Estimating Passenger Benefits from Airline Service Quality: Nonstop vs. Connecting Flight Frequencies

by
Jan K. Brueckner
University of California, Irvine, USA
jkbrueck@uci.edu

and

Ricardo Flores-Fillol
Universitat Rovira i Virgili, Spain
ricardo.flores@urv.cat

March 2026

Abstract

This paper estimates passenger benefits from airline flight frequencies, recognizing that this task is less straightforward for connecting trips than for nonstop travel. In doing so, the paper joins Yuan and Barwick (2026) as the only other study in the literature that confronts the problem of creating a flight-frequency measure for connecting trips. With airlines providing a crucial service in modern economies, the ability to measure the quality of that service is essential, not just for the nonstop service that links larger cities but for the connecting trips involving smaller endpoints that many passengers rely on.

Estimating Passenger Benefits from Airline Service Quality: Nonstop vs. Connecting Flight Frequencies

by

Jan K. Brueckner and Ricardo Flores-Fillol[†]

1. Introduction

Airlines provide an important service in modern economies, making the quality of that service an important issue for passengers and government regulators, even though the level of airfares usually gets more attention. One proposed service-quality measure is the "routing quality" of trips that connect through a hub airport, which decreases as the trip's travel distance rises relative to the distance of a nonstop trip between the endpoint cities, reflecting a less-direct routing.[1] However, a different and more important measure of service quality is flight frequency. A higher frequency on a route allows the passenger to choose a flight that arrives closer to the preferred arrival time, reducing what is known as "schedule delay." Gauging passenger benefits from flight frequency is essential in understanding network structure, airline competition, and the consequences of mergers and airline alliances.

For nonstop trips, measuring flight frequency is straightforward: it equals the number of flights the airline operates on the nonstop route. But how should flight frequency be measured for a connecting trip, where the frequencies on the two route segments are likely to differ? The question is how to combine these two asymmetric frequencies into a single measure that captures service quality for a connecting trip. Despite the importance of connecting travel, particularly for passengers traveling to and from smaller cities, the literature has largely avoided this issue.

The present paper addresses this oversight in the literature. We develop, and empirically implement, theoretically grounded measures of flight frequency that apply to both nonstop and connecting trips, building on the framework of Brueckner and Flores-Fillol (BFF, 2020). The measures rely on the reciprocal of a route's flight frequency, a formulation that captures

[†] We thank Kangoh Lee, Cliff Winston, and Zhe Yuan for helpful comments. The usual disclaimer applies.

[1] Chen and Gayle (2019) empirically explore the effect of airline mergers on routing quality.

schedule delay. We derive two alternative frequency measures for connecting itineraries, corresponding to polar assumptions about the cost of layover time. When layover time is relatively unimportant, the relevant measure is the average of reciprocal segment frequencies for the connecting trip's two route segments. When layover time is costly, the relevant measure is the reciprocal of the minimum of the two segment frequencies.[2]

We then embed these frequency measures in a nested-logit demand model following Berry (1994) and Berry, Levinsohn and Pakes (1995) and estimate passenger willingness-to-pay for flight frequency using US airline data from 2019. The empirical results favor the minimum-frequency specification, implying that passengers behave as if layover time is highly costly when evaluating connecting itineraries. Using the estimated utility coefficients, our computations show that a nonstop passenger is willing to pay \$76 for an additional daily flight, while a connecting passenger is willing to pay \$34 for an additional flight on each of the trip's two route segments. These magnitudes suggest that frequency improvements matter substantially more for nonstop passengers than for connecting passengers.

Our paper contributes to the literature in three ways. First, it shows that a theoretically derived frequency measure for connecting travel can be used in empirical work. Second, it quantifies passenger welfare gains from flight frequency. Third, by comparing alternative specifications, it provides evidence on how passengers trade off schedule delay and layover time, an issue central to airline network design and service-quality evaluation.

In other recent empirical work on flight frequencies, Richard (2003) uses data from Chicago-O'Hare nonstop routes to estimate the parameters of a theoretical model of fare and frequency determination, using it to predict the welfare effect of a hypothetical American-United merger.[3]

[2] While BFF derived these measures in the context of a model of an international airline alliance, Thomaz (2020) used BFF's approach in analyzing the frequency choices of a domestic monopoly carrier operating an unbalanced hub-and-spoke network, which serves cities of different sizes and thus has asymmetric spoke frequencies. Note that this and other approaches to capturing frequency benefits ignore the possibility that an airline's use of (dispreferred) smaller planes to boost frequency may reduce the resulting benefits.

[3] Beyond Richard (2003), several other theoretical papers focus on flight-frequency choices by airlines. Brueckner (2004) analyzes the choice of flight frequencies by a monopoly airline operating a hub-and-spoke network, showing that HS frequencies are higher than in a point-to-point network and thus providing a foundation for Morrison and Winston's evidence that frequencies rose with the shift to HS networks following deregulation. Dropping the monopoly assumption, Brueckner and Flores-Fillol (2007) analyze the competitive choice of flight frequencies on a single route served by two carriers, abstracting from network issues, while Flores-Fillol (2010) carries out a network analysis. Building on the model of Brueckner and Flores-Fillol (2007), Brueckner and Luo

While that paper avoids measurement of connecting frequencies, the well-known study of Berry and Jia (2010) also appears to finesse the issue by using the "number of departures" as a frequency measure, which on connecting trips presumably counts the trip's first-leg departures without consideration of the remaining segments.[4] The only previous paper that seriously confronts the frequency issue for connecting flights is the recent study by Yuan and Barwick (2026), whose ambitious goal of analyzing the equilibrium structure of airline networks makes consideration of connecting flights essential. Using data on arrival and departure times, they tabulate the flight combinations that lead to a layover of acceptable length on a connecting route, and then sum the logs of the flight counts on the individual connecting legs across these combinations as the frequency measure. While having a narrower focus than Yuan and Barwick (2026), the present paper offers the advantage of deriving its two candidate frequency measures theoretically, which yields their reciprocal form, and then taking the measures to the data.

The plan of the paper is as follows. Section 2 derives the form of the flight-frequency measures, adapting the presentation of Brueckner and Flores-Fillol (2020). Section 3 explains the empirical methodology, relying on Berry (1994) and Berry et al. (1995). Section 4 discusses the data and presents tables showing summary statistics and other useful information about the data. Section 5 presents the empirical findings, which include a calculation of the dollar benefits from improved flight frequencies, and section 6 offers conclusions.

2. Deriving the flight-frequency measures

The notion of schedule delay is central in the derivation of passenger benefits from flight frequency. As in Brueckner (2004) and Brueckner and Flores-Fillol (2007, 2020), we avoid the complexities of spatial models in capturing these benefits by using a framework where consumers ultimately care about overall flight frequency rather than the departure times of

(2014) test empirically for strategic interaction between carriers in their choices of flight frequencies, estimating frequency reaction functions.

[4] Yan and Winston (2014), using an empirical framework like that of Berry and Jia (2010), report passenger benefits from higher nonstop and connecting frequencies, although the paper does not provide detail on how connecting frequencies are measured. In a much older study, Morrison and Winston (1986) estimate a traditional demand function with price and frequency as arguments (using a "full price" approach), also computing the gain from an increase in frequency. Their apparent focus is on nonstop trips.

individual flights. This approach relies on the implicit assumption that a passenger's preferred arrival time is unknown prior to the purchase of the airline ticket and is thus viewed as random, being uniformly distributed around the clock. Under this assumption, schedule delay (the difference between a passenger's preferred and actual arrival times) depends on flight departure times but is otherwise random, although its expected value (which matters to the consumer) can be derived conditional on flight times. Note that, by assuming a uniform distribution of preferred arrival times, the model suppresses some passengers' actual preferences for peak-hour travel.[5]

To simplify the discussion and without loss of generality, we assume that flights are instantaneous, so that flight departure and arrival times are the same. To derive a frequency valuation measure for nonstop flights under this and the previous assumptions, note that expected schedule delay equals the expected gap between the preferred arrival time and the closest flight arrival time. Assuming that flight departures (and hence arrivals) are equally spaced around the clock (whose circumference is T hours), the gap between flight departure times equals T/f, where f is the number of departures. With uniformly distributed preferred arrival times, the expected gap between the preferred time and the nearest flight arrival (expected schedule delay) is equal to one quarter of the departure-time gap, or $T/4f$. The cost of schedule delay is then $\tau T/4f$, where τ is the cost per minute of delay. Letting $\gamma \equiv \tau T/4$, this cost can then be written as γ/f. Therefore, schedule-delay cost is decreasing in flight frequency, as captured by the number of departures. Letting $freq$ denote this schedule-delay-based frequency measure, it is then given by $freq = \gamma/f$ for nonstop flights, which varies inversely with f.

While this frequency measure would apply to nonstop flights between cities X and H in Figure 1, deriving a corresponding measure for a connecting trip between cities X and Y via city H (which is a hub) is much less straightforward. In Figure 2, the d_1 and d_2 markers, along with the nearby arrows, denote the various departure (hence arrival) times of flights on the two routes, with f_1 flights operated in both directions on route 1 and f_2 flights operated in both directions on route 2. In the previous nonstop case, f in the $freq$ formula would be replaced by

[5] The following discussion is similar to the corresponding presentation in Brueckner and Flores-Fillol (2020).

f_1 for nonstop flights on route 1 and by f_2 for nonstop flights on route 2. Importantly, f_1 and f_2 need not be equal, perhaps as a result of different population sizes and hence travel demands in cities X and Y. The frequency measure for a connecting trip will then depend on both f_1 and f_2, being written $freq(f_1, f_2)$, and the task is to find the nature of this dependence.

A crucial observation in the case of a connecting trip is that, in addition to preferring less (expected) schedule delay, passengers also dislike layover time, which affects frequency benefits for such a trip. Depending on the cost of layover time relative to the cost of schedule delay, different scenarios arise, which yield different functional forms for the function $freq(f_1, f_2)$. Two polar cases are considered, with the cost of layover time either equal to zero or equal to a large enough value that minimization of layover time is the passenger's main goal, with schedule delay being a secondary consideration. In the analysis of connecting trips, we again assume that the carrier evenly spaces its flights around the clock. This pattern is shown in Figure 2, which illustrates a case where $f_1 > f_2$.

2.1. The form of freq with zero-cost layover time

Suppose that layover cost is zero, so that the passenger cares only about schedule delay in choosing flights, a case that could apply to leisure passengers, who have a low value of time. Focusing on outbound connecting trips originating at X, the expected arrival schedule delay depends only on the flight frequency f_2 on route 2, regardless of the relative values of f_1 and f_2. This claim will be demonstrated using Figure 3, which also shows the passenger's preferred arrival time.

Suppose that $f_1 \geq f_2$, as shown in panel I of Figure 3. The passenger prefers the route-2 flight C, which arrives nearest to his preferred time, but is indifferent between route-1 flights A and B since both allow a connection with flight C, whose departure (and instantaneous arrival) is closest to the preferred arrival time. The longer layover generated by flight A is immaterial since layover cost is zero. The upshot is that additional route-1 flights yield no benefit for the passenger, with expected schedule delay depending only on the gap between airline 2's flights, which equals T/f_2. Expected schedule delay is again 1/4 of this gap, $T/4f_2$, and schedule-delay cost is $\tau T/4f_2 = \gamma/f_2$.

When $f_1 < f_2$ (panel II), the passenger takes route-1 flight A and waits costlessly at the hub airport to take flight D, which minimizes schedule delay (thus shunning flight C). Again, expected schedule delay depends only on f_2, and the cost of this delay is given by γ/f_2.

In the inbound direction of a roundtrip (the return trip from Y to X), the roles of the routes are reversed, so that expected inbound schedule delay is γ/f_1. Average schedule-delay cost in both directions, which yields the frequency measure given the absence of layover costs, is then

$$freq \;=\; \frac{1}{2}\left[\frac{\gamma}{f_1} \;+\; \frac{\gamma}{f_2}\right] \qquad \text{(zero-cost layover)}, \qquad (1)$$

equal to the average of the reciprocals of the route flight frequencies.

2.2. The form of freq with high-cost layover time

When layover time is costly (as for business travelers), the passenger's main goal is to minimize it, with schedule delay being a secondary consideration. In order to analyze this case, additional assumptions about the spacing of flights are needed. We assume that when the carrier operates the same number of flights on routes 1 and 2, with $f_1 = f_2$, the flights operate at the same time. When $f_1 > f_2$, flight times coincide where possible, with the extra route-1 flights evenly filling the gaps between the route-2 flights, as shown in Figures 3 and 4. Route 2 flights are thus given by the rule $f_1 = 2^k f_2$, where $k = 0, 1, 2, \ldots$, so that route-1 flight density increases with k. Under this rule, f_1 doubles with each successive increase in k, with the extra flights filling the gaps between existing route-2 flights. The opposite pattern occurs when $f_1 < f_2$ with $f_2 = 2^k f_1$. The same reasoning applies to inbound flights, whose volume exactly matches that of outbound flights.

Starting with the case where $f_1 \geq f_2$, a passenger will always choose flights whose arrival and departure times coincide so as to avoid any layover, as shown in Figure 4. Consider panelI and suppose as before that the passenger's preferred arrival time lies between route-2 flights C and D. Then, depending on the exact location of the preferred time, the passenger will choose either route-1 flight A or E, along with the corresponding route-2 flight. The E and D flights will be chosen in the case shown in the figure, yielding a zero layover along with less schedule delay than the A-C combination. Route 1 flight B is irrelevant, as in Figure 3-I, and the expected schedule delay is again γ/f_2.

Suppose that $f_1 < f_2$, as in panel II of Figure 4. Despite the presence of route-2 flight F, the passenger will make the same choice as in panel I, combining either the route-1 A and route-2 C flights or the route-1 E and route-2 D flights. When the preferred arrival is as shown, the E and D flights will be used, leading to a zero layover and the schedule delay magnitude shown in panel II. This choice occurs even though a shorter schedule delay would result from taking the route-1 A flight and connecting to the route-2 F flight. But since this option involves a layover equal to the gap between the A and F flights it will be avoided in favor of the option with no layover. In contrast to panel I, it is now route 2's F flight that is irrelevant, and the result is that expected schedule delay equals 1/4 of the gap between the route-1 flights. Expected schedule-delay cost is then γ/f_1. Combining the results from the two panels of Figure 4, expected schedule-delay cost for the outbound trip is thus $\gamma/min\{f_1, f_2\}$.

Using the same reasoning for inbound flights, we get the same schedule-delay expressions: γ/f_2 for $f_1 \geq f_2$ and γ/f_1 for $f_1 < f_2$, expressed again as $\gamma/min\{f_1, f_2\}$. Since outbound and inbound expressions are the same, the average schedule-delay cost in both directions is given by this common expression. Since layover costs are zero given the absence of layovers, the *freq* function again consists entirely of schedule-delay costs and is given by

$$freq \quad = \quad \frac{\gamma}{min\{f_1, f_2\}} \qquad \text{(high-cost layover)}, \qquad (2)$$

equal to the reciprocal of the minimum of the route flight frequencies.[6]

The foregoing analysis can easily be adapted to the case of connecting travel that is oneway instead of roundtrip. In the high-cost layover case, the fact that the same formula applies to the outbound and inbound directions of a roundtrip means the *freq* formula given in (2) also applies to oneway travel (which consists of only the outbound portion). In the zero-cost layover case, the outbound schedule delay from above was given by γ/f_2. As a result, for oneway travel,

[6] Consider relaxing the assumptions on flight departure times in the high-cost layover case, maintaining equal flight spacing on both routes but with an arbitrary alignment that may preclude a zero-layover option. Then, the passenger will again choose flights to minimize the layover, incurring some (small) layover cost along with schedule delay. This scenario is difficult to analyze formally, but the formulation leading to (2) can be viewed as an approximation to it.

the frequency measure in the zero-cost case is given by this expression, with $freq = \gamma/f_2$, so that only route-2 frequency matters.

3. Empirical methodology

The methodology follows the now-standard approach to nested-logit demand estimation developed in Berry (1994) and Berry, Levinsohn and Pakes (1995).[7] For simplicity, we suppress passenger heterogeneity, thus avoiding the complexities involved in estimating the random-coefficient version of the demand model.

Let an airline product j in city-pair market m be defined as a vector of ticket characteristics, which include the fare p_{jm}, the frequency measure $freq_{jm}$, the identity of the airline, whether the trip is nonstop or connecting, and whether the trip is roundtrip or oneway. Letting the last three characteristics be represented by the vector z_{jm}, the utility of consumer i purchasing an airline product j in city-pair market m is given by

$$u_{ijm} \;=\; \alpha p_{jm} \;+\; \beta freq_{jm} \;+\; z_{jm}\gamma \;+\; \xi_{jm} \;+\; \epsilon_{ijm}(\lambda). \tag{3}$$

In (3), α, β, and γ are demand coefficients (the latter a vector), ξ_{jm} captures unobserved product/market characteristics, and ϵ_{ijm} is an error term that captures further unobserved characteristics associated with the consumer, the airline, and the market. This latter error term follows a generalized extreme value distribution with two nests, one consisting of an outside good (corresponding to $j = 0$) and the other containing all the airline choices, with the parameter $1 - \lambda$ indicating the extent of utility correlation across airlines in the second nest ($0 < \lambda \leq 1$). The outside good represents any travel choice other than airline travel, including surface transportation or no travel, and its utility is purely random and captured by the error term ϵ_{i0m}.

Letting $\delta_{jm} = \alpha p_{jm} + \beta freq_{jm} + z_{jm}\gamma + \xi_{jm}$ denote the mean utility associated with product j in market m. Then the choice probability, and thus the market share, for product j conditional on the consumer choosing to fly is given by the logit formula

$$S_{j,m|fly} \;=\; \frac{\exp(\delta_{jm}/\lambda)}{\sum_{k>0}\exp(\delta_{km}/\lambda)} \tag{4}$$

[7] See Bontemps, Remmy and Wei (2022) for an especially transparent exposition.

for $j > 0$. The share of consumers who choose to fly rather than taking the outside option is given by the nested-logit formula

$$S_{fly,m} \quad = \quad \frac{[\sum_{j>0} \exp(\delta_{jm}/\lambda)]^{\lambda}}{1 \; + \; [\sum_{all\ k} \exp(\delta_{km}/\lambda)]^{\lambda}}. \tag{5}$$

The market share of product j among all choices, including the outside option, is then

$$S_{j,m} \quad = \quad S_{j,m|fly} \; \times \; S_{fly,m}. \tag{6}$$

Recognizing that the share of the outside good is given by $S_{0,m} = 1 - S_{fly,m}$, manipulations described in Berry (1994) lead to the following relationship[8]

$$\ln(S_{j,m}/S_{0,m}) \quad = \quad \alpha p_{jm} \; + \; \beta freq_{jm} \; + \; z_{jm}\gamma \; + \; (1-\lambda)\ln(S_{j,m|fly}) \; + \; \xi_{jm}. \tag{7}$$

In computing the dependent variable in (7), a value for the market size, denoted N, must be specified. In the empirical work, we set N equal to the quadratic mean of the populations of the market's endpoint cities, or the market's "population potential" (*pop_pot*). Then, the number of people flying equals $S_{fly,m}N$ and the number of people choosing the outside option equals $N - S_{fly,m}N$.

In words, equation (7) says that, in market m, the log of the ratio of the market share of product j among all choices and the share of the outside good equals mean utility plus $1 - \lambda$ times the log of the share of product j among the flying choices. A regression based on this equation can be estimated, but an instrumental-variables approach must be used given that p_{jm}, $freq_{jm}$ and $ln(S_{j,m}|fly)$ are endogenous. In the empirical results presented below, (7) is estimated using the two different versions of *freq* from equations (1) and (2) of section 2, with the variables in (7) rewritten as $freq_{jm}^{avg}$ and $freq_{jm}^{min}$, respectively.

[8] Using (5), (6), and $S_{0,m} = 1/[\sum_{all\ k} \exp(\delta_{km}/\lambda)]^{\lambda}$,

$$\frac{S_{j,m}}{S_{0,m}} = \frac{S_{fly,m}}{S_{0,m}} S_{j,m|fly} = \left(\sum_{k>0} \exp(\delta_{km}/\lambda)\right)^{\lambda} \times S_{j,m|fly} = \left(\sum_{k>0} \exp(\delta_{km}/\lambda)\right)^{\lambda} \frac{\exp(\delta_{jm}/\lambda)}{\sum_{k>0} \exp(\delta_{km}/\lambda)}$$

$$= (\exp(\delta_{jm}/\lambda))^{\lambda} \left(\frac{\exp(\delta_{jm}/\lambda)}{\sum_{k>0} \exp(\delta_{km}/\lambda)}\right)^{1-\lambda},$$

and taking logs yields (7), recognizing that the last term is $S_{j,m|fly}^{1-\lambda}$.

4. Data and summary statistics

4.1. Data structure

The empirical analysis draws on two standard data sources: the DB1B Passenger Origin-Destination Survey, a 10%ticket sample that provides trip routings and fares and identifies ticketing and operating carriers for each route segment of the trip; and the T-100 database, which shows flight frequencies for individual carriers on nonstop route segments. We use data for the four quarters of 2019, the last year prior to the pandemic-induced upheaval in the airline industry.

Attention is restricted to four types of itineraries: 1-segment oneway trips, which are nonstop; 2-segment nonstop roundtrips, with a single (nonstop) segment in each direction; 2-segment one-way trips with a connection; 4-segment roundtrips, with a connection in each direction. 3-segment roundtrips, which are nonstop in one direction and connecting in the other, are fairly common but excluded. The reason is that their combination of one-way and connecting travel would complicate the estimation of frequency effects, with a blending of the distinct *freq* measures for nonstop and connecting travel required within a single itinerary. Additionally, for 4-segment itineraries, we require that the connecting airport be the same on the outbound and inbound directions of the itinerary.

For each type of itinerary, we require a common ticketing carrier across all the route segments. But for a given ticketing carrier, the operating carrier(s) may vary across itineraries. For example, while Delta could be both the ticketing and operating carrier on each of the four segments of a connecting trip, a different Delta itinerary with the same routing may show one of Delta's regional partner airlines as the operating carrier on one or more of the itinerary's route segments. Distinguishing between these cases is needed for proper measurement of flight frequencies, which are identified through the operating carrier using the T-100 database.

The T-100's monthly flight departures on a nonstop route segment are aggregated to the quarter level and divided by 90 to yield an approximate daily number of flights. The relevant operating-carrier flight frequencies are then generated for each itinerary, in some cases using an averaging process, with the results in turn used to generate the *freq* measures, as explained further below. For a 1-segment (nonstop) one-way itinerary, the flight frequency is simply the frequency on that segment. For a 2-segment one-way connecting itinerary, the separate frequencies on the two trip legs are tabulated. For a 2-segment nonstop roundtrip itinerary, frequency is set equal to the average of the outbound and inbound frequencies. A variant of the 2-segment roundtrip approach is used for 4-segment itineraries. First, we compute the average of the frequencies on the first legs of the outbound and inbound trip portions, which link the origin to the hub on the outbound trip and the destination to the hub on the return inbound trip, respectively. Next, we compute the average of the frequencies on the *second* legs of the outbound and inbound trip portions, which link the hub to the destination on the outbound trip and the hub to the origin on the return inbound trip, respectively. The two resulting averages are the roundtrip equivalents to the separate frequencies on the legs of a 2-segment connecting one-way itinerary.

One more step is needed prior to computation of the *freq* measures. In particular, the frequencies just computed are averaged by quarter, origin, destination, ticketing carrier, roundtrip and one-way, with passenger weighting. This averaging step collapses the frequencies that may differ only across the itinerary's operating carrier(s) into an average value by quarter, origin, destination, ticketing carrier, one-way, and roundtrip. Frequency variation due to operating-carrier differences within these categories is not substantial, but it must be taken into account.

Passenger-weighted average fares are computed in the same way by averaging across itineraries differentiated by quarter, origin, destination, ticketing carrier, roundtrip and one-way. To put one-way and roundtrip fares on the same basis, roundtrip fares are divided by 2.

The frequencies used in the *freq* measures are written as follows, relying on the discussion above. For nonstop itineraries, the frequency is denoted f^{ns}, and it equals the outbound frequency for one-way trips or the average of the outbound and inbound frequencies for round trips, as described above. For connecting itineraries, the frequencies are denoted f_1^{ct} and f_2^{ct}, and they equal the actual first- and second-leg outbound frequencies for one-way trips or the outbound/inbound average of the first- and second-leg frequencies (as described above) for connecting trips. Using these definitions, the $freq^{avg}$ measure, which applies to the low-cost layover case, is written as follows, adding superscripts to the notation in (1):

$$freq^{avg} = \begin{cases} \frac{1}{f^{ns}} & \text{nonstop} \\ \frac{1}{2}\left[\frac{1}{f_1^{ct}} + \frac{1}{f_2^{ct}}\right] & \text{connecting and roundtrip} \\ \frac{1}{f_2^{ct}} & \text{connecting and one-way.} \end{cases} \tag{8}$$

To understand that last line of (8), recall from section 2 that, for connecting trips that are one-way, only the frequency on the second leg is relevant with low-cost layovers. The $freq^{min}$ measure, which applies to the high-cost layover case, is written as follows using (2):

$$freq^{min} = \begin{cases} \frac{1}{f^{ns}} & \text{nonstop} \\ \frac{1}{min\{f_1^{ct}, f_2^{ct}\}} & \text{connecting.} \end{cases} \tag{9}$$

To exclude unrepresentative itineraries, we drop observations where $freq^{avg}$ or $freq^{min}$ exceeds 1, a cutoff that is violated, for example, when a nonstop itinerary has less than one flight per day.[9] In addition, to avoid thin city-pair markets, we drop nonstop itineraries for which total nonstop passengers across all carriers in the city-pair market is less than 90 per quarter (recall that data consist of a 10% ticket sample). For connecting itineraries, we use a smaller quarterly cutoff of 50 total connecting passengers across all carriers in the city-pair market. Finally, to exclude carriers with a minor presence in a market, we drop nonstop itineraries where the carrier accounts for less than 10% of total nonstop traffic in the city-pair market and drop connecting itineraries where the carrier accounts for less than 5% of total connecting traffic in the city-pair market. These exclusions yield a sample consisting of 118,344 itineraries across the 4 quarters of 2019, which is reduced to 114,512 observations by missing values for one of the instruments, as indicated below.

4.2. Summary statistics

To get a sense of the apportionment of itineraries across the one-way/roundtrip and nonstop/connecting categories, let *one-way* denote a dummy variable that takes the values 1 (0)

[9] In imposing this restriction, we use only line 2 of equation (8) for connecting flights, ignoring the different expression for connections that are one-way.

for one-way (roundtrip) itineraries and *nonstop* denote a dummy variable that takes the values 1 (0) for nonstop (connecting) itineraries. Table 1 shows crosstabs for these dummies, revealing that the sample itineraries are roughly equally split between one-way and roundtrip, but that connecting itineraries are much more numerous than nonstop itineraries, accounting for 85% of all itineraries, with the connecting shares among roundtrip and one-way itineraries being similar. The reason for this imbalance is that nonstop trips mostly occur between endpoints with relatively large populations, while connecting-trip endpoints tend to be smaller, leading to many more possible combinations of origins and destinations.

Table 2 shows summary statistics. The mean of the dependent variable, $\ln(S_{j,m}/S_{0,m})$, is negative, indicating that an airline product's share among all product choices (carrier, nonstop, connecting, outside option) is less than the share of the outside option, which makes the S ratio less than 1. Similarly, since $S_{j,m|fly} < 1$, the mean of $\ln(S_{j,m|fly})$ is negative. The mean fare (on a one-way basis) is \$286, and the means of $freq^{avg}$ and $freq^{min}$ are 0.467 and 0.369, corresponding to more than two flights a day if an itinerary is nonstop. The means of the carrier dummy variables indicate that the network carriers AA, DL and UA, which serve many connecting passengers, naturally account for the greatest numbers of observations (American is the default carrier in the regressions). Observations are very evenly split across the quarters, with quarter 1 being the default, and the mean distance (expressed on a one-way basis for roundtrips) is 1281 miles. Distance and quarter are additional product characteristics. The shares of one-way and nonstop itineraries are 0.514 and 0.144, respectively, as in Table 1.

Four instruments are used in the estimation. The first is the market's "income potential," *inc_pot*, equal to the geometric mean of the per capita incomes of the market's endpoint cities (analogous to population potential from above). The second is *tot_nonstop_other*, equal to the total number of nonstop itineraries offered by other carriers in the market, with a mean of 0.138 (and a maximum of 5). The next instrument is the dummy variable *hub*, equal to 1 if either endpoint of the route is a hub for the ticketing carrier, with a mean of 0.150. The last instrument is *manage_shr*, equal to the managerial share of employment in the origin city of the itinerary, with a mean of 0.048 (this is the variable with missing values). Both *inc_pot* and *manage_shr* are exogenous shifters of the demand for air travel in the city-pair market and are thus appropriate instruments. The *tot_nonstop_other* variable partly captures the extent of competition in the market, and thus may affect fares, flight frequencies and $S_{j,m|fly}$. Note that these effects may arise mostly for nonstop itineraries, which may coexist with nonstop service by other carriers, although connecting itineraries in markets also served nonstop may see an effect. As for the *hub* variable, an endpoint's hub status may affect fares and flight frequencies, especially for nonstop itineraries.

To understand the last six variables listed in Table 1, observe that the specification in (7), along with (8) and (9), implicitly assumes that the effects of $freq^{avg}$ (or $freq^{min}$) on utility are the same for nonstop and connecting trips (being captured by a single coefficient β), despite the fact that flight frequencies translate into different measures for these two trip types. Accordingly, it may be appropriate to allow the utility effects of *freq* to differ between nonstop and connecting itineraries. This modification is achieved by replacing $\beta freq_{jm}$ in (7) by

$$\beta^{ns}\, nonstop * freq_{jm} \;+\; \beta^{ct}\,(1 - nonstop) * freq_{jm}, \tag{10}$$

where β^{ns} and β^{ct} give the effects of *freq* for nonstop and connecting itineraries. In (10), $freq_{jm}$ would acquire *avg* and *min* superscripts in the cases of low-cost and high-cost layover time.

Dropping the observation subscripts for simplicity, using (9), and focusing on the *min* case, the variable $nonstop * freq^{min}$ would equal $1/f^{ns}$ for nonstop itineraries and zero otherwise, while the variable $(1-nonstop) * freq^{min}$ would equal $1/min\{f_1^{ct}, f_2^{ct}\}$ for connecting itineraries and zero otherwise. In the regression tables, $nonstop * freq^{min}$ is denoted $freq^{min,ns}$, and $(1 - nonstop) * freq^{min}$ is denoted $freq^{min,ct}$. The analogous variables for the *avg* case are $freq^{avg,ns}$ and $freq^{avg,ct}$. The last four lines of Table 2 show that the means of these variables are similar to the means of the *freq* variables near the top of the table that do not distinguish between nonstop and connection itineraries.

Note also that summary statistics for the separate nonstop and connecting fares are shown at the bottom of Table 2. The connecting fare is higher despite the lower convenience of such trips, presumably because connecting trips are longer and more costly for the carrier, with an average distance of 1333 miles vs. 973 miles for nonstop trips.

If the frequency difference between the first and second segments on connecting itineraries, equal to $f_1^{ct} - f_2^{ct}$, were small, then the average and minimum *freq* measures for these itineraries would be similar in size, undermining the need for a distinction between them. Table 3, however, shows that the frequency difference is often large, so that the two *freq* measures often diverge even though their means from Table 2 are similar in size. The table shows the percentiles of the difference between the first- and second-segment frequencies for connecting one-way (first column) and roundtrip (second column) itineraries. While the medians are close to zero, the table shows substantial variation around the medians.[10]

5. Empirical findings

5.1. Estimation results

The estimation results, which rely on two-stage-least-squares (2SLS), are shown in Tables 4 and 5. Consider first the results in Table 4, which pertain to the high-cost layover case, using the *min* version of *freq*. The first column shows the results where a common $freq^{min}$ coefficient applies to nonstop and connecting itineraries, while the second column shows separate coefficients for the two types of itineraries.

The qualitative results in the first column are as expected. The $fare$ and $freq^{min}$ variables both have significantly negative coefficients, indicating that increases in either variable reduce utility (recall that a higher $freq^{min}$ means lower frequency, which is dispreferred). The coefficient of $\ln(S_{j,m|fly})$ is less than one, as required by the empirical model. The coefficient of *distance* is positive, reflecting a higher demand (greater utility) from air travel when distance is high and non-air substitutes are inconvenient. The positive nonstop coefficient indicates that such trips yield greater utility than less-convenient connecting itineraries, while the positive *one-way* coefficient indicates higher demand for one-way relative to roundtrip travel, possibly because such open-ended trips are booked in response to an urgent need for travel (as in family emergencies, for example). For our purposes, the main lesson of these results is that the

[10] In generating Table 3, a handful of connecting itineraries involving Hawaii, which contain extremely high-frequency segments between the Hawaiian islands, were dropped.

$freq^{min}$ measure, which reflects the underlying assumption of high-cost layover time, appears to properly capture (in an inverse fashion) passenger benefits from flight frequency.

The regression diagnostics, shown at the bottom of the Table 4, ease any concerns about weakness of the instruments given the relatively large size (32.099) of the minimum Eigenvalue statistic. In addition, although the p-value of the Sargan overidentification statistic (0.0717) is not substantial, it nevertheless indicates that exogeneity of the instruments cannot be rejected at conventional significance levels.

The first-stage regressions show that the instruments often have the predicted effects. By raising travel demand, an increase in *inc_pot* raises the fare and reduces $freq^{min}$ by raising frequencies; an increase in *tot_nonstop_other* reduces the fare (reflecting greater competition), reduces $freq^{min}$ via higher frequencies (evidently capturing a market-size effect), and reduces $\ln(S_{j,m|fly})$ as the carrier's market share falls; endpoint hub status raises the fare, likely reflecting the well-known hub premium, and reduces $freq^{min}$ via the higher frequencies that a hub can support. A higher *manage_shr* is associated with a higher fare and a smaller $freq^{min}$ via higher frequencies, as expected, although neither coefficient is significant.

The second column of Table 4 shows the results with separate $freq^{min,ns}$ and $freq^{min,ct}$ coefficients. Both coefficients are significantly negative, and the effects of the remaining variables in the regression are qualitatively the same as in column 1. The larger size of the $freq^{min,ns}$ coefficient relative to the coefficient of $freq^{min,ct}$ is revealing, suggesting that passengers care more about flight frequency when their trips are nonstop than when the trips are connecting. Given that the latter trips are already by compromised by the need to connect, less passenger attention to flight frequency makes sense. This difference in coefficient sizes translates into a higher dollar willingness-to-pay for additional frequency for nonstop as opposed to connecting travel, as will be shown in the paper's next subsection. As for the diagnostics, the addition of an extra endogenous variable makes the regression just-identified, eliminating the overidentification statistic, while the minimum Eigenvalue statistic is similar in size to that in column 1.[11]

[11] In first-stage regressions, the effects of *inc_pot*, *tot_nonstop_other*, and *hub* on $freq^{min,ns}$ and $freq^{min,ct}$ are in the same directions as their effects on $freq^{min}$ in the first-column regression. The *manage_shr* coefficient is now significantly negative in the first-stage $freq^{min,ns}$ regression, as expected, although it is significant with

Table 5 shows the estimation results pertaining to the low-cost layover case, using the *avg* version of *freq*. While the results in the first column are qualitatively similar to the corresponding results in Table 4 (except for the *one-way* coefficient's negative sign), the Sargan overidentication statistic now resoundingly rejects exogeneity of the instruments, with a p-value of 0.0000. Evidently, changing from the minimum to average formulation in the construction of *freq* is enough to yield this different conclusion. The results in Table 5's second column also contain anomalies. The $\ln(S_{j,m|fly})$ coefficient is larger than 1, in violation of the underlying model, and the minimum Eigenvalue statistic is much smaller than in the previous regressions.

The upshot from the anomalies in both columns of Table 5 is that the performance of the *avg* version of *freq*, based on the low-cost layover assumption, is inferior to that of minimum version, which is based on high-cost layovers. Thus, the minimum *freq* version fits the data better, which provides indirect empirical evidence that passengers behave as if layover time is highly costly relative to schedule delay. Accordingly, a connecting flight-frequency measure equal to the reciprocal of the smaller of the itinerary's segment frequencies appears to be appropriate and could be used in future research.[12]

5.2. Willingness-to-pay for higher flight frequency

Having successfully estimated both the $fare$ and $freq^{min}$ coefficients for the high-cost layover case in Table 4, we can use them to compute the willingness-to-pay for additional flights in dollar terms, as follows. To begin, consider the calculation based on the results from the second column of Table 4, where the $freq^{min}$ coefficients differ between the nonstop and connecting cases. Starting with the nonstop case, we use the median value of $freq^{min,ns} = 1/f^{ns}$, equal to 0.435 and translate this value into a flight frequency f, equal to $1/0.435 = 2.30$. Then, we increase this frequency number in increments of 1, adding 1 flight, 2 flights and 3 flights to the median (yielding 3.30, 4.30, and 5.30 flights). Next, we convert these changes back into changes in $freq^{min,ns}$. The change in moving from the median to 1 additional flight equals $\Delta freq^{min,ns} = 1/3.30 - 1/2.30$, from 3.30 to 4.30 flights equals $1/4.30 - 1/3.30$, and

the opposite sign in the first-stage $freq^{min,ct}$ regression.

[12] BFF show that flight frequency falls with formation of an airline alliance under the *min* formulation, a conclusion that does not appear to be empirically accurate.

from 4.30 to 5.30 equals $1/5.30 - 1/4.30$. These negative values, which indicate beneficial reductions in schedule delay, are computed in the first panel of Table 6, and then multiplied by the $freq^{min,ns}$ coefficient from the second column of Table 4, equal to -6.87, to get the nonstop utility increase from the increment to flight frequency. To cancel this utility increase, the fare must rise, and the amount is given by $\Delta freq^{min,ns} \times (-6.87)/0.012$, which equals the passenger's willingness-to-pay for an increment to nonstop flight frequency (-0.012 is the fare coefficient). The resulting values are shown in third column of the first panel of Table 6, and they equal \$75.57 for one additional flight, \$40.07 for a second additional flight, and \$25.19 for a third additional flight. These values represent 32%, 17%, and 11% of the mean nonstop fare of \$236.24.

The second panel of Table repeats this exercise for connecting flight frequency. The median value of $freq^{min,ct} = 1/min\{f_1^{ct}, f_2^{ct}\}$ is 0.330, which translates to a minimum f value of 3.03. If 1 is added to both the f_1^{ct} and f_2^{ct} values underlying this median, their minimum value also increases by 1, leading to a change in $freq^{min,ct}$ of $1/4.03 - 1/3.03$, and similarly for the second and third frequency increments. The subsequent calculations parallel those in the first panel, leading to willingness-to-pay values for the incremental flights of \$33.89, \$20.25, and \$13.64, as seen in the table (representing 12%, 7%, and 5% of the mean connecting fare of \$294.15). These values are smaller than the willingness-to-pay values for the increments to nonstop flight frequency, reflecting both the higher baseline frequency (3.03 vs. 2.30) and the smaller absolute size of the $freq^{min,ct}$ coefficient relative to the $freq^{min,ns}$ coefficient (4.96 vs. 6.87), from Table 4. Lower willingness-to-pay for higher connecting frequencies makes sense given that such trips are already compromised by the need to change planes. Therefore, the message of the first two panels of Table 6 is highly intuitive.

Carrying out this same exercise using the estimates from the first column of Table 4, where nonstop and connecting itineraries have a common $freq^{min}$ coefficient, is problematic. The difficulty is that, since $freq^{min}$ is given by different formulas in the nonstop and connecting cases, choosing a baseline value for this variable is not straightforward. Nevertheless, the calculations in Table 6 are sufficiently informative regarding willingness-to-pay for higher frequencies.

6. Conclusion

This paper estimates passenger benefits from airline flight frequencies, recognizing that this task is less straightforward for connecting trips than for nonstop travel. In doing so, the paper joins Yuan and Barwick (2026) as the only other study in the literature that confronts the problem of creating a flight-frequency measure for connecting trips. With airlines providing a crucial service in modern economies, the ability to measure the quality of that service is essential, not just for the nonstop service that links larger cities but for the connecting trips involving smaller endpoints that many passengers rely on.

Our results favor a connecting frequency measure based on the minimum of the two segment frequencies on a connecting trip, which applies when layover cost is high. Using the estimated coefficients, our calculations show that a nonstop passenger's willingness-to-pay for an extra daily flight is about $76, while an extra daily flight on each segment of a connecting trip is worth only $34 to the passenger. Thus, flight frequency matters less for connecting passengers, a natural result given that their trip is already compromised by the need for a hub layover. These conclusions deepen our understanding of airline service quality, which affects millions of travelers world wide.

Table 1: One-way vs. nonstop crosstabs

	nonstop		
one-way	0	1	Total
0	46,450	9,167	55,617
	(0.405)	(0.080)	(0.485)
1	51,538	7,357	58,895
	(0.450)	(0.064)	(0.514)
Total	97,988	16,524	114,512
	(0.856)	(0.144)	(1.000)

Table 2: Summary statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
$\ln(S_{j,m}/S_{0,m})$	-7.887159	1.247925	-13.18801	-1.325523
$\ln(S_{j,m\|fly})$	-1.240119	.8864111	-7.637877	0
fare	285.7928	87.26442	38.2732	1388.667
freq^{avg}	.4673792	.2056657	.0365854	1
freq^{min}	.3689609	.1931052	.0365854	1
AA (American)	.3766156	.4845393	0	1
AS (Alaska)	.0385724	.1925743	0	1
B6 (JetBlue)	.0061828	.0783874	0	1
DL (Delta)	.301654	.4589779	0	1
F9 (Frontier)	.0030041	.0547271	0	1
G4 (Allegiant)	.0013448	.0366475	0	1
HA (Hawaiian)	.0038162	.0616576	0	1
NK (Spirit)	.0038686	.0620778	0	1
SY (Sun Country)	.0007772	.0278678	0	1
UA (United)	.1600007	.3666083	0	1
WN (Southwest)	.1041638	.3054742	0	1
q2 (quarter 2)	.2557636	.4362915	0	1
q3 (quarter 3)	.2670288	.4424094	0	1
q4 (quarter 4)	.2520347	.434183	0	1
distance	1281.032	720.925	70	5811
one-way	.5143129	.4997973	0	1
nonstop	.1442993	.3513945	0	1
Instruments				
inc_pot	48308.93	7434.708	27862.29	125470.3
tot_nonstop_other	.1378371	.4157224	0	4
hub	.1504384	.3575022	0	1
manage_shr	.0483659	.0116678	.0239811	.0854049
Separate freq, fare variables				
$\text{freq}^{avg,ns}$	.4804185	.2718904	.0365854	1
$\text{freq}^{avg,ct}$	.3501655	.1693054	.0365854	1
$\text{freq}^{min,ns}$	.4804185	.2718904	.0365854	1
$\text{freq}^{min,ct}$	.4651803	.192178	.0810811	1
fare^{ns}	236.24	89.59	38.27	1177.85
fare^{ct}	294.15	84.03	53.33	1388.67

Observations = 114,512, but means of the separate *freq* variables are computed over the 97,988 and 16,524 nonzero values for the nonstop and connecting variables, respectively.

Table 3: Difference between first- and second-segment frequencies on connecting itineraries

Percentile	$f_1^{ct} - f_2^{ct}$ one-way	$f_1^{ct} - f_2^{ct}$ rountrip
10%	-4.62	-5.39
25%	-1.90	-2.35
50%	0.08	-0.02
75%	2.12	2.26
90%	4.87	5.38
95%	6.61	5.38

Table 4: Estimates for high-cost layover case (using min version of *freq*)

VARIABLES	(1) $\ln(S_{j,m}/S_{0,m})$	(2) $\ln(S_{j,m}/S_{0,m})$
fare	-0.0114**	-0.0122**
	(0.00107)	(0.00117)
freq^{min}	-5.516**	–
	(0.528)	
$\text{freq}^{min,ns}$	–	-6.872**
		(0.929)
$\text{freq}^{min,ct}$	–	-4.956**
		(0.619)
$\ln(S_{j,m\|fly})$	0.695**	0.735**
	(0.0844)	(0.0882)
AS	0.299**	0.320**
	(0.0337)	(0.0359)
B6	0.0116	0.0449
	(0.0641)	(0.0674)
DL	-0.0858**	-0.0590**
	(0.0160)	(0.0221)
F9	0.466**	0.745**
	(0.120)	(0.198)
G4	0.467**	0.733**
	(0.138)	(0.204)
HA	2.715**	2.781**
	(0.172)	(0.177)
NK	-0.113	0.0822
	(0.100)	(0.149)
SY	-0.266	-0.213
	(0.171)	(0.175)
UA	0.612**	0.541**
	(0.0776)	(0.0880)
WN	-0.163**	-0.200**
	(0.0255)	(0.0332)
q2	0.300**	0.308**
	(0.0185)	(0.0192)
q3	0.195**	0.200**
	(0.0129)	(0.0134)
q4	0.116**	0.122**
	(0.0126)	(0.0131)
distance	0.000899**	0.000926**
	(9.33e-05)	(9.54e-05)
nonstop	1.227**	2.087**
	(0.0251)	(0.483)
one-way	0.249**	0.288**
	(0.0819)	(0.0857)
Constant	-2.879**	-2.915**
	(0.468)	(0.473)
min. eigenvalue statistic	32.099	29.630
Sargan overid p-value	0.0717	–
Observations	114,512	114,512

Standard errors in parentheses
** p<0.01, * p<0.05
Instruments for 2SLS estimation: *inc_pot*, *tot_nonstop_other*, *hub*, *manage_shr*

Table 5: Estimates for low-cost layover case (using avg version of *freq*)

VARIABLES	(1) $\ln(S_{j,m}/S_{0,m})$	(2) $\ln(S_{j,m}/S_{0,m})$
fare	-0.00588**	-0.0243**
	(0.00110)	(0.00389)
freq^{avg}	-1.860**	–
	(0.412)	
$\text{freq}^{avg,ns}$	–	-15.85**
		(2.486)
$\text{freq}^{avg,ct}$	–	-5.123**
		(1.053)
$\ln(S_{j,m\|fly})$	0.151*	1.414**
	(0.0711)	(0.261)
AS	0.323**	0.0905
	(0.0389)	(0.0937)
B6	-0.0879	-0.128
	(0.0555)	(0.122)
DL	-0.122**	0.192**
	(0.0168)	(0.0637)
F9	-0.143	1.726**
	(0.0799)	(0.356)
G4	0.109	1.416**
	(0.110)	(0.324)
HA	1.284**	2.946**
	(0.0703)	(0.315)
NK	-0.449**	0.474*
	(0.0821)	(0.236)
SY	-0.142	-0.691*
	(0.146)	(0.332)
UA	0.0491	0.521**
	(0.0534)	(0.141)
WN	-0.238**	-0.600**
	(0.0268)	(0.0840)
q2	0.211**	0.420**
	(0.0147)	(0.0473)
q3	0.159**	0.224**
	(0.00940)	(0.0232)
q4	0.0997**	0.155**
	(0.00946)	(0.0227)
distance	0.000315**	0.00162**
	(8.08e-05)	(0.000279)
nonstop	1.556**	6.465**
	(0.0296)	(0.815)
one-way	-0.222**	1.061**
	(0.0780)	(0.273)
Constant	-5.930**	-0.402
	(0.389)	(1.251)
min. eigenvalue statistic	24.763	8.260
Sargan overid p-value	0.0000	–
Observations	114,512	114,512

Standard errors in parentheses
** p<0.01, * p<0.05
Instruments for 2SLS estimation: *inc_pot*, *tot_nonstop_other*, *hub*, *manage_shr*

Table 6: Willingness-to-pay for increments to flight frequency

NONSTOP		
median $freq^{min,ns} = 0.435$; corresponding $f = 2.30$		
additional flights	$\Delta freq$	$\Delta fare = \Delta freq \times (-6.87)/0.012$
+1	$\frac{1}{3.30} - \frac{1}{2.30} = -0.132$	\$75.57
+2	$\frac{1}{4.30} - \frac{1}{3.30} = -0.070$	\$40.07
+3	$\frac{1}{5.30} - \frac{1}{4.30} = -0.044$	\$25.19

CONNECTING		
median $freq^{min,ct} = 0.330$; corresponding $f = 3.03$		
additional flights	$\Delta freq$	$\Delta fare = \Delta freq \times (-4.96)/0.012$
+1	$\frac{1}{4.03} - \frac{1}{3.03} = -0.082$	\$33.89
+2	$\frac{1}{5.03} - \frac{1}{4.03} = -0.049$	\$20.25
+3	$\frac{1}{6.03} - \frac{1}{5.03} = -0.033$	\$13.64

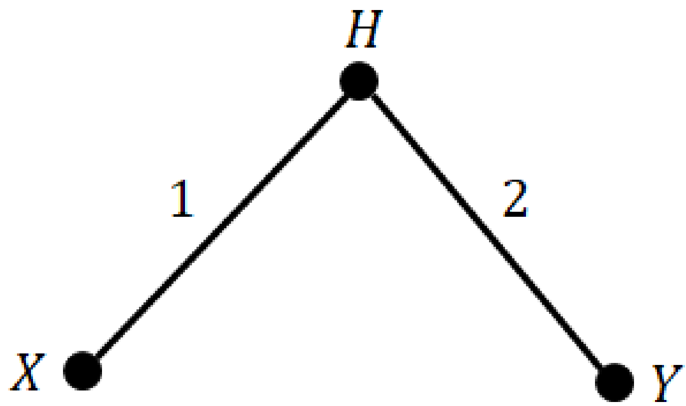


Figure 1: Connecting routes

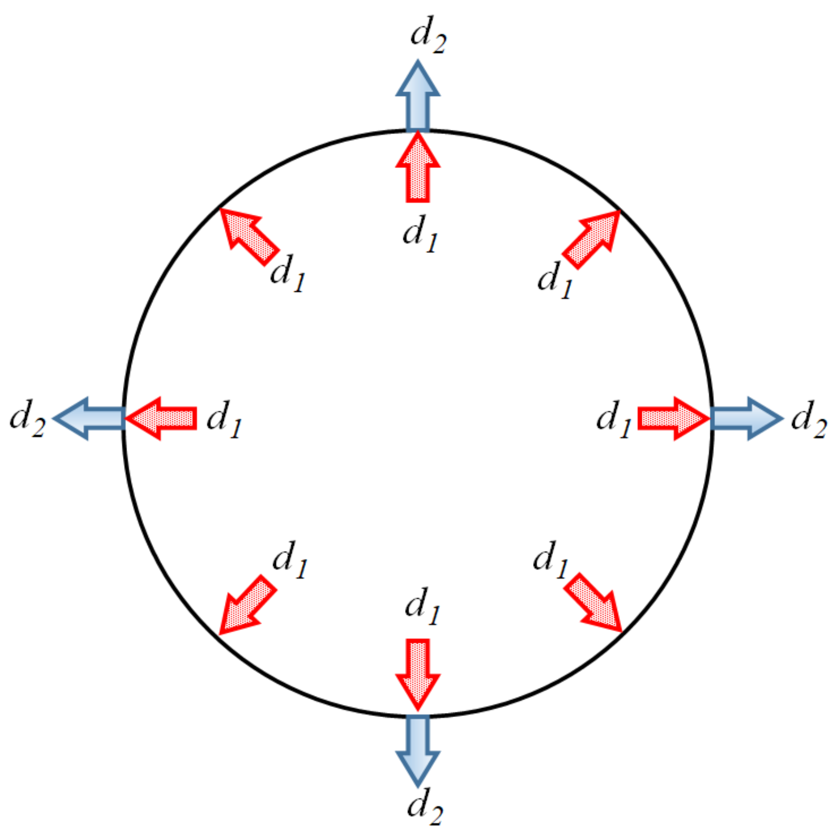
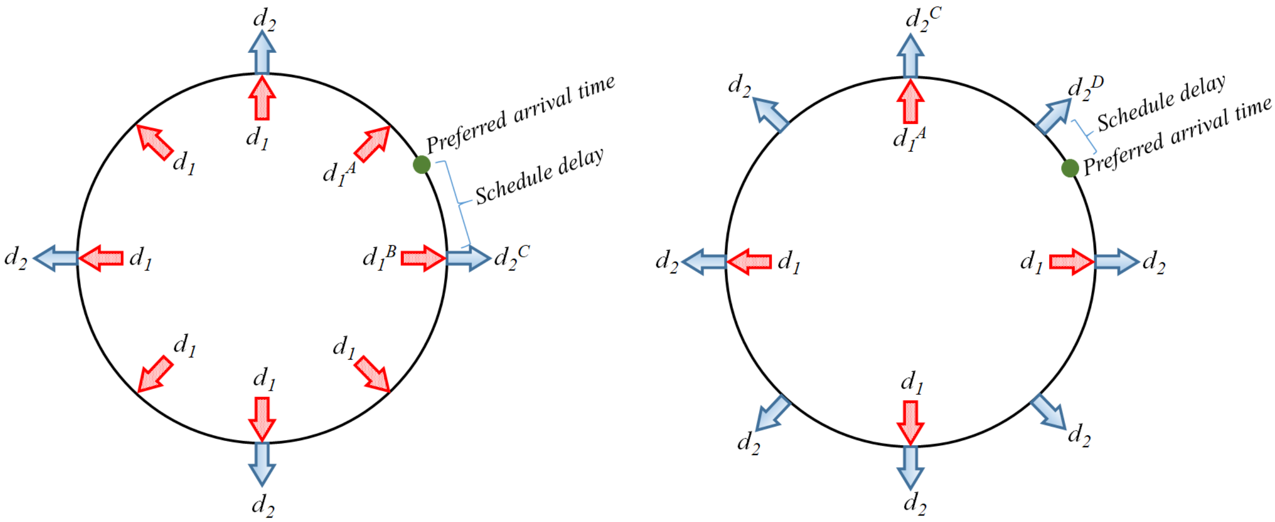
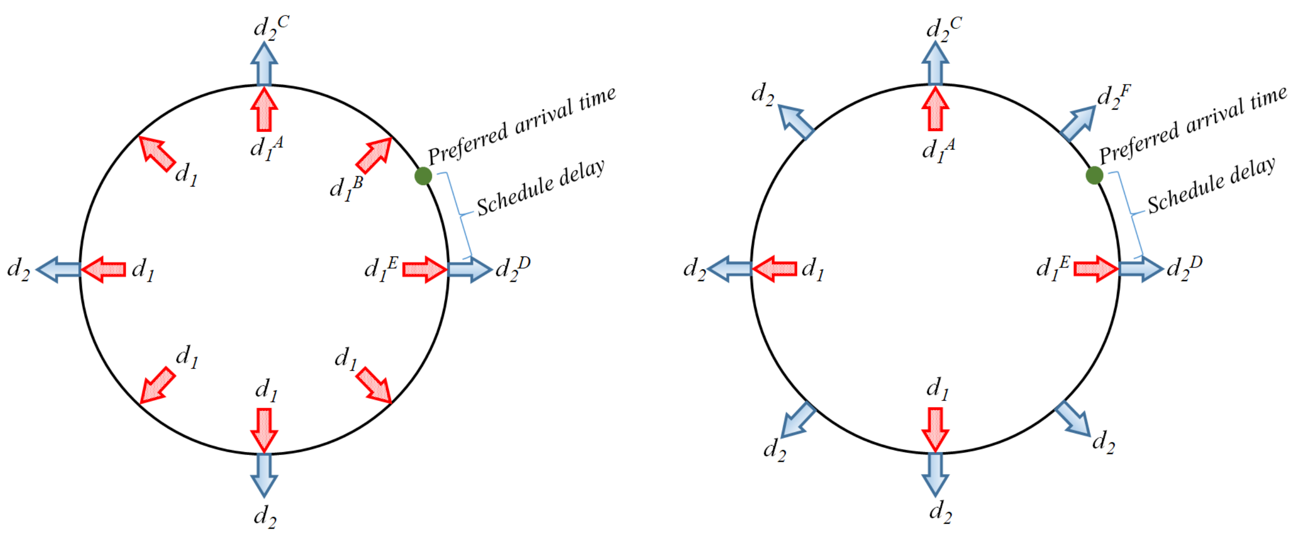


Figure 2: Departure pattern



Panel I: Case $f_1 \geq f_2$. Panel II: Case $f_1 < f_2$.

Figure 3: Zero-cost layover



Panel I: Case $f_1 \geq f_2$. Panel II: Case $f_1 < f_2$.

Figure 4: High-cost layover

References

Berry, S., 1994. Estimating discrete choice models of product differentiation. *Rand Journal of Economics* 25, 242-262.

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. *Econometrica* 63, 841-890.

Berry, S., Jia, P., 2010. Tracing the woes: An empirical analysis of the airline industry, *American Economic Journal: Microeconomics* 2, 1-43.

Brueckner, J.K., 2004. Network structure and airline scheduling, *Journal of Industrial Economics* 52, 291-312.

Brueckner, J.K., Flores-Fillol, R., 2007. Airline schedule competition, *Review of Industrial Organization* 30, 161-177.

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

Brueckner, J.K., Flores-Fillol, R., 2020. Market structure and quality determination for complementary products: Alliances and service quality in the airline industry. *International Journal of Industrial Organization* 68, article 102557.

Chen, Y., Gayle, P.G., 2019. Mergers and product quality: Evidence from the airline industry. *International Journal of Industrial Organization* 62, 96-135.

Flores-Fillol, R., 2010. Congested hubs. *Transportation Research Part B* 44, 358-370.

Morrison, S.A., Winston, C., *The Economic Effects of Airline Deregulation*. Washington, D.C., Brookings Institution, 1986.

Richard, O., 2003. Flight frequency and mergers in airline markets. *International Journal of Industrial Organization* 21, 907-922.

Thomaz, S., 2020. Effects of asymmetric demands on airline scheduling decisions in a network. *Economics of Transportation* 22, article 100169

Yan, J., Winston, C., 2014. Can private airport competition improve runway pricing? The case of San Francisco Bay area airports. *Journal of Public Economics* 115, 146-157.

Yuan, Z., Barwick, P.J., 2026. Network competition in the airline industry: An empirical framework. *Rand Journal of Economics*, in press.