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Service-quality and pricing strategies in the airline industry: The role of distance[☆]

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ABSTRACT

This paper analyzes airlines' fare and frequency decisions, both theoretically and empirically. These decisions depend on route distance, as only short-haul routes are affected by intermodal competition from personal transportation. Although fares increase with distance both on short- and long-haul routes, the effect of distance on frequencies depends on the presence of intermodal competition. Frequencies decay with distance on long-haul routes. However, on short-haul routes, frequencies increase with distance because airlines try to boost profits by attracting demand from other transportation modes. Finally, on short-haul routes, intermodal competition from personal transportation affects more intensively network carriers than low-cost carriers as distance rises, which produces an increased differentiation between both types of airlines.

1. Introduction

Intramodal competition in transportation markets has received substantial attention in previous literature. Similarly, several studies have also examined the effect of intermodal competition from high-speed rail (HSR) on air transportation markets.[1] However, the effect of intermodal competition from personal transportation has been often overlooked. We focus on this latter source of intermodal competition, which constitutes a key factor influencing air carriers to adopt differentiated strategic decisions between long-haul routes (where there is no intermodal competition) and short-haul routes (where intermodal competition from personal transportation can be very intense). Furthermore, network carriers and low-cost carriers also follow differentiated strategies, both in terms of *service quality* and pricing decisions. A broad concept of service quality comprises many different dimensions on the ground (e.g., bag handling, gate location) and in the air (e.g., in-flight services, legroom, seat characteristics). However, there is a clear consensus in the literature that convenient scheduling, characterized by adequate flight frequency, is the main quality attribute for airline services.[2] Therefore, in this study, service quality and flight frequency are used interchangeably.

Longer routes are more expensive to operate for scheduled carriers and this additional cost is passed through in higher prices. However, this unambiguous statement becomes more complex when analyzing carriers' decisions on service quality as route distance increases. The reason is that a higher service quality raises passengers' willingness to pay. Therefore, to assess the effect of route distance on posted prices, it is important to account for the evolution of service quality. And this analysis should include intermodal competition from personal transportation on short-haul routes and asymmetric intramodal competition between network and low-cost carriers that follow differentiated strategies in terms of service quality and pricing decisions.

This study looks at the strategic decisions of carriers with the ultimate purpose of understanding the effect of such bidimensional competition (intramodal and intermodal from personal transportation). More precisely, we will try to provide answers to the following *questions*: (i) What is the effect of route distance on carriers' service-quality

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[1] See Givoni and Dobruszkes (2013) and Zhang et al. (2019) for reviews. Other recent studies include Bergantino and Madio (2020), Bernardo and Fageda (2020), Gu and Wan (2022), Ma et al. (2020), Su et al. (2020), and Wang et al. (2021). Studies focusing on airline-HSR cooperation include Albalate et al. (2015), Avenali et al. (2018, 2022), Jiang et al. (2017), Li et al. (2018), Xia et al. (2019), and Zhang et al. (2018).

[2] See Bilotkach et al. (2010), Brueckner (2004, 2010), Brueckner and Flores-Fillol (2007, 2020), Brueckner and Pai (2010), Brueckner and Luo (2014), de Palma et al. (2018), Fageda and Flores-Fillol (2012a,b), Fageda et al. (2020), and Pai (2010).

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and pricing strategies?, (*ii*) On short-haul routes, what is the effect of a tougher intermodal competition from personal transportation on carriers' service-quality and pricing strategies?, and (*iii*) What is the effect of route distance on the differentiation between network and low-cost carriers (in terms of their fare and frequency decisions)?

This paper provides a simple theoretical model accounting for the needed elements to capture the effects of both asymmetric intramodal competition (between network and low-cost carriers) and intermodal competition from personal transportation, with the purpose of answering the previous questions and providing some clear testable predictions. These predictions are then used as a reference for an empirical application using monthly data on flights within Europe. Two data sources from RDC Aviation are used: *Apex-schedules* and *Apex-fares*. The first one provides supply data for all scheduled flights within Europe over the period 2007- 2019 (flight frequency, aircraft size, and distance) and allows building a sample of 1.1 million observations. The second one provides monthly fare data at the airline-route level over the period 2013–2019 (including different fare classes) and allows building a sample of 475,000 observations. Unlike the US airline industry, European airline markets have been relatively under-researched (due predominantly to the lack of sufficient data). Therefore, this study contributes to the research in airline economics at the European level.

Our theoretical results provide responses to the questions formulated above. As for the first question, fares increase with distance both on short- and long-haul routes. Instead, the effect of distance on frequencies depends on the presence of intermodal competition from personal transportation and, therefore, differs between short- and long-haul routes. Frequencies increase with distance on short-haul routes, while the opposite effect is observed on long-haul routes. On short-haul routes, frequencies increase with distance because airlines try to boost profits by attracting demand from other transportation modes. This produces an upward pressure on fares because higher frequencies (i.e., service quality) entail a certain "product upgrade" that translates into a higher passenger willingness to pay (and also because longer routes are more costly to operate). Instead, frequencies decay with distance on long-haul routes.

As for the second question, on short-haul routes, fares and frequencies fall as intermodal competition from personal transportation becomes tougher. The reason is that the car becomes a better option and more passengers choose it instead of air travel. Therefore, airlines lose demand and decrease frequencies. They also decrease fares in an effort to be more competitive and because of the lower passengers' willingness to pay derived from poorer frequencies.

With respect to the third question, even though route distance produces a similar *qualitative* effect on the fare and frequency strategies of network airlines and low-cost airlines, the *quantitative* effect is different. Assuming that network airlines provide a high-quality scheduled service while low-cost airlines provide a low-quality scheduled service, the *fare gap* and *frequency gap* are defined as the difference between fares and frequencies of network and low-cost airlines. We conclude that these gaps are positively related, so that both of them move in the same direction as distance varies. The ultimate effect of route distance on these gaps remains an empirical issue that is ascertained in our empirical application.

Our theoretical results on the effect of route distance on fares and frequencies are tested empirically. However, the effect of the intensity of intermodal competition from personal transportation on short-haul routes cannot be tested empirically (beyond the effect that is already captured by distance), as there are no data on alternative transportation modes. Our first empirical challenge consists in identifying the cutoff distance that separates short- and long-haul routes, which is found to be around 600 km.

With respect to the effect of distance on fares and frequencies, we confirm our theoretical results as fares increase with distance both on short- and long-haul routes, while frequencies increase with distance on short-haul routes and decay with distance on long-haul routes.

Finally, the analysis of the fare and frequency gaps reveals that both of them increase with route distance on short-haul routes, which is consistent with our theoretical predictions. Therefore, we can conclude that there is an increased differentiation between network and low-cost airlines as the distance rises. A possible explanation would suggest that personal transportation affects more intensively network carriers than low-cost carriers (which would make sense as low-cost passengers are characterized by lower income, value of time, and car ownership). Consequently, network carriers would increase their fares and frequencies faster than low-cost carriers as route distance increases. However, our empirical results for long-haul routes reveal that the frequency gap decreases with distance while the fare gap increases with distance, a finding that does not match our theoretical predictions and that could be explained by the hub-and-spoke route configuration of network airlines that concentrate traffic in their hub airports and by the different composition of aircraft fleets between network and low-cost airlines, as network airlines make use of different aircraft models while low-cost airlines typically restrict their aircraft choice to a single family model.

The plan of the paper is as follows. Section 2 presents a literature review with the purpose of highlighting the contribution of the paper. Section 3 introduces the model and Section 4 obtains the equilibrium and derives the main comparative-static effects. The empirical application is provided in Section 5 and a brief conclusion closes the paper. All the proofs and some supplementary material are provided in the Appendix.

2. Literature review

The proposed theoretical setup builds on the literature on vertical differentiation initiated by Gabszewicz and Thisse (1979), followed by Shaked and Sutton (1982, 1983), and summarized by Tirole (1988), where consumers are differentiated in terms of their *valuation for quality* (i.e., flight frequency in our setup). However, consumer heterogeneity in our model arises from differentiated *values of time* (more details are provided in Section 3).[3]

Some previous studies include service quality (flight frequency) in an additive manner (Flores-Fillol, 2009; Heimer and Shy, 2006; Bilotkach et al., 2013; Fageda et al., 2020). However, our setup captures the effect of flight frequency by modeling *schedule delay* as the gap between passengers' preferred and actual departure times. More precisely, the schedule delay is a negative term in passengers' utility function that is decreasing with flight frequency (Bilotkach et al., 2010; Brueckner, 2004; Brueckner and Flores-Fillol, 2007, 2020).[4]

Our model is also related to Fageda and Flores-Fillol (2012a,b), which focus on the different strategies adopted by network and low-cost carriers when deciding whether to operate a certain city-pair market directly (point-to-point connection) or indirectly requiring a layover (hub-and-spoke connection). While they study network configurations, our focus is on service-quality and pricing strategies.

The closest reference to our model is found in (Bilotkach et al., 2010), which is the only study examining the differentiated effect of distance on service quality in the framework of a monopoly-airline model. Our paper departs from that model to study the effect of distance on carriers' frequency and pricing decisions in the presence of both intermodal competition from personal transportation and asymmetric intramodal competition between network and low-cost carriers. Therefore, there are two clear contributions of our paper with respect

[3] Bilotkach et al. (2013) and Fageda et al. (2020) propose models applied to the airline industry where consumers are differentiated in terms of their valuation for quality (i.e., flight frequency).

[4] Brueckner (2004) considers a monopoly airline's network choice, incorporating frequency decisions in the model. (Brueckner and Flores-Fillol, 2007) use this framework to analyze fare and frequency choices in duopoly markets. Brueckner and Flores-Fillol (2020) look at the effect of airline alliances on flight frequencies.

to (Bilotkach et al., 2010). The first one is to consider a more complex market structure, with vertically-differentiated air services (capturing the competition between network and low-cost carriers), which allows identifying the different reaction of both types of carriers as distance increases and as intermodal competition from personal transportation becomes tougher. The second one is to look at the effect of distance and intermodal competition from personal transportation on fares, as Bilotkach et al. (2010) focuses exclusively on the effect of distance on frequencies.

Shifting now attention to the empirical literature, previous studies have mostly analyzed the determinants of airlines' fares and frequencies. First, there is a strand of literature that focuses on intramodal competition. The intensity of competition has been approximated through measures of concentration at the route and/or airport level (Berry et al., 2006; Borenstein, 1989; Carlsson, 2004), liberalization policies (Abate and Christidis, 2020; Bernardo and Fageda, 2017; Schipper et al., 2002) or mergers (Borenstein, 1990; Kim and Singal, 1993; Richard, 2003; Carlton et al., 2019; Kwoka and Shumilkina, 2010). Differently, our approach underlines the asymmetric nature of intramodal competition between network and low-cost carriers.

Second, the effect of product differentiation as a relevant determinant of flight frequencies has also received attention from the empirical literature. Some studies focus on horizontal differentiation (Borenstein and Netz, 1999; Salvanes et al., 2005) while others consider vertical differentiation by incorporating service quality (Brueckner and Luo, 2014; Fageda et al., 2020). Our study contributes to this second literature strand of vertical differentiation as we have high-quality (network) carriers and low-quality (low-cost) carriers.

Finally, the effect of route distance on service quality has been studied by Pai (2010), Wei and Hansen (2007), and Bilotkach et al. (2010). Pai (2010) 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. Bilotkach et al. (2010) confirms the results of Pai (2010) and Wei and Hansen (2007) on long-haul routes and provides new insights for short-haul routes, where service quality can increase with distance due to the presence of intermodal competition. Our study also contributes to this literature by examining the role of distance on frequency and price differentiation strategies in a context of asymmetric intramodal competition.

From a different perspective, there is also a strand of literature relating intermodal competition and the choice of transportation mode. However, only Combes and Linnemer (2000) consider intermodal competition from personal transportation in 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 by Bel (1997), González-Savignat (2004), Janic (2003), and López-Pita and Robusté (2004). Some studies on choice of transportation mode conclude that commuters mostly consider frequencies (and, more generally, convenience of service) as the key factor determining their elasticity (Voith, 1997; Asensio, 2002) and the impact of urban transit projects (Baum-Snow and Kahn, 2000). A contribution to this literature is to incorporate distance in our analysis to distinguish between long-haul routes (where there is no intermodal competition) and short-haul routes (where intermodal competition can be very intense). Quite logically, scheduled services become more attractive than non-scheduled services (i.e., personal transportation) for longer distances.[5]

[5] Finally, there are some studies examining the effect of high-speed rail (HSR) on air traffic and fares (literature provided in footnote 1) and the effect of airline competition on price dispersion (Borenstein and Rose, 1994; Gerardi and Shapiro, 2009; Gaggero and Piga, 2011; Siegert and Ulbricht, 2020). Our approach is different as intermodal competition comes from non-scheduled transportation alternatives and we do not analyze price discrimination but the different strategies adopted by network and low-cost carriers.

3. The model

3.1. Utility functions

The proposed model is based on indirect utilities of heterogeneous travelers choosing among two scheduled services (high and low quality) and a non-scheduled transportation mode (personal transportation). As compared to the low-quality scheduled service (denoted by L), the high-quality scheduled service (denoted by H) is more convenient and brings the passenger faster to her final destination at a higher full price. These heterogeneous scheduled services can capture the competition between a major and a low-cost carrier.[6] Similarly to Bilotkach et al. (2010), the utility for a traveler making use of the H scheduled service is given by $Consumption - Schedule\ delay\ disutility + Value\ of\ available\ time$. $Consumption$ is $y - p_H$ where y is the common level of income and p_H is the carrier's fare.

Letting Z denote the time circumference of the circle, there is a uniform distribution of consumers around it in terms of preferred departure times and consumer utility then depends on *expected schedule delay* (defined as the difference between the preferred and actual departure times), which equals $Z/4f_H$ where f_H is the number of (evenly spaced) scheduled services operated by the carrier (flights in the case of air services). The $Schedule\ delay\ disutility$ is equal to a disutility parameter $\delta > 0$ times the expected schedule delay expression from above, thus equaling $\delta Z/4f_H = \gamma/f_H$, where $\gamma \equiv \delta Z/4$. We assume that all passengers value frequency equally and, thus, the parameter γ is common for all of them. Passenger heterogeneity arises instead through travelers' value of time, as explained below.[7]

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 carrier's *convenience* (V), thus equaling $T - d/V$, where $T > d/V$ is assumed. The concept of *convenience* encompasses speed, accessibility, and flexibility of the connection. Hence, 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 uniformly distributed over the range $[0, 1]$. Therefore, consumer heterogeneity in our model arises from differentiated *values of time* and not from different *valuations for quality* , as in the standard models à la Gabszewicz and Thisse (1979) and Shaked and Sutton (1982, 1983). It is important to realize that the valuation-for-quality approach makes it hard to compare scheduled services with non-scheduled services that do not provide consumers with any quality/frequency. Our approach overcomes that problem as both scheduled and non-scheduled services are comparable along this dimension. Furthermore, in the valuation-for-quality models, frequency enters linearly in the utility function. Therefore, schedule delay cannot be expressed as γ/f, which seems a suitable way to capture scheduling decisions (with the microeconomic foundations explained above). Therefore, the utility obtained from the high-quality scheduled service is

$$u_H = y - p_H - \gamma/f_H + \alpha\left[T - d/V\right], \tag{1}$$

[6] Alternatively, the model could also capture intermodal competition between air and HSR services, whenever HSR services are less convenient than air services. However, in our analysis, intermodal competition refers to competition from a non-scheduled transportation mode (i.e., personal transportation).

[7] Bilotkach (2009) introduces a similar valuation of time in a model of airlines' network choice.

where $p_H + \gamma/f_H$ denotes the full price of the H air service. The utility from making use of the low-quality scheduled service is derived analogously and is given by

$$u_L = y - p_L - \gamma/f_L + \alpha\left[T - d/(\lambda V)\right], \tag{2}$$

where $p_L + \gamma/f_L$ denotes the full price of the L air service and $\lambda \in (0,1)$ captures the *convenience differential* between both scheduled services. T is assumed to be large, so that $T > d/(\lambda V)$.

Finally, travelers can also make use of a non-scheduled transportation mode (denoted by ϕ), obtaining a utility of $Consumption + Value\ of\ available\ time$,[8] which can be written as

$$u_\phi = y - cd + \alpha\left[T - d/(\beta V)\right], \tag{3}$$

where cd denotes the full price of the non-scheduled service that increases with distance (d), with $c > 0$. The parameter $\beta \in (0,1)$ captures the *convenience differential* with respect to the H scheduled service, with $T > d/(\beta V)$. The inequality $\lambda < \beta/(2-\beta)$ is assumed, so that $\lambda < \beta$, meaning that u_ϕ is steeper than u_L. Therefore, the L scheduled service is *less convenient* than the non-scheduled service, which can be justified by the greater flexibility of personal transportation (on short-haul routes) for car owners (exceeding a certain income). This assumption is thoroughly discussed in Appendix *B*.

A traveler will choose the H scheduled service when $u_H > \max\{u_\phi, u_L\}$. The inequality $u_H > u_\phi$ requires $\alpha > \widetilde{\alpha}$ with

$$\widetilde{\alpha} = \frac{\left(p_H + \gamma/f_H - cd\right)\beta V}{(1-\beta)\,d}, \tag{4}$$

where the full price of the H scheduled service is larger than the full price of the non-scheduled service ($p_H + \gamma/f_H > cd$). The inequality $u_H > u_L$ holds for $\alpha > \overline{\alpha}$ with

$$\overline{\alpha} = \frac{\left(p_H + \gamma/f_H - p_L - \gamma/f_L\right)\lambda V}{(1-\lambda)\,d}, \tag{5}$$

where the full price of the H scheduled service is larger than the full price of the L scheduled service ($p_H + \gamma/f_H > p_L + \gamma/f_L$).

Finally, a traveler will choose the non-scheduled service when $u_\phi > \max\{u_H, u_L\}$. The condition $u_\phi > u_H$ requires $\alpha < \widetilde{\alpha}$ while $u_\phi > u_L$ requires $\alpha > \widehat{\alpha}$ with

$$\widehat{\alpha} = \frac{\left(cd - p_L - \gamma/f_L\right)\lambda\beta V}{(\beta-\lambda)\,d}, \tag{6}$$

where the full price of the non-scheduled service is larger than the full price of the L scheduled service ($cd > p_L + \gamma/f_L$).

Travelers with a sufficiently high value of time will choose the H scheduled service while travelers with a sufficiently low time value will choose the L scheduled service. Consequently, we are left with two possible scenarios depending on whether the non-scheduled service is a dominated alternative or not: the *case with an active non-scheduled service* where $0 < \widehat{\alpha} < \widetilde{\alpha} < 1$ (Scenario 1); and the *case without an active non-scheduled service* with $0 < \widetilde{\alpha} < \widehat{\alpha} < 1$ (Scenario 2). These two scenarios are represented in Figs. 1–2, where we observe that u_H is steeper than u_ϕ whereas u_ϕ is steeper than u_L, as $0 < \lambda < \beta < 1$.

Scenario 1 requires $\widehat{\alpha} < \widetilde{\alpha}$, which yields $d < d^* \equiv \frac{(p_H+\gamma/f_H)(\beta-\lambda)+(p_L+\gamma/f_L)\lambda(1-\beta)}{(1-\lambda)c\beta}$. Therefore, we conclude that Scenario 1 is only relevant for short distances, meaning that the non-scheduled service is considered a viable alternative by some travelers only for short-distance trips, i.e., for short-haul routes.[9] Proposition 1 below summarizes this result.

Proposition 1. *There exists a cutoff distance d^* such that*

(i) if $d < d^*$, Scenario 1 (with an active non-scheduled service) occurs, and

(ii) if $d > d^*$, Scenario 2 (without an active non-scheduled service) emerges.

A similar result was found in Bilotkach et al. (2010) in a framework with a monopoly carrier. Therefore, Proposition 1 extends this finding to a setting with two asymmetric scheduled carriers and a non-scheduled travel alternative.[10]

Looking at our data for the European airline markets (used in the empirical application presented in Section 5), this cutoff distance d^* is evaluated at around 600 kilometers (373 miles). Therefore, Proposition 1 suggests that non-scheduled services only constitute a competitive alternative in short-haul city-pair markets where the route distance does not exceed this threshold.

3.2. Demand functions

3.2.1. Scenario 1: Short-haul routes with intermodal competition

In this scenario, the non-scheduled service competes with the two scheduled services on short-haul markets (so that route distance does not exceed d^*, as pointed out in Proposition 1).

In terms of modeling, scheduled services could also be provided by HSR or intercity bus operators. However, the analysis that follows considers scheduled services to be provided by airlines, while the non-scheduled transportation alternative refers to the use of personal transportation. Therefore, consumers/travelers can undertake a trip either booking a flight with one of these two airlines or, alternatively, making use of their own car. By assuming carriers to be airlines, it is natural to interpret that the H and L air services are provided by a network and a low-cost carrier, respectively. Furthermore, interpreting carriers as airlines and non-scheduled transportation as personal transportation allows having a natural connection between both scenarios. Departing from Scenario 2 where both airlines operate on long-haul routes, Scenario 1 adds a new transportation mode (personal transportation) that becomes viable on short-haul routes. Finally, focusing on airlines is the natural choice, given that our empirical application makes use of data on flights within the European Economic Area.

A traveler will choose the H scheduled service when $\alpha > \widetilde{\alpha}$. Then, using (4), the demand for H scheduled services is given by

$$q_H = \int_{\widetilde{\alpha}}^{1} d\alpha = 1 - \widetilde{\alpha} = 1 - \frac{\left(p_H + \gamma/f_H - cd\right)\beta V}{(1-\beta)\,d}. \tag{7}$$

In a similar way, a traveler will choose the L scheduled service when $\alpha < \widehat{\alpha}$. Then, using (6), the demand for L scheduled services is given by

$$q_L = \int_{0}^{\widehat{\alpha}} d\alpha = \widehat{\alpha} = \frac{\left(cd - p_L - \gamma/f_L\right)\lambda\beta V}{(\beta-\lambda)\,d}. \tag{8}$$

[8] There is no schedule delay because this alternative transportation mode is non-scheduled. Furthermore, the model could also incorporate an outside option (not to travel) with utility $u_0 = y$, as in Bilotkach et al. (2010). With this additional element, the Scenario 1 (short-haul) can also be solved yielding similar qualitative results. However, the computations become more complex without gaining any further insight.

[9] This cutoff distance depends on the relative values of $\widehat{\alpha}$ and $\widetilde{\alpha}$, which depend on the heights of the utilities in Figs. 1–2 that are determined by the fare-and-frequency choices of the airlines. Therefore, this cutoff distance is endogenously determined. If the fare-and-frequency combinations determined by both carriers are very "attractive" for consumers, then the non-scheduled service becomes inactive, ending up in Scenario 2. If this is not the case, the setup is the one presented in Scenario 1.

[10] A more sophisticated version of the model could consider the convenience of personal transportation to be decreasing with distance, so that $\beta(d)$ with $\beta'(d) < 0$. This modeling choice would affect the threshold value d^* in Proposition 1, thereby complicating the analysis. In any case, our Scenario 1 would arise as long as route distance is sufficiently small.

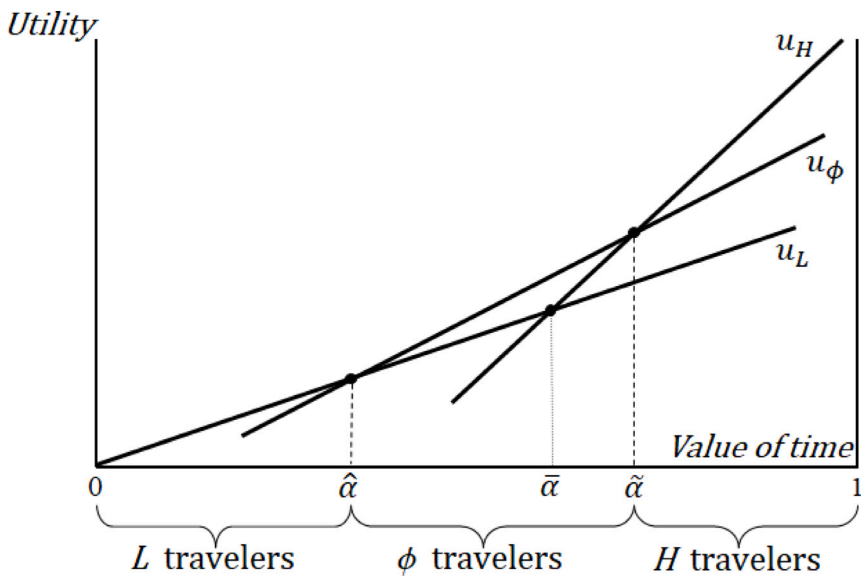

Fig. 1. Utilities in Scenario 1 (short-haul routes).

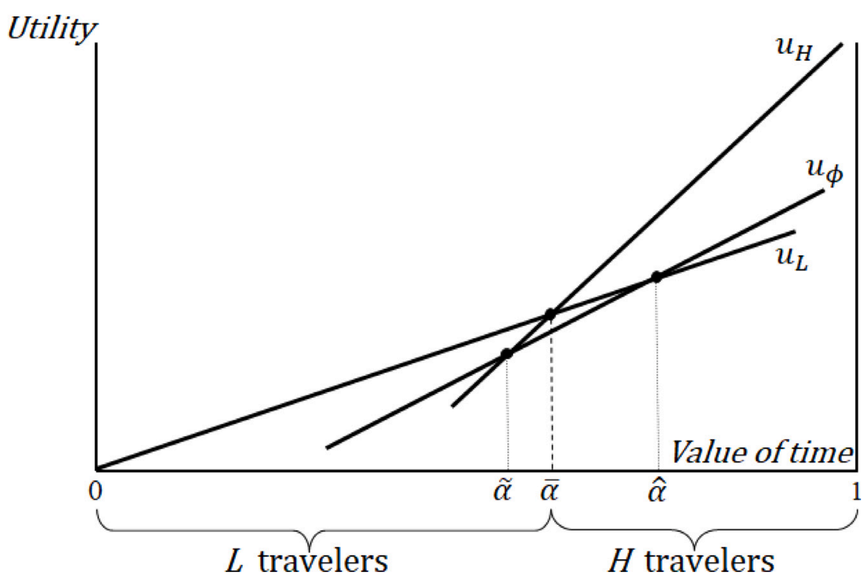

Fig. 2. Utilities in Scenario 2 (long-haul routes).

3.2.2. Scenario 2: Long-haul routes without intermodal competition

On long-haul routes (where the route distance exceeds d^*, as pointed out in Proposition 1), the non-scheduled service is not competitive. Therefore, two asymmetric duopoly carriers (e.g., a major carrier and a low-cost carrier) compete for passengers.

Ascertaining the effect of route distance on fares and frequencies on long-haul routes is more complex in our setup. Furthermore, our focus is clearly on short-haul routes, as we are interested in studying the effect of intermodal competition from personal transportation. In spite of all this and for the sake of completeness, we also present the analysis of long-haul routes, from which we can ascertain the effect of route distance on aggregate fares and frequencies.

A traveler will choose the H scheduled service when $\alpha > \overline{\alpha}$. Then, using (5), the demand for H scheduled services is given by

$$q_H = \int_{\overline{\alpha}}^{1} d\alpha = 1 - \overline{\alpha} = 1 - \frac{\left(p_H + \gamma/f_H - p_L - \gamma/f_L\right)\lambda V}{(1-\lambda)\,d}. \tag{9}$$

In a similar way, a traveler will choose the L scheduled service when $\alpha < \overline{\alpha}$. Then the demand for L scheduled services is given by

$$q_L = \int_{0}^{\overline{\alpha}} d\alpha = \overline{\alpha} = \frac{\left(p_H + \gamma/f_H - p_L - \gamma/f_L\right)\lambda V}{(1-\lambda)\,d}. \tag{10}$$

3.3. Cost and profit functions

Similarly to Bilotkach et al. (2010), the *operating cost* of an H flight is given by $\theta(d)+\tau s_H$ where s_H 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 twice continuously differentiable with $\theta'(0) = 0$ and $\theta'(d) > 0$ for $d > 0$ because fuel consumption increases with distance. As in Brueckner (2004), all seats are assumed to be filled, so that load factor equals 100%. Therefore, aircraft size can be determined residually dividing the airline's total traffic on a route by the number of flights, i.e., $s_H =$

q_H/f_H. The cost per seat, which can be written $\theta(d)/s_H + \tau$, visibly decreases with s_H 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.[11]

Therefore, airline's H total cost is $f_H\left[\theta(d) + \tau s_H\right]$ or, equivalently,

$$c_H = \theta(d) f_H + \tau q_H. \tag{11}$$

In a similar way, airline's L total cost is

$$c_L = \theta(d) f_L + \tau q_L, \tag{12}$$

where, for simplicity reasons, we assume equal cost parameters between both scheduled services (the extension with an asymmetric cost per seat is provided in footnote 14). Airlines' profits are $\pi_H = p_H q_H - c_H$ and $\pi_L = p_L q_L - c_L$, which can be rewritten using (11) and (12) as

$$\pi_H = \left(p_H - \tau\right) q_H - \theta(d) f_H, \tag{13}$$

$$\pi_L = \left(p_L - \tau\right) q_L - \theta(d) f_L. \tag{14}$$

4. Equilibrium analysis

4.1. Scenario 1: Short-haul routes with intermodal competition

After plugging (7) into (13), (8) into (14) and maximizing for p_H, p_L, f_H, and f_L, the following expressions emerge:

$$p_H = \frac{1}{2}\left(cd + \tau - \frac{\gamma}{f_H} + \frac{(1-\beta)d}{\beta V}\right), \tag{15}$$

$$p_L = \frac{1}{2}\left(cd + \tau - \frac{\gamma}{f_L}\right), \tag{16}$$

$$f_H = \left[\frac{\left(p_H - \tau\right)\gamma\beta V}{(1-\beta)\theta(d)d}\right]^{1/2}, \tag{17}$$

$$f_L = \left[\frac{\left(p_L - \tau\right)\gamma\lambda\beta V}{(\beta-\lambda)\theta(d)d}\right]^{1/2}, \tag{18}$$

where second-order conditions $\partial^2\pi_H/\partial p_H^2$, $\partial^2\pi_H/\partial f_H^2 < 0$, $\partial^2\pi_L/\partial p_L^2$, $\partial^2\pi_L/\partial f_L^2 < 0$ are satisfied by inspection and the positivity condition on the Hessian determinants is discussed below (see footnote 12). By combining (15) and (17) on the one hand and (16) and (18) on the other hand, the following equilibrium conditions are obtained:

$$\underbrace{\frac{2(1-\beta)\theta(d)d}{\gamma\beta V} f_H^3}_{Cf_H^*} = \underbrace{\left[cd - \tau + \frac{(1-\beta)d}{\beta V}\right] f_H - \gamma}_{Lf_H^*}, \tag{19}$$

$$\underbrace{\frac{2(\beta-\lambda)\theta(d)d}{\lambda\gamma\beta V} f_L^3}_{Cf_L^*} = \underbrace{(cd - \tau) f_L - \gamma}_{Lf_L^*}. \tag{20}$$

The equilibrium frequency f_H^* is shown graphically in Fig. 3 , as in Brueckner (2004) and Bilotkach et al. (2010). It is found at an intersection between a cubic expression (Cf_H^*) and a linear expression (Lf_H^*) whose vertical intercept is negative. The slope of Lf_H^* is positive as the full price of the non-scheduled service is larger than the full price of the L scheduled service ($cd > p_L + \gamma/f_L$) and $p_L > \tau$. Although two positive solutions are possible, only the second one satisfies the second-order conditions.[12]

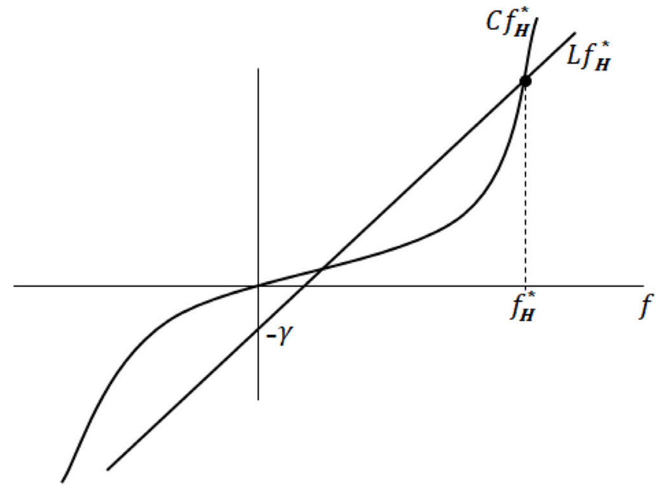

Fig. 3. The f_H^* solution in Scenario 1 (short-haul routes).

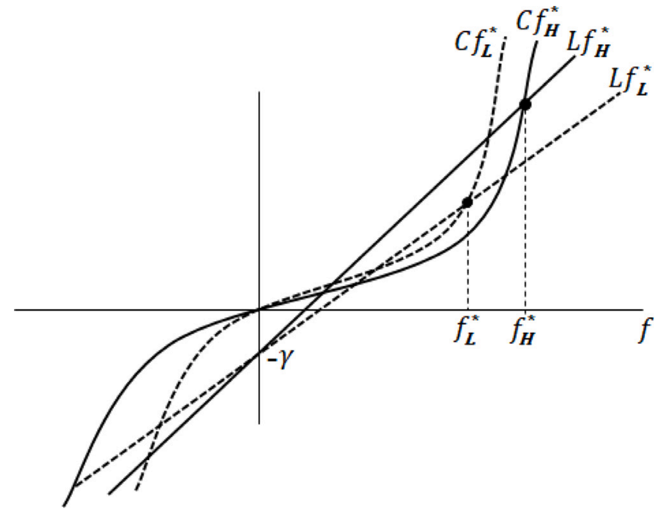

Fig. 4. Comparing f_H^* and f_L^* in Scenario 1 (short-haul routes).

The same procedure can be applied to show f_L^* graphically. Given that $Cf_H^* < Cf_L^*$ and that $slope\left(Lf_H^*\right) > slope\left(Lf_L^*\right)$, the natural result $f_H^* > f_L^*$ emerges graphically, as depicted in Fig. 4.[13] This result also implies $p_H^* > p_L^*$, given that the full price of the H scheduled service is larger than that of the L scheduled service (i.e., $p_H + \gamma/f_H > p_L + \gamma/f_L$).[14]

[11] For a given capacity, the use of larger aircraft implies reducing the number of flights. Furthermore, per-seat fuel consumption decreases with aircraft size.

[12] Positivity of the Hessian determinants requires $p_H - \tau > \frac{\gamma}{4f_H}$ and $p_L - \tau > \frac{\gamma}{4f_L}$, respectively. For the second intersection to be relevant, the slope of the cubic expression must exceed the slope of the linear expression, i.e., $\frac{6(1-\beta)\theta(d)d}{\gamma\beta V} f_H^2 > cd - \tau + \frac{(1-\beta)d}{\beta V}$ and $\frac{6(\beta-\lambda)\theta(d)d}{\gamma\lambda\beta V} f_L^2 > cd - \tau$, respectively. Using the first-order conditions for p_H and f_H on the one hand and those for p_L and f_L on the other hand, these expressions reduce to $p_H - \tau > \frac{\gamma}{4f_H}$ and $p_L - \tau > \frac{\gamma}{4f_L}$, respectively, which are the conditions required by the positivity of the Hessian determinants.

[13] $Cf_H^* < Cf_L^*$ requires $1 - \beta < \frac{\beta-\lambda}{\lambda}$, which can be rewritten as $\lambda < \frac{\beta}{2-\beta}$ and this condition is assumed to hold.

[14] An extension of the model could consist in introducing asymmetry in the cost per seat, given that low-cost carriers have lower operational costs than network carriers. Looking at the equilibrium conditions (19) and (20) along with Fig. 4, it is easy to ascertain the effect of introducing a cost gap, so that $\tau_L < \tau < \tau_H$. More precisely, we would have τ_H in (19) and τ_L in (20), so that $slope\left(Lf_H^*\right)$ would be lower thereby pushing down f_H^* while $slope\left(Lf_L^*\right)$ would be higher thereby pushing up f_L^*. Under this specification, the condition $slope\left(Lf_H^*\right) > slope\left(Lf_L^*\right)$ that is required to obtain $f_H^* > f_L^*$ would require to observe $\tau_H - \tau_L < \frac{(1-\beta)d}{\beta V}$. In words, given that higher operation costs force

Looking at the equilibrium conditions (19)–(20) together with Figs. 3–4, a comparative-statics analysis for the parameters can be carried out. Although some effects do not seem trivial from inspection of (19)–(20), their overall effect can be ascertained analytically. The proposition below focuses on the effect of the route distance (d) on the equilibrium frequency.

Proposition 2. *On short-haul routes, the equilibrium frequencies (f_H^* and f_L^*) rise with an increase in the route distance for sufficiently short distances.*

This result appears counterintuitive as it would be natural for airlines to reduce frequencies on longer routes. The explanation comes from the fact that there are two opposing effects of distance on frequencies: a *negative direct effect* (that can be observed in (17)–(18) holding p_H and p_L fixed), and a *positive indirect effect* through fares (that can be identified from the joint observation of (15)–(16) and (17)–(18)). This result is explained by the competitive pressure exerted by personal transportation. In this environment, increasing service quality (along with fares) allows carriers attracting more demand and boosting their profits.[15]

Let us now study the effect of distance on fares. The optimal conditions for p_H and p_L (see (15)–(16)) reveal that, holding f_H and f_L fixed, distance has a *positive direct effect* on equilibrium fares. Furthermore, there is an additional *positive indirect effect* through frequencies for sufficiently short distances, given that there is a positive relationship between equilibrium fares and frequencies and that Proposition 2 shows a positive impact of distance on frequency.

Proposition 3. *On short-haul routes, the equilibrium fares (p_H^* and p_L^*) rise with an increase in the route distance for sufficiently short distances.*

On the one hand, longer routes are more expensive (*positive direct effect*) and, on the other hand, the positive effect of distance on service quality (Proposition 2) raises passengers' willingness to pay (*positive indirect effect*). All in all, Propositions 2–3 show that, under intermodal competition from personal transportation on short-haul routes, carriers increase their service quality with route distance at higher fares.

The proposition that follows looks at the effects of changes on the cost of driving (c), which can be interpreted as the intensity of intermodal competition from personal transportation.

Proposition 4. *On short-haul routes, the equilibrium frequencies (f_H^* and f_L^*) and fares (p_H^* and p_L^*) fall as intermodal competition from personal transportation becomes tougher.*

A lower c (i.e., tougher intermodal competition from personal transportation) decreases the slope of Lf_H^* and Lf_L^* in Figs. 3–4, so that the equilibrium frequencies (f_H^* and f_L^*) decrease. The reason is that the car becomes a better option and more passengers choose it instead of air travel. Looking at the effect on fares, as the alternative non-scheduled service becomes more competitive (lower c), airlines react by decreasing fares (*negative direct effect*). Furthermore, poorer frequencies lower passengers' willingness to pay (*negative indirect effect*). Overall, Proposition 4 shows that a tougher intermodal competition from personal transportation on short-haul routes results into poorer service quality at lower fares.

From (15) and (16), the following relationship arises

$$p_H - p_L = -\frac{1}{2}\left(\frac{\gamma}{f_H} - \frac{\gamma}{f_L}\right) + \frac{(1-\beta)\,d}{2\beta V} \tag{21}$$

where $p_H - p_L$ is clearly positive, given that $f_H > f_L$. The expression (21) allows stating the following corollary.

Corollary 1. *On short-haul routes, there is a positive relationship between the equilibrium frequency gap ($f_H^* - f_L^*$) and the equilibrium fare gap ($p_H^* - p_L^*$).*

Whenever the equilibrium frequency gap rises with distance, there is a *positive effect* of route distance on the fare gap as well (that can be decomposed into a direct effect and an indirect effect through the frequency gap). The ultimate effect of route distance on both gaps is empirically ascertained in Section 5.

All in all, distance has a positive effect on frequencies on short-haul routes (where there is competition from personal transportation), as carriers can attract demand and boost profits by increasing service quality (see Proposition 2). Fares follow the same pattern because longer routes are more costly to operate, but also because a higher service quality entails a "product upgrade" that translates into a higher passenger willingness to pay (see Proposition 3).

Similarly, a tougher competition from personal transportation makes it a better alternative, thereby attracting more passengers. As a consequence, flight frequencies decrease and produce a "product downgrade" that translates into a lower passenger willingness to pay that exert a downward pressure on fares (see Proposition 4).

Even though distance and the intensity of intermodal competition from personal transportation produce a similar *qualitative* effect on the fare and frequency strategies of network and low-cost airlines (see Propositions 2–4), their *quantitative* effect can be different. Corollary 1 shows that the fare gap ($p_H - p_L$) and the frequency gap ($f_H - f_L$) are positively related. Therefore, whenever the gaps increase, the differentiation between network and low-cost airlines becomes more marked. The ultimate effect of route distance on these gaps remains an empirical issue that will be ascertained in Section 5.

4.2. Scenario 2: Long-haul routes without intermodal competition

After plugging (9) into (13), (10) into (14) and maximizing, the reaction functions are

$$p_H = \frac{1}{2}\left(p_L + \tau - \frac{\gamma}{f_H} + \frac{\gamma}{f_L} + \frac{(1-\lambda)\,d}{\lambda V}\right), \tag{22}$$

$$p_L = \frac{1}{2}\left(p_H + \tau + \frac{\gamma}{f_H} - \frac{\gamma}{f_L}\right), \tag{23}$$

$$f_H = \left[\frac{(p_H - \tau)\,\gamma\lambda V}{(1-\lambda)\,\theta(d)\,d}\right]^{1/2}, \tag{24}$$

$$f_L = \left[\frac{(p_L - \tau)\,\gamma\lambda V}{(1-\lambda)\,\theta(d)\,d}\right]^{1/2}. \tag{25}$$

From (22)–(23),[16] the following relationships arise:

$$p_H + p_L = 2\tau + \frac{(1-\lambda)\,d}{\lambda V}, \tag{26}$$

$$p_H - p_L = -\frac{2}{3}\left(\frac{\gamma}{f_H} - \frac{\gamma}{f_L}\right) + \frac{(1-\lambda)\,d}{3\lambda V}, \tag{27}$$

where (27) reveals a positive relationship between the fare gap ($p_H - p_L$) and the frequency gap ($f_H - f_L$), just as observed on short-haul routes (see (21)). Finally, computing $f_H^2 + f_L^2$ using (24)–(25) and substituting (26) yields

$$f_H^2 + f_L^2 = \frac{\gamma}{\theta(d)}. \tag{28}$$

In Scenario 2, computing equilibrium conditions for f_H and f_L in the format of (19)–(20) is very complex. However, expressions (26) and

network airlines to reduce frequencies, having $f_H^* > f_L^*$ requires the cost gap favoring low-cost carriers not to be very big. This is a very sensible result but complicates the analysis and deviates from the main point of the paper that has to do with the effect of distance and intermodal competition from personal transportation on price and frequency decisions.

[15] A similar result is found in Bilotkach et al. (2010) in a setting with a monopoly airline.

[16] The second-order conditions $\partial^2\pi_H/\partial p_H^2$, $\partial^2\pi_H/\partial f_H^2 < 0$, $\partial^2\pi_L/\partial p_L^2$, $\partial^2\pi_L/\partial f_L^2 < 0$ are satisfied by inspection and the positivity conditions on the Hessian determinants are as under Scenario 1, i.e., $p_H - \tau > \frac{\gamma}{4f_H}$ and $p_L - \tau > \frac{\gamma}{4f_L}$, respectively.

(28) allow ascertaining the effect of distance on overall equilibrium fares and frequencies.

There is no intermodal competition on long-haul routes because the non-scheduled service is not viable. Therefore, our attention focuses exclusively on the effect of distance on fares and frequencies. The proposition that follows is obtained from the observation of (28).

Proposition 5. *On long-haul routes, overall equilibrium frequencies* ($f_H^* + f_L^*$) *fall with an increase in route distance.*

The negative effect of distance on flight frequency is a non-surprising result, as service quality is typically lower on more distant long-haul routes (where there is no intermodal competition). This finding is consistent with Wei and Hansen (2007), Bilotkach et al. (2010), and Pai (2010). The absence of intermodal competition reduces the incentives of scheduled carriers to increase service quality with distance to attract demand from other transportation modes. Besides, carriers also need to rationalize operating costs when deciding service quality on long-routes. Looking at (26), the effect of distance of overall fares is easily ascertained.

Proposition 6. *On long-haul routes, overall equilibrium fares* ($p_H^* + p_L^*$) *rise with an increase in route distance.*

Therefore, on long-haul routes, air services provided on more distant routes are more expensive as they are more costly (even though overall service quality decreases).

As suggested before, the expression (27) reveals a positive relationship between the fare and the frequency gap. These gaps provide a measure of the different fare and frequency strategies adopted by network and low-cost carriers.

Corollary 2. *On long-haul routes, there is a positive relationship between the equilibrium frequency gap* ($f_H^* - f_L^*$) *and the equilibrium fare gap* ($p_H^* - p_L^*$).

As mentioned in the analysis for short-haul routes, the ultimate effect of route distance on these gaps will be empirically explored in Section 5.

The joint observation of Propositions 2 and 5 shows an opposite effect of distance on frequencies, depending on whether routes are either short- or long-haul. Combining these results with Proposition 1 allows formulating the following corollary.

Corollary 3. *Overall equilibrium frequencies* ($f_H^* + f_L^*$)

(i) *increase with distance for* $d < d^*$ *(short-haul routes) for sufficiently short distances; and*

(ii) *decrease with distance for* $d > d^*$ *(long-haul routes).*

This corollary highlights the importance of having intermodal competition from personal transportation on short-haul routes, thereby extending to a competitive environment the results obtained in Bilotkach et al. (2010) in the framework of a monopoly model.

Instead, as revealed by Propositions 3 and 6, fares increase with route distance both on short- and long-haul routes because distant routes are more costly (an effect that is reinforced on short-haul routes because higher frequencies raise passengers' willingness to pay).

Corollary 4. *Overall equilibrium fares* ($p_H^* + p_L^*$) *increase with distance both on short-haul routes (for sufficiently short distances) and long-haul routes.*

Finally, Corollaries 1–2 allow formulating the following statement.

Corollary 5. *There is a positive relationship between the equilibrium frequency gap* ($f_H^* - f_L^*$) *and price gap* ($p_H^* - p_L^*$) *both on short- and on long-haul routes. Therefore, when the equilibrium frequency gap rises with distance, the equilibrium fare gap* ($p_H^* - p_L^*$) *rises as well.*

The empirical application that follows explores the actual effect of route distance on fares, frequencies, and both the frequency and the fare gap.

5. Empirical application

This section offers an empirical application of the obtained predictions using detailed data for the European aviation market. A key element of the model is the distinction between short- and long-haul routes, which depends on whether the non-scheduled service is a viable alternative or not (Proposition 1). Hence, a first empirical challenge consists in identifying the cutoff distance that separates these two types of routes.

Looking at the effect of distance on frequencies, our theoretical predictions suggest a positive relationship on short-haul routes (Proposition 2) and a negative one on long-haul routes (Proposition 5). With respect to the effect of distance on fares, a positive relationship is expected both on short- and long-haul routes (Propositions 3 and 6). These predictions can be tested, as the considered dataset contains information on frequencies, fares, and distance.

The model also predicts a positive relationship between the frequency gap and the price gap both on short- and long-haul routes (Corollaries 1–2), where both gaps are built assuming that network airlines provide a high-quality scheduled service, while low-cost airlines provide a low-quality scheduled service. This prediction and the ultimate effect of route distance on both gaps are also checked empirically in this section.

Our predictions on the effect of the intensity of intermodal competition from personal transportation on short-haul routes (Proposition 4) cannot be tested empirically, as there are no data on alternative transportation modes (beyond the effect that is already captured by distance). Using a measure of road quality could be a reasonable way to proxy the viability of personal transportation on a certain route. However, the size of our dataset (that contains 25,883 routes) makes this option unfeasible.[17]

Finally, this section also provides an extension that offers some interesting results for short-haul routes that are not directly linked to our theoretical predictions. This extension has to do with the relationship between route distance and the observed intertemporal price dispersion (using mean posted fares by airlines at certain moments before the flight departure).

5.1. Data

We use monthly data on flights within the Europe Economic Area (European Union, Norway, and Iceland), Switzerland, and the United Kingdom. Therefore, we account for most European air traffic although there are some European countries that are not included in the sample.[18] Data are at the airline-route level, where *routes* denote city-pair markets, so that multi-airport cities are considered as a single origin and/or destination. For example, the city-pair market Vienna-Paris may include flights from Vienna to the airports of Paris-Charles de Gaulle (CDG), Paris-Orly (ORY), and Paris-Beauvais (BVA).

There are two dependent variables in the analysis: (i) frequencies supplied by airlines at the route level and (ii) posted fares by airlines at the route level. Both fare data and supply data come from RDC Aviation, which is a recognized data provider in aviation research. More precisely, two data sources from RDC Aviation are considered: *Apex-schedules* and *Apex-fares*.

On the one hand, *Apex-schedules* provides supply data for all scheduled flights (frequency, aircraft size, and distance). Our sample contains monthly data for all flights within Europe over the period 2007-2019.

[17] Using a smaller dataset that controls for the quality of roads, Bilotkach et al. (2010) find evidence of a positive relationship between road quality and flight frequencies for routes longer than 550 km.

[18] The European countries that are not included in our sample are: Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Georgia, Macedonia, Montenegro, Moldova, Russia, Serbia, Turkey, and Ukraine.

This sample includes around 2 million observations in an unbalanced panel dataset, given that some airline-route pairs registered no traffic during several months. The analysis is therefore restricted to routes shorter than 2000 km, which allows having a more balanced sample between short- and long-haul routes. This restricted sample has around 1.1 million observations. Airlines that cannot be classified as either network or low-cost are excluded, given that our focus is on the frequency and price gaps between both types of airlines (details on the way airlines are considered to be network or low-cost are provided later on).

On the other hand, *Apex-fares* provides monthly fare data at the airline-route level over the period 2013–2019. These data include mean posted fares at certain moments before the flight departure (six months, three months, one month, and one week before the departure), along with the estimated weighted fare, which is the main fare variable used in the econometric analysis.[19] These variables refer to one-way flights and include all government taxes, such as airport and departure taxes. Different fare classes are also considered, including Economy, Business, and Premium. This sample includes around 660,000 observations in an unbalanced panel dataset, although the restricted sample to routes shorter than 2000 km has around 475,000 observations. It should be acknowledged that, although *Apex-schedules* provides supply data for all scheduled flights, *Apex-fares* provides extensive but not exhaustive data, as some fare information for certain city-pair markets (with scheduled services) may be missing.

Additional data have also been collected to build control variables. For every city-pair market in the sample, these controls are the population and the per-capita income of the region surrounding each of the two endpoints (weighted mean values of the origin and destination cities).[20] These data are at the NUTS-3 level and have been obtained from Eurostat.[21]

Information about rail and bus services in intercity markets is very limited, considering that our sample includes many routes over the period 2007–2019. However, we have built two dummies to capture this potential competition. First, a dummy that takes the value one for city-pairs with non-stop HSR services (information from the International Union of Railways). As mentioned before, several empirical studies provide evidence on the relevant impact of HSR on air services. Second, a dummy that takes the value one for domestic routes (with no islands as endpoints) of countries having liberalized their intercity bus market since the implementation year: Poland (1988), Sweden (1998), Norway (2003), Germany (2013), Italy (2014), France (2015), and Portugal (2019). Previous studies have found that the liberalization of the interurban bus market results into lower prices and/or higher connectivity (Aarhaug and Fearnley, 2016; Alexandersson et al., 2010; Avenali et al., 2023; Beria and Bertolin, 2019; Blayac and Bougette, 2017; Buri et al., 2024; Dürr and Hüschelrath, 2015).[22]

As in previous studies, network airlines are former flag carriers and/or airlines integrated in global alliances (Oneworld, Star Alliance, and SkyTeam).[23] Low-cost airlines are those included in the classification provided by the International Civil Aviation Organization (ICAO). The main network airlines in our sample are: Adria Airways, Aegean, Air Berlin, Air Europa, Air France, Alitalia, Austrian, British Airways, Brussels Airlines, Czech Airlines, Croatia Airlines, Finnair, Iberia, KLM, LOT, Lufthansa, Malev, Olympic Air, SAS, Spanair, TAP, and TAROM. And the main low-cost airlines in our sample are: Belle Air, Bmi Baby, Blue Air, Blue Panorama, Condor, Easyjet, Eurowings, Germanwings, Helvetic Airways, Intersky, Jet2, Meridiana, Monarch, Niki, Norwegian, Ryanair, Sky Europe, Smartwings, Sun Express, Transavia, Volotea, Vueling, Wizz Air, and XL Airways. The group of carriers that are neither network nor low-cost airlines includes regional carriers, airlines with a hybrid business model, and some charter airlines providing scheduled flights (as mentioned above, these airlines are excluded). In our sample, the overall mean weighted fare considering *all airlines* is EUR 84.22, being lower for *low-cost airlines* (EUR 76.81) and higher for *network airlines* (EUR 119.32). Therefore, the fare gap between low-cost and network airlines seems to be relevant.

Fig. 5 provides a non-parametric estimation of the relationship between flight frequency and route distance. According to the theoretical analysis presented before, we may expect a positive relationship between frequency and distance on short-haul routes and a negative one on long-haul routes (Corollary 3). Data in Fig. 5 confirms our theoretical prediction and suggests a cutoff distance located around 600 km.

5.2. Estimation

We estimate the following model at the airline-route level k for month m and year y:

$$Y_{kmy} = \alpha + \beta Distance_k + \theta X_{kmy} + \lambda_m + \delta_y + \varepsilon_{kmy}, \tag{29}$$

where the dependent variable denotes either frequencies supplied or weighted fares charged by airlines. The main explanatory variable is route distance (*Distance*). We consider several controls (X) that capture the influence of demand, the intensity of intramodal and intermodal competition (from scheduled services), the type of airline operating the route, and origin and destination fixed effects. Finally, month (λ) and year (δ) fixed effects are also included.

The empirical analysis has two goals related to the predictions derived from our model. First, to examine whether the sign of the relationship between frequencies/fares and distance differs between short- and long-haul routes. We test whether the relationship between distance and frequencies may reverse in Scenario 1 (short-haul routes) by interacting the *Distance* variable with a dummy variable for routes shorter than 600 km (considering the entire sample).

Second, to analyze the relationship between distance and the frequency/fare gaps on short- and long-haul routes (i.e., Scenarios 1 and 2) by interacting the *Distance* variable with a dummy for network airlines. In line with our model, network airlines are assumed to provide a high-quality while low-cost airlines are assumed to provide a low-quality scheduled service. We split the sample between routes shorter and longer than 600 km to identify possible differences between short- and long-haul routes.

Making use of both the entire sample and subsamples seems sensible because our analysis relies on the interaction between the *Distance* variable and dummies for short/long routes and for network/low-cost airlines. Considering two interactions of the *Distance* variable along with the uninteracted *Distance* variable in the same regression (using the entire sample) would yield a high correlation between the two interaction variables, thereby preventing from identifying the individual effect of each of them. This conclusion advises against combining in a single regression the analysis of the relationship between distance and frequencies/fares and the analysis of the relationship between distance and the frequency/fare gaps.

A number of relevant control variables (both for frequencies and weighted fares) are incorporated. First, we take into account two demand shifters: population and income per capita. Income per capita may also approximate travelers' willingness to pay. Given that demand on routes that connect richer and more populated endpoints should be higher, a positive effect of both variables is expected in the frequency

[19] Weights are based on the number of registered bookings in each of the aforementioned periods.

[20] In the case of the per-capita income, the weighted mean values of the origin and destination cities use population as the weighting criterion.

[21] The NUTS taxonomy is a hierarchical system that classifies the territory of the European Union using three different territorial units: NUTS-1, NUTS-2, and NUTS-3, from larger to smaller.

[22] International routes are liberalized in Europe since 2011, but this is a common shock for all routes in our sample that we cannot identify beyond what is captured by the year dummies.

[23] See Fageda and Flores-Fillol (2012b, 2016).

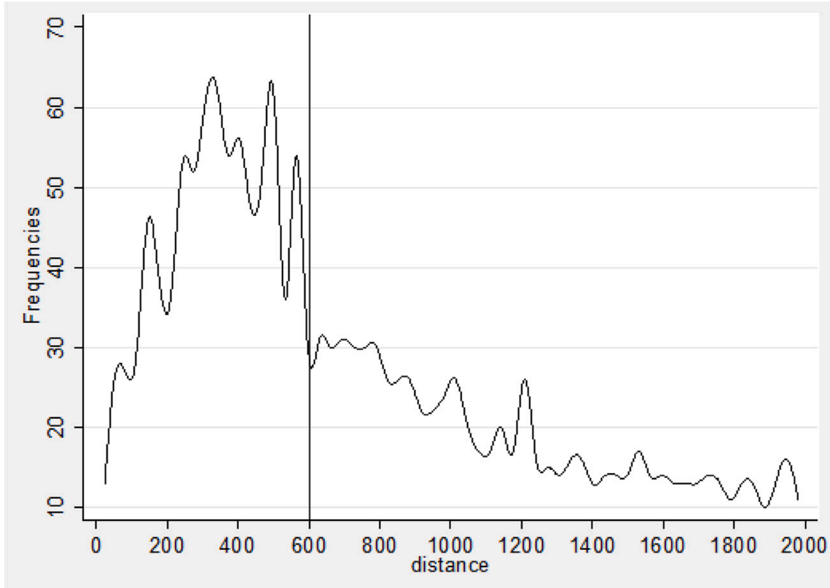

Fig. 5. Spline of total frequency with respect to route distance.

regressions. The expected result in the fare regressions is less clear. On the one hand, a higher demand may enable airlines to charge higher mark-ups. However, on the other hand, airlines could also operate with lower costs due to a better exploitation of density economies.

Second, several variables account for competition intensity. The *Herfindahl–Hirschman Index (HHI)* in terms of flights per route measures the intensity of intramodal competition. Hence, a negative effect is expected in the frequency regressions while a positive effect is expected in the fare regressions. A variable measuring *airlines' presence at airports*, defined as the airline's share of total flights operated at the airport is also considered. This variable may capture the market power of the airline at the airport but also a potential better exploitation of density economies. We also include a dummy for routes having an *island as endpoint*. The island dummy is explained by the absence of intermodal competition, as there is no possible surface transportation on such routes.[24] Furthermore, many domestic routes having an island as endpoint are subject to policy interventions in the form of public service obligations (PSOs) and resident discounts. Finally, the intensity of the intermodal competition from trains and buses is approximated by adding a dummy for routes having *HSR services* and a dummy for domestic routes where the *intercity bus market is liberalized*. A more intense intermodal competition could exert a downward pressure on airfares. Instead, the expected effect on frequencies seems less clear.

Third, a dummy for network airlines is included since their route configuration and cost structure are different from those of low-cost airlines. We also add a dummy for the Economy fare class in equations having weighted fares as dependent variable. All regressions include month and year fixed effects to account for seasonal variations and common shocks.

Finally, separate endpoints fixed effects (i.e., origin and destination fixed effects) are also incorporated to account for city-specific time-invariant characteristics like tourist attractions, city amenities, whether a city is a capital/major hub airport, number of airports per city, distance of airports with respect to the city-center, etc.

[24] The variables *HHI* and *airline's presence at airports* could be affected by an endogeneity bias. The difficulty in finding good instruments imposes a challenge to properly identify the effect of such competition variables. However, these variables are used as controls while the main explanatory variable is *Distance*.

Table 1 shows the mean values of the variables used in the empirical analysis considering the entire sample and the subsamples for short- and long-haul, respectively. Some data deserve to be highlighted. First, short-haul frequencies more than double long-haul frequencies, which can be explained by the existence of a higher demand on shorter routes along with the effect of intermodal competition. Second, fares are only slightly higher on long-haul routes, which means that fares per kilometer are much higher on short-haul routes. There are several reasons explaining that the cost per kilometer increases less than proportionally with respect to the number of kilometers flown: long-haul routes involve higher average speeds, less intense fuel consumption, and lower per-kilometer fixed costs. Third, there is a higher proportion of low-cost airlines (as compared to network airlines) on long-haul routes. Fourth, HSR intermodal competition affects only around 3% of observations on short-haul routes, while its presence is marginal on long-haul routes. Fifth, a relevant proportion of routes (between 15% and 18% of total observations, depending on the specification) has at least one island as endpoint, both on short- and long-haul routes. Sixth, airline competition is weak in general, even though it may be intense on some dense routes. This can be observed both in the high values of the HHI (exceeding 0.70 in all samples) and in the high mean values of the airport presence variable, which suggest that airlines concentrate flights in few airports. Finally, a high proportion of short-haul routes are affected by a liberalized intercity bus market.

5.3. Results

5.3.1. Flight frequencies

Table 2 shows the results of regressions with frequencies as dependent variable. The entire sample is considered in column 1, where the *Distance* variable is interacted with a dummy for short-haul routes taking into account that the cutoff distance separating short- from long-haul routes is around 600 km (see Proposition 1 and Fig. 5).

Results in Table 2 provide evidence of a (general) negative relationship between frequencies and distance. However, such negative relationship is reversed for short-haul routes. This result is consistent with our predictions (Propositions 2 and 5) and with the empirical results obtained in Bilotkach et al. (2010).

Columns 2 and 3 show the results on the relationship between *Distance* and the frequency gap (defined as the difference between frequencies provided by network and low-cost airlines) on short- and

Table 1
Mean values of variables used in the empirical analysis.

	Frequency sample			Fare sample		
	All (N=1,096,887)	Short-haul (N=250,961)	Long-haul (N=845,926)	All (N=476,052)	Short-haul (N=75,270)	Long-haul (N=400,782)
Frequency (#flights)	47.695	84.677	36.909	–	–	–
Fare (EUR)	–	–	–	89.374	83.802	90.424
Distance (km)	1,055.071	407.252	1,243.57	1,127.268	437.128	1,258.208
Population (#inhabitants)	2,761,590	2,354,898	2,879,691	2,967,410	2,703,512	3,014,475
Income (EUR per capita)	39,604.13	39,742.28	39,560.06	41,429.92	44,502.77	40,853.03
HSR (dummy)	0.010	0.039	0.001	0.008	0.042	0.001
Island (dummy)	0.176	0.156	0.181	0.162	0.154	0.163
HHI (range 0–1)	0.712	0.742	0.703	0.704	0.719	0.701
Domestic (dummy)	0.228	0.576	0.111	0.147	0.490	0.096
Intercity bus liberalized (dummy)	0.062	0.185	0.025	0.072	0.264	0.036
Airport presence (share of flights)	0.228	0.298	0.208	0.226	0.272	0.217
Network_airline (dummy)	0.413	0.649	0.344	0.262	0.474	0.223
Economy (dummy)	–	–	–	0.928	0.891	0.935

Table 2
Relationship between distance and frequency (and frequency gap).

VARIABLES	(1) Frequency	(2) Frequency	(3) Frequency
Distance	−0.0215*** (0.00110)	−0.0178 (0.0178)	−0.00233 (0.00174)
Distance X Short (<600 km)	0.0307*** (0.00373)		
Network_airline		50.828*** (8.126)	51.29*** (3.691)
Distance X Network_airline		0.0585*** (0.0188)	−0.0322*** (0.00297)
Intercity bus liberalized	53.99*** (3.516)	21.43*** (2.918)	31.69*** (5.047)
HSR	48.51*** (13.73)	−9.100 (9.287)	107.5*** (37.03)
Island	1.784 (9.380)	−27.78** (13.52)	−3.910 (3.040)
HHI	−15.57*** (1.270)	−5.704 (4.808)	−4.619*** (1.393)
Population	−8.23e−06*** (9.84e−07)	−1.52e−05*** (3.93e−06)	−7.52e−06*** (7.68e−07)
Income	−0.000175** (8.58e−05)	−0.000310 (0.000201)	−0.000411*** (9.75e−05)
Airport presence	163.9*** (4.700)	207.6*** (11.85)	128.5*** (5.272)
Constant	38.16 (24.86)	−76.53* (43.93)	−50.34*** (15.35)
Observations	1,096,887	250,961	845,926
R-squared	0.501	0.584	0.523
Origin and destination FE	yes	yes	yes
Year and month FE	yes	yes	yes
Sample	all	short-haul	long-haul
Clusters	route-airline	route-airline	route-airline

Note: Standard errors in parenthesis (robust to heteroscedasticity and clustered at the route-airline level). F-test (statistical significance Distance + Distance X Short): 4.29**.
*** Statistical significance at 1%.
** Statistical significance at 5%.
* Statistical significance at 10%.

long-haul routes. In these regressions, the dummy for network airlines is interacted with the *Distance* variable. As expected, network airlines provide higher frequencies than low-cost airlines. The interaction variable allows testing the relationship between *Distance* and the frequency gap. On short-haul routes, the frequency gap increases with distance. Indeed, the coefficient of the interaction between *Distance* and the dummy for network airlines is positive and statistically significant. Instead, on long-haul routes, the frequency gap decreases with distance. The coefficient of the interaction between *Distance* and the dummy for network airlines is negative and statistically significant. The results on the frequency gap are commented later on, taking into account the effect of distance on the fare gap.

Regarding the controls, the variables of population and income per capita do not work as expected because of the presence of origin and destination fixed effects.[25] The negative coefficient of the HHI variable shows that airlines compete in frequencies, although it is only statistically significant for long-haul routes. Frequencies are higher on long-haul routes with HSR services. However, this result should be interpreted with caution due to the limited number of observations of long-haul routes with HSR services. In addition, airlines provide higher frequencies on routes where intercity urban services are liberalized. This could be explained by a higher demand in these domestic markets. Furthermore, it could also be that airlines do not really take competition from buses into account in their frequency decisions, given that the willingness to pay of bus users is usually lower than that of air travelers. The lack of intermodal competition explains the negative impact of the island variable. Finally, we also find that airlines with a higher presence in the origin and destination airports provide more frequencies on both short- and long-haul routes.

5.3.2. Fares

Table 3 contains the results of regressions using fares charged by airlines as dependent variable. We first explore the interaction between *Distance* and the dummy for short-haul routes using the entire sample. Then, we consider the interaction between the *Distance* variable and the dummy for network airlines splitting the sample between short- and long-haul routes.

As expected, the relationship between *Distance* and fares is positive on short- and long-haul routes. The coefficient of *Distance* is positive and statistically significant and the interaction between *Distance* and the coefficient of the dummy for short-haul routes is also positive. The non-significance of this interaction term implies no differences between short- and long-haul routes. This is consistent with our theoretical predictions (Propositions 3 and 6). Furthermore, as expected, network airlines charge higher fares than low-cost airlines.

We test the relationship between distance and the fare gap by adding the interaction between the dummy for network airlines and the *Distance* variable. Both on short- and long-haul routes, the results contained in Table 3 reveal a clear positive relationship between distance and the fare gap, as there is a stronger positive effect of *Distance* on fares charged by network carriers as compared to the effect on fares charged by low-cost airlines. Therefore, on short-haul routes, both the frequency gap and the fare gap increase with route distance,

[25] Unreported regressions without origin and destination fixed effects confirm this statement.

Table 3
Relationship between distance and fare (and fare gap).

VARIABLES	(1) Fare	(2) Fare	(3) Fare
Distance	0.0341*** (0.000737)	0.00888* (0.00532)	0.0297*** (0.000670)
Distance X Short (<600 km)	0.00318 (0.00194)		
Network_airline	49.44*** (0.773)	20.50*** (5.531)	33.00*** (3.147)
Distance X Network_airline		0.0434*** (0.0121)	0.0134*** (0.00252)
Economy	−158.4*** (2.196)	−133.5*** (3.327)	−165.6*** (2.630)
Intercity bus liberalized	0.217 (1.021)	−6.375*** (2.007)	−1.267 (1.006)
HSR	−11.50*** (2.888)	−8.168** (3.545)	−5.175** (2.510)
Island	12.34** (4.882)	11.46* (6.252)	1.731 (2.868)
HHI	3.722*** (0.961)	23.08*** (2.980)	2.010** (0.975)
Population	−2.92e−06*** (2.79e−07)	−4.61e−06*** (6.30e−07)i	−2.36e−06*** (3.06e−07)
Income	0.000279*** (4.01e−05)	−0.000135 (0.000110)	0.000258*** (4.57e−05)
Airport presence	−28.74*** (2.778)	−25.86*** (6.075)	−25.80*** (3.102)
Constant	178.3*** (10.87)	195.5*** (22.64)	184.1*** (8.388)
Observations	476,052	75,270	400,782
R-squared	0.703	0.761	0.708
Origin and destination FE	yes	yes	yes
Year and month FE	yes	yes	yes
Sample	all	short-haul	long-haul
Clusters	route-airline	route-airline	route-airline

Note: Standard errors in parenthesis (robust to heteroscedasticity and clustered at the route-airline level).
*** Statistical significance at 1%.
** Statistical significance at 5%.
* Statistical significance at 10%.

which is consistent with our theoretical predictions (Corollary 1), so that there is an increased differentiation between network and low-cost airlines as the distance rises. A possible explanation would suggest that personal transportation affects more intensively network carriers than low-cost carriers (which would make sense as low-cost passengers are characterized by lower income, value of time, and car ownership).[26] Consequently, network carriers would increase their fares and frequencies faster than low-cost carriers as route distance increases.

However, on long-haul routes, our empirical results reveal that the frequency gap decreases with distance while the fare gap increases with distance. These findings do not match our theoretical predictions (Corollary 2). This result could be explained by the hub-and-spoke route configuration of network airlines. Network airlines concentrate their traffic in their hub airports, so that their flights within the European market exploit the connecting traffic generated by passengers that have a non-European final destination. Therefore, network airlines would offer relatively lower frequencies on longer routes where connecting traffic is less relevant. Another potential explanation could be found in the difference between network and low-cost airlines in terms of composition of aircraft fleets, as network airlines make use of different aircraft models while low-cost airlines typically restrict their aircraft choice to a single family model.

Regarding the controls, the coefficient of the dummy for the Economy fare class is negative and statistically significant, as expected. The negative population coefficient can be explained by a better exploitation of density economies on routes with higher demand. The negative coefficient of the airport presence variable can be interpreted similarly. By contrast, the income coefficient is positive and statistically significant on long-haul routes, suggesting that airlines charge higher fares on routes where travelers have a higher willingness to pay.

Results for the remaining competition variables are as follows. First, the coefficient of the HHI variable is positive and statistically significant in all regressions. Thus, it can be concluded that weaker intramodal competition leads to higher fares. Second, the coefficient of the island variable is positive in all regressions although it is only statistically significant for short-haul routes. The coefficient of the HSR variable is negative in all regressions while the coefficient of the variable that accounts for competition from intercity buses is negative on short-haul routes. Taking all these results together, there is evidence suggesting that weaker intermodal competition leads to higher fares.

All in all, the predictions from our theoretical model on the effect of route distance on fares and frequencies are empirically confirmed, both on short- and long-haul routes (Propositions 2-3 and 5–6). Furthermore, our empirical findings on the effect of distance on the frequency and fare gaps on short-haul routes are also consistent with our predictions (Corollary 1).

Finally, we report an additional empirical result for short-haul routes that is not directly linked to our theoretical predictions: the relationship between distance and intertemporal price dispersion. Our fare data include mean posted fares at certain moments before the flight departure (six months, three months, one month, and one week before the departure), which allows building different measures of intertemporal price dispersion. In particular, we consider as dependent variables the ratio between fares charged one month and three months before the flight departure and the ratio between fares charged one week and three months before the flight departure. The incompleteness of data for fares charged six months before the flight departure advises against their use in this analysis. As covariates, we include distance and the same variables used in the previous regressions.

Fig. 6 provides mean values of posted fares for low-cost and network airlines. As expected, fares increase as the departure date approaches. This is true for both network and low-cost airlines although the slope of the curve is steeper for network airlines. Weighted fares are at an intermediate point between average fares posted three months and one month before the flight departure, which suggests that most of bookings are made during these periods.

Table 4 shows the results of these additional regressions. The distance coefficient is positive and statistically significant in these regressions, where the aforementioned measures of intertemporal price dispersion are used as dependent variables. Therefore, the effect of route distance on intertemporal price dispersion (reported in Table 4) is similar to its effect on the fare gap (reported in Table 3), suggesting a correlation between the fare gap and the measure of intertemporal price dispersion.

Overall, we can conclude that intertemporal price dispersion is lower on shorter routes (where road transportation is more competitive in relation to air services). In other words, the presence of alternative transportation modes constitutes an obstacle for airlines to offer a wide menu of fares, which can be related to their capacity to price discriminate.

[26] In the presence of intermodal competition, low-cost passengers are characterized by a relatively low *value of time*. Taking into account that there is a strong correlation between car ownership and income (Dargay, 2001) and between *value of time* and income (Börjesson et al., 2012), it makes sense to conclude that low-cost passengers are characterized by relatively low income, value of time, and car ownership.

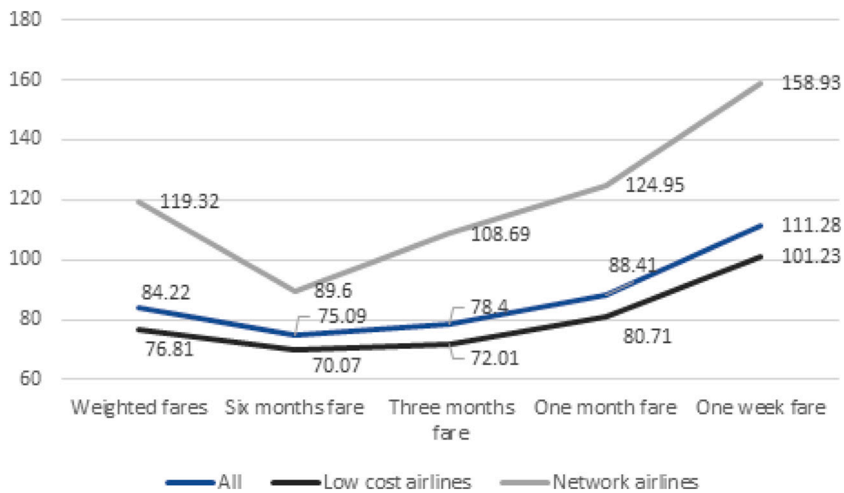

Fig. 6. Mean fares for all airlines, low-cost airlines, and network airlines.

Table 4
Relationship between price dispersion and route distance on short-haul routes.

VARIABLES	(1) Ratio 1 month/3 months	(2) Ration 1 week /3 months
Distance	0.000123***	0.000461***
	(3.25e−05)	(9.12e−05)
Intercity bus liberalized	−0.0134	−0.0443
	(0.0127)	(0.0351)
HSR	−0.00485	−0.0463
	(0.0183)	(0.0512)
Island	0.0258	0.131
	(0.0268)	(0.113)
HHI	0.0353**	−0.0229
	(0.0170)	(0.0454)
Population	−8.57e−09*	−1.50e−10
	(4.73e−09)	(1.35e−08)
Income	2.66e−06***	3.39e−06
	(7.83e−07)	(2.26e−06)
Airport presence	−0.0973***	0.169**
	(0.0305)	(0.0846)
Constant	0.696***	0.550***
	(0.0808)	(0.197)
Observations	67,073	67,073
R-squared	0.142	0.243
Origin and destination FE	yes	yes
Year and month FE	yes	yes
Sample	short-haul	short-haul
Clusters	route-airline	route-airline

Note: Standard errors in parenthesis (robust to heteroscedasticity and clustered at the route level). The sample is restricted to the economy-fare class.
*** Statistical significance at 1%.
** Statistical significance at 5%.
* Statistical significance at 10%.

6. Concluding remarks

When studying competition in transportation markets, our analysis emphasizes the relevance of taking into account route distance and intermodal competition from personal transportation. Furthermore, service quality should also be considered as a relevant competition dimension, acknowledging the relationship between service quality and passengers' willingness to pay.

In this framework, this paper highlights the relevance of distinguishing between short- and long-haul routes to analyze the fare and frequency strategies followed by airlines. It also underscores the differentiated behavior of network airlines and low-cost airlines.

The main distinction between short- and long-haul routes has to do with the presence of intermodal competition from personal transportation (and sometimes from HSR and/or intercity buses) on short-haul routes. This additional source of competition explains the positive effect of distance on flight frequencies, as airlines can attract more demand and boost profits by increasing service quality. Fares also follow the same pattern because longer routes are more costly to operate, but also because a higher service quality entails a certain "product upgrade" that translates into a higher passenger willingness to pay. Furthermore, our empirical results for short-haul routes show that both the frequency gap and the fare gap increase with distance, meaning that services provided by network and low-cost airlines become more differentiated as route distance rises.

Future research should extend the analysis to make it more comprehensive. For instance, it could be adapted to accommodate different market structures, thereby allowing for different intensities of intramodal competition. Furthermore, externalities such as air pollution or airport congestion could be incorporated as well. The presence of externalities would also enable to distinguish between polluting and clean scheduled services (i.e., airlines vs. HSR). This distinction would have a relevant effect in terms of policy recommendations. Finally, the analysis could also be adapted to account for airlines' hub-and-spoke networks, which would allow differentiating between local and connecting passengers. This differentiation may be relevant, as alternative transportation modes on short-haul routes (such as personal transportation, HSR or interurban buses) do not constitute a valid substitute for connecting passengers.

While our empirical application relates to the airline industry (a competitive industry for which relevant data are readily available), the obtained insights are applicable to any transportation market with scheduled and non-scheduled services. Furthermore, the logic of the model goes beyond the transportation sector. A similar setup, with appropriate adaptations, could be used to analyze the behavior of firms in other markets, such as the express courier industry, where services are offered by vertically-differentiated firms (in terms of reliability and speed) and competition is more intense in domestic markets.

CRediT authorship contribution statement

Xavier Fageda: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Ricardo Flores-Fillol:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Proofs

Proof of Proposition 1.

Straightforward. ■

Proof of Proposition 2.

▶ *Effect of d on* f_H^*.

From (19), let us define $\Omega_H \equiv Cf_H^* - Lf_H^* = 0$, that is

$$\Omega_H = \frac{2(1-\beta)\theta(d)d}{\gamma\beta V} f_H^3 - \left[cd - \tau + \frac{(1-\beta)d}{\beta V}\right] f_H + \gamma = 0. \tag{A1}$$

Differentiation of the equilibrium frequency with respect to a parameter x yields $\frac{\partial f_H^*}{\partial x} = -\frac{\partial\Omega_H/\partial x}{\partial\Omega_H/\partial f_H}$. Notice that $\partial\Omega_H/\partial f_H = slope\left(Cf_H^*\right) - slope\left(Lf_H^*\right) > 0$ because, at the equilibrium f_H, the slope of Cf_H^* exceeds the slope of Lf_H^* (see footnote 12). Thus, we just need to explore the sign of $\partial\Omega_H/\partial x$. Therefore, the effect of d on f_H depends on the sign of $\partial\Omega_H/\partial d$.

$\partial\Omega_H/\partial d = \frac{2(1-\beta)\theta'(d)d}{\gamma\beta V} f_H^3 + \frac{2(1-\beta)\theta(d)}{\gamma\beta V} f_H^3 - \left(c + \frac{1-\beta}{\beta V}\right) f_H$ and, using (A1), this expression can be rewritten as $\partial\Omega_H/\partial d = \frac{2(1-\beta)\theta'(d)d}{\gamma\beta V} f_H^3 - \frac{\gamma+\tau f_H}{d}$. When the cost of frequency is independent of distance, i.e., $\theta'(d) = 0$, then $\partial\Omega_H/\partial d < 0$ and $\frac{\partial f_H^*}{\partial d} > 0$. Yet, when $\theta'(d) > 0$, the result seems uncertain. Notice that $\theta(d)$ is twice continuously differentiable with $\theta'(0) = 0$ and $\theta'(d) > 0$ for $d > 0$. Therefore, at least for low values of d, we will observe $\partial\Omega_H/\partial d < 0$ and $\frac{\partial f_H^*}{\partial d} > 0$.

▶ *Effect of d on* f_L^*.

From (20), let us define $\Omega_L \equiv Cf_L^* - Lf_L^* = 0$, that is

$$\Omega_L = \frac{2(\beta-\lambda)\theta(d)d}{\gamma\lambda\beta V} f_L^3 - (cd - \tau) f_L + \gamma = 0. \tag{A2}$$

Proceeding as before, the sign of $\frac{\partial f_L^*}{\partial d}$ is determined by the sign of $\partial\Omega_L/\partial d$.

$\partial\Omega_L/\partial d = \frac{2(\beta-\lambda)\theta'(d)d}{\gamma\lambda\beta V} f_L^3 + \frac{2(\beta-\lambda)\theta(d)}{\gamma\lambda\beta V} f_L^3 - cf_L$ and, using (A2), this expression can be rewritten as $\partial\Omega_L/\partial d = \frac{2(\beta-\lambda)\theta'(d)d}{\gamma\lambda\beta V} f_L^3 - \frac{\gamma+\tau f_L}{d}$. When the cost of frequency is independent of distance, i.e., $\theta'(d) = 0$, then $\partial\Omega_L/\partial d < 0$ and $\frac{\partial f_L^*}{\partial d} > 0$. Yet, when $\theta'(d) > 0$, the result seems uncertain. Following the same reasoning as before, we conclude that, at least for low values of d, we will observe $\partial\Omega_L/\partial d < 0$ and $\frac{\partial f_L^*}{\partial d} > 0$. ■

Proof of Proposition 3.

Straightforward. ■

Proof of Proposition 4.

▶ *Effect of c on* f_H^*.

$\partial\Omega_H/\partial c = -df_H < 0$. Then $\frac{df_H^*}{dc} > 0$. We observe that a higher c increases the slope of Lf_H^* in Fig. 3, so that f_H^* increases.

▶ *Effect of c on* f_L^*.

$\partial\Omega_L/\partial c = -df_L < 0$. Then $\frac{\partial f_L^*}{\partial c} > 0$. We observe that a higher c increases the slope of Lf_L^* in Fig. 4, so that f_L^* increases. ■

Proof of Corollary 1.

Straightforward. ■

Proof of Proposition 5.

Straightforward. ■

Proof of Proposition 6.

Straightforward. ■

Proof of Corollary 2.

Straightforward. ■

Proof of Corollary 3.

Straightforward. ■

Proof of Corollary 4.

Straightforward. ■

Proof of Corollary 5.

Straightforward. ■

Appendix B. Convenience of car connections

The model assumes that the L scheduled service is *less convenient* than the non-scheduled service, i.e., $\lambda < \beta$, meaning that u_ϕ is steeper than u_L. Under this assumption, two scenarios arise: Scenario 1 (where there is an active non-scheduled service — see Fig. 1) and Scenario 2 (where there is no active non-schedule service — see Fig. 2).

The model also assumes that the full price of the non-scheduled service is higher than the full price of the L scheduled service, i.e., $cd > p_L + \gamma/f_L$. These two assumptions guarantee $\hat{\alpha} > 0$ (see (6)). The material that follows justifies the sensibleness of these modeling choices.

First, on the higher full price of the non-scheduled service as compared to the L scheduled service ($cd > p_L + \gamma/f_L$), we can certainly ascertain that car ownership (purchase and maintenance) is expensive. Taking into account that there is a strong correlation between car ownership and income (Dargay, 2001) and a strong correlation between *value of time* and income (Börjesson et al., 2012), it makes sense to conclude that car owners (i.e., drivers) should have a sufficiently high value of time and income. In this context, it makes sense to assume that owning a car is more expensive than making use of low-cost airline services.

Second, it is important to acknowledge that short-haul routes in our analysis are shorter than 600 km (which represents, in most cases, less than 5-hour driving time), as shown in our spline estimation in Fig. 5. Therefore, on short-haul routes, it makes sense to consider that a car trip is a reasonable substitute for mid-income consumers/travelers (which are car owners). More precisely, the assumption $\lambda < \beta$ (which means that car trips are *more convenient* than L scheduled services) makes sense for mid-income travelers owning a car and having time constraints, i.e., having a sufficiently high value of time. These travelers would realistically choose between a *convenient flight connection* and a *convenient car trip*, disregarding poor flight connections. This would apply to many business trips within this distance range (600 km), where a business traveler would mostly decide between a good air connection or taking his/her car (a poor air connection could imply many inconveniencies, such as leaving the day before his/her preferred departure day, having to go to secondary airports or being obliged to travel either too early in the morning or too late in the evening).

Third, the fact that some mid-income travelers owning a car and having time constraints would realistically choose between a *convenient flight connection* and a *convenient car trip* illustrates that the margin H service/car trip is relevant. This margin is only possible whenever our two assumptions hold ($\lambda < \beta$ and $cd > p_L + \gamma/f_L$), so that $\hat{\alpha} > 0$ (see (6)). Under these assumptions, the case in which there is an active non-schedule service is as considered in our Scenario 1 (which is represented in Fig. 1). The existence of this margin H service/car trip is consistent with the reality, where we observe direct competition between H scheduled services and personal transportation (as well as direct competition between L scheduled services and personal transportation)

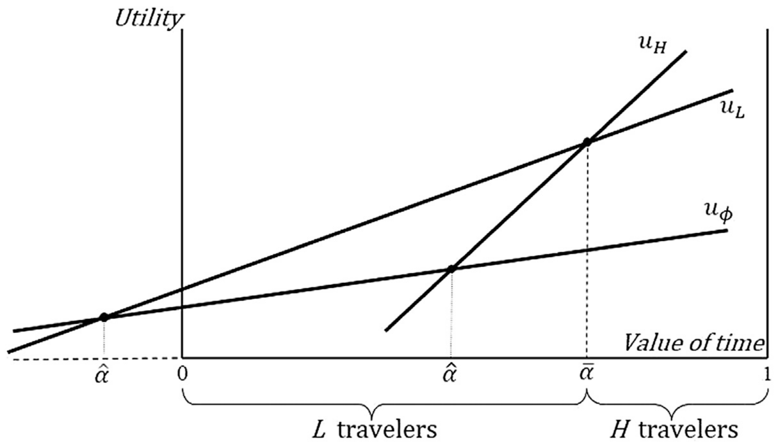

Fig. A.1. L scheduled service more convenient than car.

because there are many (quasi) monopolistic routes. In fact, our results on the effect of distance on frequencies for short-haul routes (i.e., Scenario 1) are consistent with the ones obtained in Bilotkach et al. (2010) who focus on the monopoly case.

Finally, the paper assumes $\lambda < \beta/(2-\beta)$, which is somewhat more stringent than $\lambda < \beta$ as this condition helps for an easier comparison of equilibrium frequencies (see footnote 13).

The material that follows discusses the effects of relaxing the aforementioned assumptions. First, keeping the assumption on the full price ($cd > p_L + \gamma/f_L$) but considering the L scheduled service as more convenient that the non-scheduled service ($\lambda > \beta$) would imply $\hat{\alpha} < 0$ (see (6)), as shown in Fig. A.1. Thus, the market would be fully served by both air services.
In analytical terms, this situation is the same as the one under Scenario 2 where there is no active non-schedule service and both air services compete against each other in the absence of intermodal competition. This situation clearly does not illustrate short-haul routes (i.e., Scenario 1), where car trips are a real substitute.

Second, keeping the assumption on the convenience ($\lambda < \beta$) but reversing the assumption on the full prices ($cd < p_L + \gamma/f_L$) so that $\hat{\alpha} < 0$ (see (6)) would drive the L scheduled service out of the market. The result would be a monopoly airline, as in Bilotkach et al. (2010).

Third, relaxing both assumptions simultaneously ($cd < p_L + \gamma/f_L$ and $\lambda > \beta$) would guarantee $\hat{\alpha} > 0$ (see (6)) and the three transportation alternatives would be active. However, the results would be similar (although not identical) to the ones under Scenario 2 (long-haul) because there would be direct competition between the two scheduled carriers. Therefore, we would lose the relevant margin H service/car trip that is consistent with the reality, as mentioned above.

Data availability

Data will be made available on request.

References

Aarhaug, J., Fearnley, N., 2016. Deregulation of the norwegian long distance express coach market. Transp. Policy 46, 1–6.

Abate, M., Christidis, P., 2020. The impact of air transport market liberalization: Evidence from eu's external aviation policy. Econ. Transp. 22, 100164.

Albalate, D., Bel, G., Fageda, X., 2015. Competition and cooperation between high-speed rail and air transportation services in Europe. J. Transp. Geogr. 42, 166–174.

Alexandersson, G., Hultén, S., Fearnley, N., Longva, F., 2010. Impact of regulation on the performances of long-distance transport services: A comparison of the different approaches in Sweden and Norway. Res. Transp. Econ. 29, 212–218.

Asensio, J., 2002. Transport mode choice by commuters to Barcelona's CBD. Urban Stud. 39, 1881–1895.

Avenali, A., Bracaglia, V., D'Alfonso, T., Reverberi, P., 2018. Strategic formation and welfare effects of airline-high speed rail agreements. Transp. Res. Part B 117, 393–411.

Avenali, A., D'Alfonso, T., Nastasi, A., Reverberi, P., 2022. High-speed rail and air transport integration in hub-and-spoke networks: the role of airports. In: Czerny, A., Fu, X., Lee, P.T.-W. (Eds.), Market development and policy for one belt one road. Elsevier, Amsterdam.

Avenali, A., Gregori, M., Reverberi, P., 2023. Intercity bus and rail services: Competition and welfare effects. Transp. Res. Part A 172, 103660.

Baum-Snow, N., Kahn, M.E., 2000. The effect of new public projects to expand urban rail transit. J. Public Econ. 77, 241–263.

Bel, G., 1997. Changes in travel time across modes and its impact on the demand for inter-urban rail travel. Transp. Res. Part E 33, 43–52.

Bergantino, A.S., Madio, L., 2020. Intermodal competition and substitution. HSR versus air transport: Understanding the socio-economic determinants of modal choice. Res. Transp. Econ. 79, 100823.

Beria, P., Bertolin, A., 2019. Evolving long-distance passenger services, market concentration, fares and specialisation patterns in Italy. Res. Transp. Econ. 74, 77–92.

Bernardo, V., Fageda, X., 2017. The effects of the open skies agreement between Morocco and the European union: A differences-in-differences analysis. Transp. Res. Part E 98, 24–41.

Bernardo, V., Fageda, X., 2020. Impacts of competition on connecting travelers: Evidence from the transatlantic aviation market. Transp. Policy 96, 141–151.

Berry, S., Carnall, M., Spiller, P., 2006. Airline hubs: costs, markups and the implications of customer heterogeneity. In: Lee, D. (Ed.), In: Advances in Airline Economics, vol. 1, Elsevier, Amsterdam.

Bilotkach, V., 2009. A framework for modeling real-life airline networks. Rev. Netw. Econ. 8, 255–270.

Bilotkach, V., Fageda, X., Flores-Fillol, R., 2010. Scheduled service versus personal transportation: The role of distance. Reg. Sci. Urban Econ. 40, 60–72.

Bilotkach, V., Fageda, X., Flores-Fillol, R., 2013. Airline consolidation and the distribution of traffic between primary and secondary hubs. Reg. Sci. Urban Econ. 43, 951–963.

Blayac, T., Bougette, P., 2017. Should I go by bus? The liberalization of the long-distance bus industry in France. Transp. Policy 56, 50–62.

Borenstein, S., 1989. Hubs and high fares: dominance and market power in the U.S. airline industry. RAND J. Econ. 20, 344–365.

Borenstein, S., 1990. Airline mergers, airport dominance, and market power. Am. Econ. Rev. Pap. Proc. 80, 400–404.

Borenstein, S., Netz, J., 1999. Why do all the flights leave at 8 am?: Competition and departure time differentiation in airline markets. Int. J. Ind. Organ. 17, 611–640.

Borenstein, S., Rose, N., 1994. Competition and price dispersion in the US airline industry. J. Polit. Econ. 102, 653–683.

Börjesson, M., Fosgerau, M., Algers, S., 2012. On the income elasticity of the value of travel time. Transp. Res. Part A 46, 368–377.

Brueckner, J.K., 2004. Network structure and airline scheduling. J. Ind. Econ. 52, 291–312.

Brueckner, J.K., 2010. Schedule competition revisited. J. Transp. Econ. Policy 44, 261–285.

Brueckner, J.K., Flores-Fillol, R., 2007. Airline schedule competition. Rev. Ind. Organ. 30, 161–177.

Brueckner, J.K., Flores-Fillol, R., 2020. Market structure and quality determination for complementary products: Alliances and service quality in the airline industry. Int. J. Ind. Organ. 68, 102557.

Brueckner, J.K., Luo, D., 2014. Measuring strategic firm interaction in product-quality choices: The case of airline flight frequency. Econ. Transp. 3, 102–115.

Buri, R., Heinonen, M., Kanervo, J., Karjalainen, J., 2024. The effects of entry deregulation: Evidence from interurban passenger transport. J. Regul. Econ. 66, 181–204.

Cantos-Sánchez, P., Moner-Colonques, R., Sempere-Monerris, J., Álvarez, O., 2009. Alternative pricing regimes in interurban passenger transport with externalities and modal competition. Reg. Sci. Urban Econ. 39, 128–137.

Carlsson, F., 2004. Prices and departures in European domestic aviation markets. Rev. Ind. Organ. 24, 37–49.

Carlton, D., Israel, M., MacSwain, I., Orlov, E., 2019. Are legacy airline mergers pro- or anti-competitive? Evidence from recent US airline mergers. Int. J. Ind. Organ. 62, 58–95.

Combes, P.P., Linnemer, L., 2000. Intermodal competition and regional inequalities. Reg. Sci. Urban Econ. 30, 131–184.

Dargay, D., 2001. The effect of income on car ownership: Evidence of asymmetry. Transp. Res. Part A 35, 807–821.

de Palma, A., Ordás Criado, C., Randrianarisoa, L.M., 2018. When hotelling meets vickrey, service timing and spatial asymmetry in the airline industry. J. Urban Econ. 105, 88–106.

Dürr, N.S., Hüschelrath, K., 2015. Competition in the german interurban bus industry: A snapshot two years after liberalization. Competit. Regul. Netw. Ind. 16, 188–218.

Fageda, X., Flores-Fillol, R., 2012a. On the optimal distribution of traffic of network airlines. Eur. Econ. Rev. 56, 1164–1179.

Fageda, X., Flores-Fillol, R., 2012b. Air services on thin routes: Regional versus low-cost airlines. Reg. Sci. Urban Econ. 42, 702–714.

Fageda, X., Flores-Fillol, R., 2016. How do airlines react to airport congestion? The role of networks. Reg. Sci. Urban Econ. 56, 73–81.

Fageda, X., Flores-Fillol, R., Lin, M.H., 2020. Vertical differentiation and airline alliances: The effect of antitrust immunity. Reg. Sci. Urban Econ. 81, 103517.

Flores-Fillol, R., 2009. Airline competition and network structure. Transp. Res. Part B 43, 966–983.

Gabszewicz, J.J., Thisse, J.-F., 1979. Price competition, quality, and income distribution. J. Econ. Theory 20, 340–359.

Gaggero, A., Piga, C., 2011. Airline market power and intertemporal price dispersion. J. Ind. Econ. 59, 552–577.

Gerardi, K., Shapiro, A., 2009. Does competition reduce price dispersion? New evidence from the airline industry. J. Polit. Econ. 117, 1–37.

Givoni, M., Dobruszkes, F., 2013. A review of ex-post evidence for mode substitution and induced demand following the introduction of high-speed rail. Transp. Rev. 33, 720–742.

González-Savignat, M., 2004. Competition in air transport: the case of the high speed train. J. Transp. Econ. Policy 38, 77–107.

Gu, H., Wan, Y., 2022. Airline reactions to high-speed rail entry: Rail quality and market structure. Transp. Res. Part A 165, 511–532.

Heimer, O., Shy, O., 2006. Code-sharing agreements, frequency of flights, and profits under parallel operation. In: Lee, D. (Ed.), In: Advances in Airline Economics, vol. 1, Elsevier, Amsterdam.

Janic, M., The potential for modal substitution, in: Upham, P., Maughan, J., Raper, D., and Thomas, C. (Eds.), Towards Sustainable Aviation, Earthscan, London.

Jiang, C., D'Alfonso, T., Wan, Y., 2017. Air-rail cooperation: Partnership level, market structure and welfare implications. Transp. Res. Part B 104, 461–482.

Kim, E.H., Singal, V., 1993. Mergers and market power: Evidence from the airline industry. Amer. Econ. Rev. 83, 549–569.

Kwoka, J., Shumilkina, E., 2010. The price effect of eliminating potential competition: Evidence from an airline merger. J. Ind. Econ. 58, 767–793.

Li, X., Jiang, C., Wang, K., Ma, J., 2018. Determinants of partnership levels in air-rail cooperation. J. Air Transp. Manag. 71, 88–96.

López-Pita, A., Robusté, F., 2004. Impact of high-speed lines in relations with very high frequency air services. In: Transportation Research Board 83rd Annual Meeting, Washington DC.

Ma, W., Wang, Q., Yang, H., Zhang, G., Zhang, Y., 2020. Understanding airline price dispersion in the presence of high-speed rail. Transp. Policy 95, 93–102.

Pai, V., 2010. On the factors that affect airline flight frequency and aircraft size. J. Air Transp. Manag. 16, 169–177.

Richard, O., 2003. Flight frequency and mergers in airline markets. Int. J. Ind. Organ. 21, 907–922.

Salvanes, K.G., Steen, F., Sorgard, L., 2005. Hotelling in the air? Flight departures in Norway. Reg. Sci. Urban Econ. 35, 193–213.

Schipper, Y., Rietveld, P., Nijkamp, P., 2002. European airline reform: an empirical welfare analysis. J. Transp. Econ. Policy 36, 189–209.

Shaked, A., Sutton, J., 1982. Relaxing price competition through product differentiation. Rev. Econ. Stud. 49, 3–13.

Shaked, A., Sutton, J., 1983. Natural oligopolies. Econometrica 51, 1469–1483.

Siegert, C., Ulbricht, R., 2020. Dynamic oligopoly pricing: Evidence from the airline industry. Int. J. Ind. Organ. 71, 102639.

Su, M., Luan, W., Fu, X., Yang, Z., Zhang, R., 2020. The competition effects of low-cost carriers and high-speed rail on the Chinese aviation market. Transp. Policy 95, 37–46.

Tirole, J., 1988. The Theory of Industrial Organization. MIT Press, Cambridge.

Voith, R., 1997. Fares, service levels, and demographics: what determines commuter rail ridership in the long run?. J. Urban Econ. 41, 176–197.

Wang, C., Jiang, C., Zhang, A., 2021. Effects of airline entry on high-speed rail. Transp. Res. Part B 154, 242–254.

Wei, W., Hansen, M., 2007. Airlines competition in aircraft size and service frequency in duopoly markets. Transp. Res. 43, 409–424.

Xia, W., Jiang, C., Wang, K., Zhang, A., 2019. Air-rail revenue sharing in a multi-airport system: Effects on traffic and social welfare. Transp. Res. Part B 121, 304–319.

Zhang, F., Graham, D.J., Siu, M., Wong, M.S.C., 2018. Quantifying the substitutability and complementarity between high-speed rail and air transport. Transp. Res. Part A 118, 191–215.

Zhang, A., Wan, Y., Yang, H., 2019. Impacts of high-speed rail on airlines, airports and regional economies: A survey of recent research. Transp. Policy 81, A1–A19.