: Time to Decide" of the European Commission (2001).

Thus we conclude that $\hat{\alpha}<\tilde{\alpha}$ requires either $d<d^*$ or $d>d^{**}$, where d^* and d^{**} are the two roots solving the equation $Ld=Qd$. Although d^* and d^{**} can be computed, it is easier to proceed in the following way. In the first possible region (i.e., $d<d^*$), the slope of Qd is smaller than the one of Ld and thus $d<\frac{\frac{1}{\beta}\left(p_{\text{air}}+\frac{\gamma}{f}\right)+cTV}{2c}$ and the opposite happens in the second possible region (i.e., $d>d^{**}$). From $\tilde{\alpha}>0$ we know that $d<\frac{p_{\text{air}}+\frac{\gamma}{f}}{c}$ and this condition is incompatible with $d>\frac{\frac{1}{\beta}\left(p_{\text{air}}+\frac{\gamma}{f}\right)+cTV}{2c}$ (and thus with $d>d^{**}$) either for $\beta<1/2$ (that is assumed in the model) or for a large enough T. Therefore $\hat{\alpha}<\tilde{\alpha}$ requires $d<d^*$ and thus Scenario 1 (with drivers) is only relevant for short distances. □

Proof of Lemma 2. From Eq. (13), let us define $\Omega\equiv C_f^*-L_f^*=0$, that is

$$\Omega=\frac{2\theta(d)d(1-\beta)}{\gamma\beta V}f^3-\left(cd-\tau+\frac{d(1-\beta)}{\beta V}\right)f+\gamma=0. \tag{A2}$$

The total differential of the equilibrium frequency with respect to a parameter x is $\frac{df^*}{dx}=-\frac{\partial\Omega/\partial x}{\partial\Omega/\partial f}$. Notice that $\partial\Omega/\partial f=\text{slope}(Cf^*)-\text{slope}(Lf^*)$ and thus $\partial\Omega/\partial f>/0$ because at the equilibrium frequency the slope of Cf^* exceeds the slope of Lf^*. Thus we just need to explore the sign of $\partial\Omega/\partial x$.

- $\partial\Omega/\partial\gamma=-\frac{2\theta(d)d(1-\beta)}{\gamma^2\beta V}f^3+1$ which has an ambiguous sign and is negative for small values of β (more precisely, for $\beta<\frac{2\theta(d)df^3}{V\gamma^2+2\theta(d)df^3}$). Thus, when this condition holds, we observe $\frac{df^*}{d\gamma}>0$.
- $\partial\Omega/\partial c=-df<0$. Then $\frac{df^*}{dc}>0$. We observe that $c\uparrow$ increases the slope of Lf^* in Fig. 3 so that $f^*\uparrow$.
- $\partial\Omega/\partial\tau=f>0$. Then $\frac{df}{d\tau}<0$. We observe that $\tau\uparrow$ decreases the slope of Lf^* in Fig. 3 so that $f^*\downarrow$.
- $\partial\Omega/\partial V=\frac{1}{V}\left(-\frac{2\theta(d)d(1-\beta)}{\gamma\beta V}f^3+\frac{d(1-\beta)}{\beta V}f\right)$ and, using Eq. (A2), this expression can be rewritten as $\partial\Omega/\partial V=\gamma+(\tau-cd)f/V$. We observe that $\tau>cd$ is a sufficient condition to have $\partial\Omega/\partial V>0$ and thus $\frac{df^*}{dV}<0$.
- $\partial\Omega/\partial\beta=-\frac{2\theta(d)}{\gamma}f^2+1$ that has the same sign as $\frac{1}{V}\left(-\frac{2\theta(d)d(1-\beta)}{\gamma\beta V}f^3+\frac{d(1-\beta)}{\beta V}f\right)$ which is the value of $\partial\Omega/\partial V$. Therefore the same sufficient condition ensures $\partial\Omega/\partial\beta>0$ and thus $\frac{df^*}{d\beta}<0$.
- $\partial\Omega/\partial d=\frac{2\theta'(d)d(1-\beta)}{\gamma\beta V}f^3+\frac{2\theta(d)(1-\beta)}{\gamma\beta V}f^3-\left(c+\frac{1-\beta}{\beta V}\right)f$ and, using Eq. (A2), this expression can be rewritten as $\partial\Omega/\partial d=\frac{2\theta'(d)d(1-\beta)}{\gamma\beta V}f^3-\frac{\gamma+\tau f}{d}$. Notice that when the cost of frequency is independent of distance, i.e., $\theta'(d)=0$, $\partial\Omega/\partial d<0$ and $\frac{df^*}{dd}>0$. Yet, when $\theta'(d)>0$, the result seems uncertain. Notice that $\theta'(d)$ is a continuous function starting from $d=0$ because $\theta(d)$ is continuously differentiable with respect to $d>0$. Therefore, at least for low values of d we will observe $\partial\Omega/\partial d<0$ and $\frac{df^*}{dd}>0$. □

Proof of Lemma 3. From Eq. (18), let us define $\Omega\equiv Cf^*-Lf^*=0$, that is

$$\Omega=\frac{2\theta(d)(TV-d)}{\gamma}f^3-(TV-d-\tau V)f+\gamma V=0 \tag{A3}$$

As before, the total differential of the equilibrium frequency with respect to a parameter x is $\frac{df^*}{dx}=-\frac{\partial\Omega/\partial x}{\partial\Omega/\partial f}$. Notice that $\partial\Omega/\partial f=\text{slope}(Cf^*)-\text{slope}(L_f^*)$ and thus $\partial\Omega/\partial f>0$ because at the equilibrium frequency the slope of Cf^* exceeds the slope of Lf^*. Thus we just need to explore the sign of $\partial\Omega/\partial x$.

- $\partial\Omega/\partial\gamma=-\frac{2\theta(d)(TV-d)}{\gamma^2}f^3+V<0$ assuming a large T. Then $\frac{df^*}{d\gamma}>0$.
- $\partial\Omega/\partial\tau=Vf>0$. Then $\frac{df^*}{d\tau}<0$. We observe that $\tau\uparrow$ decreases the slope of Lf^* in Fig. 3 so that $f^*\downarrow$.
- $\partial\Omega/\partial V=\frac{2\theta(d)T}{\gamma}f^3-Tf+\tau f+\gamma$ and, using Eq. (A3), this expression can be rewritten as $\partial\Omega/\partial V=\frac{2\theta(d)}{\gamma}f^2-1$, so that $\partial\Omega/\partial T<0$ requires $f^2<\frac{\gamma}{2\theta(d)}$. Then using Eq. (17) this inequality becomes $p_{\text{air}}<\frac{1}{2}(T-d/V)+\tau$, and finally using Eq. (16) we obtain $-\gamma/f<\tau$ which is always true. Therefore, $\partial\Omega/\partial T<0$ and thus $\frac{df^*}{dV}>0$.
- $\partial\Omega/\partial T=\frac{2\theta(d)V}{\gamma}f^3-Vf$, so that $\partial\Omega/\partial T<0$ requires $f^2<\frac{\gamma}{2\theta(d)}$; and we just showed this inequality always holds. Therefore $\partial\Omega/\partial T<0$ and thus $\frac{df^*}{dT}>0$.
- $\partial\Omega/\partial d=\frac{2\theta'(d)(TV-d)}{\gamma}f^3+f-\frac{2\theta(d)}{\gamma}f^3$ and, plugging Eq. (A3) into the derivative we obtain $\partial\Omega/\partial d=\frac{2\theta'(d)(TV-d)}{\gamma}f^3+\frac{\gamma V+\tau Vf}{TV-d}$ that is positive because $T>d/V$. Therefore, $\frac{df^*}{dd}<0$ and thus frequency decreases with distance. □

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