

Why do all the flights leave at 8 am?: Competition and departure-time differentiation in airline markets

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Abstract

Theoretical models of spatial product differentiation indicate that firms face two opposing incentives: (1) minimize differentiation in order to “steal” customers from competitors, and (2) maximize differentiation in order to reduce price competition. Using data on U.S. airline departure times from 1975, when fares were regulated, and 1986, when fares were not regulated, we empirically estimate the effect of competition on differentiation. We find a negative relationship in both periods. In 1986, however, reductions in exogenous scheduling constraints increase differentiation, implying that firms may be differentiating their products where possible to reduce price competition. This effect is not apparent in the 1975 data. © 1999 Elsevier Science B.V. All rights reserved.

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1. Introduction

A great deal of theoretical work on product differentiation and spatial competition has been done since Hotelling’s path-breaking 1929 paper “Stability in

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Competition.” This theory literature, however, has developed without the benefit of virtually any empirical investigation. Our paper examines a particular type of product differentiation in the airline industry—the scheduling of flight departure times—in an attempt to shed light on the predictions of the theoretical models.¹ Airline flight scheduling provides a natural, though complex, empirical test of spatial competition theories. The major theoretical findings have natural analogs in this market and a key factor in the theories—the endogeneity of price determination—changed between the 1970s and the 1980s as the airline industry was deregulated.

Hotelling’s initial model of spatial competition was very simple, assuming perfectly inelastic demand and a uniform distribution of consumers over the space. His surprising results—minimum differentiation with two firms and no stable equilibrium with three firms—spurred substantial investigation of sensitivity of the results to his assumptions.² These works extend Hotelling’s model in many directions, allowing elastic demand, a variety of conjectural variations for firms, nonuniform distributions of consumers, and various shapes and dimensions of spaces. While many of the extensions have supported Hotelling’s finding of minimum, or at least reduced, differentiation, other work has indicated that competition is consistent with, or does not differ much from, the social optimum.

The mixed results of the theoretical work arise from two conflicting incentives faced by firms competing in two dimensions. On the one hand, firms attempt to locate close to their competitors’ locations in order to “steal” customers, which we call an “attraction” force. However, reducing differentiation increases price competition, reducing the profit to be made on each sale. This effect we term a “repulsion” force since it gives each firm an incentive to locate farther from its competitors. Different assumptions cause one or the other of these forces to dominate, resulting in a tendency towards minimal or maximal differentiation, respectively.

Unfortunately for our purposes, the airline industry is much more complicated than the assumptions of any of the models: demand is elastic; passengers are distributed nonuniformly in their preferred departure times; passenger delay costs, analogous to transport costs in a typical spatial model, vary over consumers; each route is part of a network; and airlines compete on departure time, prices, and other quality factors. We attempt to control for the effects of these factors that vary across route observations in order to analyze the strategic incentives of firms to position their brands either closer to competitors’ brands or farther away than they would in the absence of competitive considerations. Our approach to this analysis

¹Greenhut et al., 1987, briefly discuss airline scheduling in the context of spatial theory, suggesting that more competition leads to less differentiation.

²As discussed below, these are not actually equilibria. Existence (and uniqueness) of equilibrium is a common problem in models of spatial equilibrium when price is endogenous.

is to ask whether, for a given number of flights on a route, the departure times of those flights are closer together or farther apart if they are scheduled by a monopolist than if different flights are scheduled by different airlines. Our results provide support for the assertion that multiple airlines on a route will locate their flights more closely together in time than will a single firm controlling the same number of flights. We argue, however, that this result may capture effects other than competitive positioning of brands. Results indicate that when scheduling possibilities are more constrained by landing slot availability and other factors, the observed scheduling exhibits less differentiation than does unconstrained scheduling.

In Section 2, we review some theoretical models of spatial competition and discuss the factors that seem to determine the degree of product differentiation that obtains. The application of these theories to the airline industry is discussed in Section 3. The most important complication is that flights are part of a network, which affects the incentives for a firm to strategically reschedule flights on a specific route. In Section 4, we describe the data and their sources, introduce the measures we use for analyzing departure-time differentiation, and present simple summary statistics that begin to address the empirical issues. These statistics indicate that as competition on a route increases, the degree of differentiation declines. We present an empirical model of departure-time differentiation in Section 5 and discuss the econometric issues that arise in attempting to estimate this model. The results from our 1986 postderegulation dataset are presented and discussed in Section 6. Analysis using data from 1975, prior to deregulation of the airline industry, is shown in Section 7. Section 8 concludes with some further interpretations of our results.

2. Theories of spatial differentiation

Hotelling (1929) proposed his model of spatial competition in order to explain a certain puzzle: when there are two sellers of a homogeneous good and price is not equal, why doesn't the firm charging the higher price lose all its customers instantaneously? Hotelling assumed that buyers are distributed uniformly over a line of finite length; that consumers pay the seller's price plus a transport cost per unit distance; that demand is perfectly inelastic; that firms choose price and location in an effort to maximize profits; and that relocation is costless. Hotelling considers a game where firm A is permanently located. Firm B then locates, and then firms choose price. The equilibrium with two firms proposed by Hotelling is characterized by minimum differentiation, i.e., the two firms are paired at the center of the market. This is in contrast to the socially optimal locations that minimize transport costs, where the firms locate at the first and third quartiles and realize identical profits as under minimum differentiation. In the case of three firms, Hotelling finds no stable equilibrium.

d'Aspremont et al. (1979) analytically demonstrate that Hotelling's proposed two-firm equilibrium is not an equilibrium. At minimum differentiation, price would be driven to marginal cost, but if price is equal to marginal cost, either firm has an incentive to relocate further from its competitor and raise its price. Given one firm's location and price, however, the other firm always has an incentive to locate infinitesimally close and to undercut the first firm's price. A number of alternatives have been proposed to guarantee an equilibrium in a model similar to Hotelling's.³ Alternative strategies include (1) eliminating the problem by assuming that price is given exogenously; (2) permitting firms to randomize over prices; (3) allowing one firm to be a Stackelberg leader; (4) assuming that transportation costs are quadratic in distance; and (5) introducing heterogeneity in consumer preferences across brands (i.e., gross surplus varies across brands and consumers). The results of all this theoretical analysis indicate that the degree of differentiation is very sensitive to the exact specification of the competitive interaction.

Osborne and Pitchik (1985) allow firms to randomize over prices while otherwise maintaining Hotelling's assumptions. Their proposed equilibrium has firms located very close to the quartiles. Hence the locations are close to the social optimum, in contrast to Hotelling's finding. Anderson (1987) invokes a Stackelberg framework. The equilibrium in this case involves the first firm to enter the market locating at the mid-point. The second firm enters relatively close to one of the ends. Anderson's equilibrium locations are asymmetric, in contrast to the equilibria in most other models. The asymmetry arises from the sequential play; in the equilibrium the second entrant becomes the price leader. In Prescott and Visscher's (1977) model, which is similar to Anderson's, but which takes prices as exogenous, symmetry obtains. If there is only one potential entrant, equilibrium involves minimum differentiation. If there are additional potential entrants, the first two firms will locate symmetrically, but at some distance from the center in order to deter additional entry. d'Aspremont et al. (1979) assume quadratic transportation costs and find an equilibrium in which firms locate as far apart as possible. DePalma et al. (1985) introduce heterogeneity in consumer demand. If there is sufficient consumer heterogeneity, minimum differentiation obtains regardless of the number of firms.⁴

Apart from extensions designed to guarantee existence of an equilibrium, Hotelling's model has been extended in numerous other directions to make the model more applicable to real-world situations. Eaton and Lipsey (1975) and Denzau et al. (1985) each present rigorous expositions of Hotelling's model in

³For thorough discussions on existence of equilibria in spatial models, see Anderson, 1987, and Gabszewicz and Thisse, 1986.

⁴With consumer heterogeneity, consumers no longer necessarily buy from the firm with the cheapest (net) price; other factors now matter. With sufficient consumer heterogeneity, existence of an equilibrium is guaranteed.

which sellers locate simultaneously and compete via location only. These papers analyze the properties of location equilibria for any number of firms. By assuming that firms compete only in location, they skirt the existence problem. They also ignore the complication of potential entry. They are able to specify equilibria for any number of firms with the exception of three. Although minimum differentiation obtains only for two agents, equilibria for more firms is characterized by pairing of firms. For example, on a line of unit length with four firms, the equilibrium has two firms at $\frac{1}{4}$ and two at $\frac{3}{4}$. With five firms, two locate at $\frac{1}{6}$, one at $\frac{1}{2}$, and two at $\frac{5}{6}$. Multiple equilibria exist for greater than five firms, and all equilibria are characterized by a pairing of firms, at least near the endpoints of the line, and by symmetry.

Location theory also has been applied to situations where firms locate more than one outlet. For example, Martinez-Giralt and Neven (1988) examine a duopoly where firms first locate two outlets, then choose price. Based on an assumption of quadratic transportation costs, they find that firms will minimally differentiate their own locations and maximally differentiate relative to each other.^{5,6} However, the result of maximum differentiation with respect to competitors is not robust. For one thing, the assumption of quadratic transportation costs is crucial. Models allowing each firm to locate a single outlet (with price endogenous) also find maximal differentiation under quadratic transportation costs. However, if equilibrium is achieved by changing another assumption, for example, by introducing heterogeneity in consumer preferences, minimal differentiation obtains, as discussed above. Work by Gabszewicz and Thisse (1986) and Bensaid and dePalma (1993) suggest that the finding of maximal differentiation may be driven by the assumption that each firm locates two outlets or the assumption that there are only two firms, respectively. Gabszewicz and Thisse allow two firms to locate as many plants as they desire.⁷ In this case, the equilibrium will involve competitive pairs of plants located evenly over the market space, similar to the equilibria in the above models for even numbers of firms. That is, the firms differentiate their own outlets, but locate next to their competitors. Bensaid and de Palma extend the analysis to three firms each locating up to two outlets. While confirming Martinez-Giralt and Neven's maximum differentiation result for two firms with two outlets each, they find that (almost) anything goes when there are three firms. The three candidate equilibria under a two-stage, locate then price, game include: an equilibrium where outlets are evenly spaced, with each firm locating its two outlets at opposite sides of the circle; an equilibrium where each firm reduces differentiation of its own

⁵Hence, on a bounded line, each firm locates its outlets at one of the ends of the market. On a unit circle, each firm locates its outlets together and directly across the circle from its competitor's location.

⁶In contrast, a monopolist would never locate two firms at the same point. Thus, a monopolist leads to more differentiation than more competitive market structures.

⁷Fixed costs are assumed to exist, which limits the number of plants each firm will establish.

outlets (though not to the point of minimum differentiation), while increasing differentiation relative to competitors' outlets; and a mixed equilibrium, where two firms bunch their own outlets at opposite sides of the circle, while the third firm locates its outlets between the competitors, on opposite sides of the circle.⁸ Thus, it appears that the literature with regard to firms locating multiple outlets leads to roughly the same equilibria as the literature constraining firms to locate only one outlet: reduced (but not minimal) differentiation, maximal differentiation, and a variety of outcomes in between these two extremes.

Hotelling's model also has been extended to allow for elastic demand and various conjectural variations on the part of firms. Smithies (1941) allows elastic, albeit linear, demand and examines several conjectural variations. Again firms are competing across two dimensions, price and location. When one firm assumes that its competitor will react via price but maintain its location, or assumes its competitor will strategically react via price and location, Smithies concludes the firms will locate towards the center, although minimum differentiation may not obtain. With elastic demand, moving toward the center can result in the loss of customers near the endpoints, depending on parameter values, hence this will mitigate the tendency towards minimum differentiation. Eaton (1972) confirms Smithies' most important results in a more mathematically rigorous investigation. He then derives the parameter values that result in minimum differentiation, showing that for a market length less than a critical value, which is a function of the demand parameters and the transport cost, minimum differentiation obtains. However, Eaton also notes that this equilibrium is unstable as no pure strategy price choices exist. Furthermore, with elastic demand, Eaton demonstrates that an equilibrium with three firms can be reached in which the middle firm makes lower profits, charges a lower price, and has a smaller market share.

Eaton and Lipsey (1976) analyze the sensitivity of minimum differentiation to the conjectural variations of firms and to the distribution of consumers on one- and two-dimensional, bounded and unbounded spaces. While they maintain some simple assumptions—that demand is completely inelastic and that firms charge the same base price—their contribution comes from allowing any distribution of customers that can be represented by a well-behaved density function. In the case of a finite linear space with zero conjectural variations, i.e., firms assume rivals will leave their location unchanged, minimum differentiation occurs as both firms locate at the median of the density function. However, for a unimodal density,

⁸Bensaid and dePalma also consider equilibrium locations when two firms each locate two outlets but recognize that a third firm may enter and locate up to two outlets. In that case outlets of the original two firms are more differentiated, and depending on the magnitude of the fixed cost, the third firm may be blockaded from the market, may locate one outlet, or may locate two outlets. This effect does not seem relevant to the case of airline scheduling, since airlines can re-schedule flights very quickly in response to entry. Netz and Taylor (1997) find that in locating retail gas stations, where the cost of re-locating in response to entry is high, firms will increase locational differentiation in order to reduce the likelihood of entry.

there is no equilibrium for more than two firms. Eaton and Lipsey establish that “[w]ith a variable customer density function that is not rectangular over any finite range of [the line], a necessary condition for equilibrium is that the number of firms does not exceed twice the number of modes.”⁹ This theorem also applies to unbounded one-dimensional, e.g., circular, spaces. Eaton and Lipsey conclude that Hotelling’s results are sensitive to changes in conjectural variation and changes in the distribution of customers. Importantly for our analysis, however, they show that their results are generally not sensitive to market shapes and boundaries, e.g., as one moves from a linear to a circular space. One characteristic of the equilibria of Hotelling’s model for more than three firms—pairing of the firms closest to the endpoints—is of course not applicable to a circular space.

Thus, much of the theoretical work to date has concluded that less product differentiation results when many different firms control location choices than when a single firm controls all outlets. Some studies, however, have found that the difference between the monopoly and competitive location choices may be quite small if the firms compete in price as well as location, with the degree of differentiation also depending on conjectural variations and the elasticity of demand. With prices set exogenously, the pure location decision yields only an “attraction” force, which systematically results in minimum or decreased differentiation as each firm tries to steal customers from its competitors. When price is endogenous, the desire of each firm to limit price competition by increasing the degree of differentiation results in the opposing “repulsion” force. Which influence dominates when price is set endogenously depends upon the assumptions made, especially with regard to conjectural variations. We empirically estimate the degree of differentiation in the airline industry to get a sense of whether the “repulsion” force or the “attraction” force dominates in this particular industry.¹⁰

3. Applying location theory to airline scheduling

The scheduling of airline departure times can be analyzed within a spatial framework, where the space on which we study airline location competition is a one-dimensional circle, in essence a 24-hour clock. Instead of consumers being

⁹Eaton and Lipsey, 1976, p. 35. Wherever the density function is rectangular, the number of modes is infinite.

¹⁰While little empirical work has been done on the issue of spatial differentiation, Brown-Kruse et al., 1993, have conducted experimental work that supports the idea of minimum differentiation. In the theoretical model on which they base the experiment, minimum differentiation is in the set of possible equilibria. The observed equilibrium in the one-shot game experiment is minimum differentiation. In a repeated game with an unknown ending and without communication, players exhibit some, largely unsuccessful, attempts to signal to the unknown partner a willingness to coordinate to the collusive locations (at the quartiles), but in general minimum differentiation obtains. However, with non-binding communications the observed location pattern is at the quartiles.

physically located, their “most preferred departure times,” as termed by Douglas and Miller (1974), are located over time. Given the distribution of preferred departure times, airlines then schedule their flights. In reality, of course, airlines choose many strategic variables in a market simultaneously—including number of flights, departure times, prices, and service quality—in order to maximize profits. The airline industry deviates from theoretical models in a variety of other respects as well: flight schedules on a route must be integrated into the carrier’s network of flights; the cost of rescheduling flights is neither prohibitive nor zero; and each carrier may schedule several flights on the same route. We do not attempt to create or estimate a full-blown model of an airline manager’s decision-making process. Instead, we estimate a structural equation for departure-time differentiation on a route and attempt to account in the estimation for some of the network effects and other constraints faced by an airline.

One question that the literature does not tend to address is the effect of competition in general on locational patterns. That is, how does the locational pattern differ between a market characterized by two firms each locating three outlets compared to a market characterized by six firms each locating one outlet? The literature that assumes each firm locates one outlet in some cases compares the equilibria to outcome that obtains if a monopoly locates all the outlets. A monopolist locates to minimize transportation costs (thus maximizing gross surplus to consumers, allowing the monopolist to set higher prices). Thus, models that predict minimal differentiation will find that a less competitive market (a monopoly market) has a more differentiated outcome,¹¹ while models that predict maximal differentiation will find that a monopoly market has a less differentiated outcome. The literature on multiproduct firms appears to support the above conclusions, though Bensaid and dePalma show that one candidate equilibrium involves firms replicating the monopoly outcome of equal-spacing over the market. None of the models studies asymmetric markets where firms locate a different numbers of outlets. The routes that we analyze range from monopolies to each carrier locating one flight, and any outcome in between. We assume that the relationship between the degree of competition and the degree of differentiation is monotonic, and attempt to discover whether the relationship is positive or negative. Some models suggest that, for a given number of flights on a route, an increase in the number of firms competing on the route might decrease departure-time differentiation.¹² On the other hand, alternative assumptions, for example quadratic transportation costs or elastic demand, may mitigate or even reverse this tendency.

With differentiation by departure time in an airline market, the cost to a consumer of taking a certain flight is the ticket price plus the cost to the consumer

¹¹Greenhut et al., 1987, suggest this is the case for airlines, though their argument rests in part on the possibility that more concentrated markets lead to collusion.

¹²In the next section we define an index for measuring the degree of differentiation.

of adapting travel plans to the flight's departure time. Passengers' most preferred departure times (MPDTs) are distributed around the clock, analogously to consumers being physically located in a market relative to the physical location of stores. A passenger incurs a cost from what Douglas and Miller term schedule delay, i.e., the time between the MPDT and the flight taken. The cost per unit time will vary across passengers according to their value of time, e.g., delay costs will be greater for business travelers than for tourists. This departs from the theories discussed above, which assume equal transport cost per unit distance for all consumers. Of course, passengers' MPDTs are not distributed uniformly about the 24-hour clock. As Eaton and Lipsey's analysis indicates, one can expect a nonuniform distribution to lead to a demand-driven lessening of departure-time differentiation, with the degree of this effect influenced by the amount of competition on the route.

Airlines obviously compete on price as well as departure times in a market. Another complication lies in the fact that, unlike the theoretical work that assumes each firm charges a single price, airlines charge a wide range of prices on most routes. However, average fares do not usually differ much among competing airlines on the same route. On routes with two or more active competitors (defined as a market share above 10%), less than 5% of the variance in fares on a route is due to cross-carrier variation in average fares; the remainder is attributable to within-firm price variation.¹³ In the analysis below, we therefore assume all carriers on a route charge the same average fare, though we recognize that the level of that average fare is determined simultaneously with the differentiation of flights through departure times. To gain more insight into the role that price competition plays in influencing the degree of differentiation, we empirically analyze data from 1986, when prices were unregulated and determined endogenously, and 1975, when the Civil Aeronautics Board set price exogenously, at least relative to departure times on any one route.

Finally, the analysis must take into account the complicating factors referred to earlier. In particular, the analysis must take into account the externality that scheduling a flight imposes on the rest of the network, since the plane used on one route is in use in prior and subsequent routes; scheduling constraints that arise at slot-constrained airports; and capacity constraints.

4. Data sources and measures of departure-time differentiation

We begin our empirical study of departure-time crowding in the airline industry by examining airline schedules in 1986, eight years after the industry was deregulated. The flights are taken from the May 15, 1986 Official Airline Guide (OAG), North American Edition, which lists all scheduled direct flights between

¹³See Borenstein and Rose, 1994.

all North American airports.¹⁴ Our sample is limited to routes between the largest 200 domestic airports.¹⁵ The Herfindahl index, based on carrier shares of nonstop flights, is also derived from the OAG listings.

All traffic data are from the Department of Transportation's Database 1A (DB1A) for the second quarter of 1986, a 10 percent sample of all airline tickets sold in the United States. We further limit the sample to routes on which at least 80% of all passengers fly direct and at least 36 passengers appeared in the DB1A during the quarter. If a substantial proportion of passengers do not fly direct, then the direct flights will be competing with connecting itineraries for which we cannot control given data limitations. We also assume that on routes with 3 to 6 nonstop flights per day (in one direction), indirect flights that make one or more intermediary stops are considered substantially inferior products that are largely ignored by airlines when they set departure times.¹⁶ Routes with less than 36 passengers are excluded because we do not have sufficient data to calculate many of the variables for these routes.

In order to analyze the causes of differentiation of departure times on a route, we must first construct a measure of it. In most spatial competition models, each of the outlets competes with only its most nearby neighbors for marginal sales. In reality, however, every flight competes with every other flight on a route to a greater or lesser extent. For example, if two flights are scheduled around 8 am and one is scheduled at 10 am, each of the 8 am flights competes about equally with the 10 am departure, even if one departs at 7:58 am and the other at 8:03 am; it would be misleading to assume that the 10 am flight and the 7:58 am flight are not competing for the same passengers. For this reason, our analysis focuses on a measure of departure time differentiation that takes into account the differentiation between every pair of flights on a route.

On a route with n daily departures departing at d_1, \dots, d_n each expressed as minutes after midnight, we study the average distance between flights measured as:¹⁷

$$AVGDIFF = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j>1}^n [\min\{|d_i - d_j|, 1440 - |d_i - d_j|\}]^\alpha, \quad (1)$$

$0 < \alpha < 1.$

AVGDIFF is the average of the absolute time difference between each pair of flights on the route raised to the α power. It is minimized at zero, when all flights

¹⁴To be eligible to be included in an observation, a flight had to be operating during the week that included May 15 and had to be scheduled to operate at least 5 days per week.

¹⁵The 200th largest airport is Prudhoe Bay, Alaska, with average daily enplanements of 136 in the second quarter of 1986.

¹⁶Inclusion in our regression analysis of a variable representing the number of multi-stop direct flights did not affect our results and was never significant.

¹⁷The number 1440 appears because this is the number of minutes in a day.

depart at the same time. It is maximized when the n flights are equally spaced around the 24-hour clock. If α is near 0, then the measure is much more strongly influenced by changes in the time between flights that are close together to begin with. For instance, a one minute increase in the time between two flights that are ten minutes apart will increase the index by more than a one minute increase in the time between two flights that are three hours apart. As α increases, a change in the time difference between two flights that are close together has a relatively smaller effect on *AVGDIFF*. As α approaches 1, the index is almost equally affected by changes in the distance between flights that are close together or far apart to begin with.

We arbitrarily choose $\alpha=0.5$, but also explore alternative values.^{18,19} We then normalize the average distance by the maximum possible time difference, given the number of flights, i.e., the *AVGDIFF* that would result if the flights were equally spaced around the circle, which we term *MAXDIFF*.^{20,21} The measure used, then, is

¹⁸We also try α equal to 1/3 and 2/3. The results are robust to these variations.

¹⁹The primary results of the analysis are also robust to two alternative measures. Both of these alternatives depend only on the time between each flight and its immediate neighbors in time. The first alternative measure assumes that the last flight of the day competes with the first flight out the next morning (as well as with the next-to-last flight of the day). The second alternative assumes that the first flight of the day only competes with the second flight, and that the last flight of the day only competes with the second-to-last flight of the day. Mathematically, the two measures are computed as

$$ALLNEIGHBORS = \frac{(d_1 + (1440 - d_n))^\alpha + \sum_{i=2}^n [(d_i - d_{i-1})^\alpha]}{1440^\alpha},$$

and

$$SOMENEIGHBORS = \frac{\sum_{i=2}^n [(d_i - d_{i-1})^\alpha]}{1440^\alpha}.$$

The two variables are then normalized by the value of the variable when all flights are spread evenly over the day. Three values of α are examined: 1/3, 1/2, and 2/3. The results are robust to these alternative measures. In addition, we tried removing from the daily clock a period in the early morning hours when no flights are generally scheduled, i.e., 2 am to 5 am; that variation also had no effect on the basic conclusions.

$$^{20} MAXDIFF = \begin{cases} \left[3 \cdot \left(\frac{1440}{3} \right)^\alpha \right] / 3, & n = 3 \\ \left[4 \cdot \left(\frac{1440}{4} \right)^\alpha + 2 \cdot \left(2 \cdot \frac{1440}{4} \right)^\alpha \right] / 6, & n = 4 \\ \left[5 \cdot \left(\frac{1440}{5} \right)^\alpha + 5 \cdot \left(2 \cdot \frac{1440}{5} \right)^\alpha \right] / 10, & n = 5 \\ \left[6 \cdot \left(\frac{1440}{6} \right)^\alpha + 6 \cdot \left(\frac{1440}{6} \right)^\alpha + 3 \cdot \left(3 \cdot \frac{1440}{6} \right)^\alpha \right] / 15, & n = 6 \end{cases}$$

²¹Normalizing in this manner allows for comparisons of *DIFF* across samples with different numbers of flights on the route.

$$DIFF = \frac{AVGDIFF}{MAXDIFF}. \quad (2)$$

Thus, *DIFF* gives the proportion of the maximum possible differentiation in flight times, and has a value in the interval [0, 1]. The closer the index to 1, the closer the flights are to being evenly distributed over a 24-hour clock.

Table 1 presents the average values of the differentiation index for each of the *n*-flight samples we study from May 1986 and the average index values for each of the observed market structures within each sample.²² Each observation includes all nonstop flights on a directional route, e.g., from Oakland to Denver (Denver to Oakland is treated as a separate observation). This preliminary evidence supports

Table 1
Average differentiation index by sample and market structure¹

3-flight markets—236 observations (<i>DIFF/HERF</i> correlation: 0.520)										
Mkt Struc	3–0	2–1	1–1–1							All
Obs	182	44	10							236
Avg <i>DIFF</i> †	0.884*	0.794*	0.463							0.850
SE of Avg‡	(0.006)	(0.019)	(0.092)							(0.009)
4-flight markets—222 observations (<i>DIFF/HERF</i> correlation: 0.497)										
Mkt Struc	4–0	3–1	2–2	2–1–1	1–1–1–1					All
Obs	110	46	50	14	1					222
Avg <i>DIFF</i> †	0.877*	0.807	0.777	0.728	0.649					0.829
SE of Avg‡	(0.005)	(0.013)	(0.015)	(0.051)	(0.057)					(0.007)
5-flight markets—166 observations (<i>DIFF/HERF</i> correlation: 0.492)										
Mkt Struc	5–0	4–1	3–2	3–1–1	2–2–1	2–1–1–1				All
Obs	63	25	65	5	9	1				166
Avg <i>DIFF</i> †	0.901*	0.875*	0.846	0.828	0.794	0.737				0.878
SE of Avg‡	(0.006)	(0.011)	(0.006)	(0.027)	(0.044)	–				(0.005)
6-flight markets—152 observations (<i>DIFF/HERF</i> correlation: 0.286)										
Mkt Struc	6–0	5–1	4–2	4–1–1	3–3	3–2–1	3–1–1–1	2–2–1–1	All	
Obs	21	6	40	3	58	16	1	7	152	
Avg <i>DIFF</i> †	0.877	0.854	0.828	0.805	0.850	0.861*	0.635*	0.747	0.842	
SE of Avg‡	(0.010)	(0.015)	(0.009)	(0.041)	(0.007)	(0.013)	–	(0.030)	(0.005)	

¹The market structure indicates the number of flights by each carrier, e.g., 4–2 means one carrier schedules four flights and one carrier schedules two flights.

*Indicates the mean is significantly different than that of the neighbor to the right at the 5% level.

†The mean value of the differentiation index is significantly different from 1 at the 1% level for all samples and market structures, except 1–1–1–1, which is significantly different from 1 at the 10% level.

‡Standard errors of averages calculated under the assumption that all observations are independent.

²²The market structure refers to the distribution of flights among firms. Observations are divided into different samples depending on the number of flights on the route.

the conjecture that competition is associated with less differentiation than monopoly. In all four samples, *DIFF* is positively and significantly correlated with the Herfindahl index based on the number of flights. The average index increases monotonically with the Herfindahl index in the three-, four-, and five-flight samples. In several of the cases, the averages are significantly different between neighboring cells.

Table 1 does not indicate the source of the decline in product differentiation with competition. One explanation is that each firm schedules its flights more closely to competitors' flights, as suggested by Hotelling, in an effort to sell to more consumers. Alternatively, competition might lead to market segmentation, with each firm trying to schedule its flights far from the competitor's flights and, as a result, crowding together its own flights, in an effort to reduce price competition. For instance, one firm might schedule all its flights on a route (in a given direction) in the morning and the other firm might schedule all its flights in the evening. The former explanation would imply that the interfirm differentiation would be less than intrafirm competition, while the latter would imply the opposite.

The measure of differentiation in a market can be partitioned into average within- and between-firm differentiation, since each pair of flights considered in the measure is either scheduled by the same airline or is scheduled by different airlines. Simply comparing the average within and between measures of differentiation across routes, however, could be misleading, because the possible values of each measure depend on the market structure that determines the number of within and between pairings. To compare within-firm with between-firm differentiation, we use a measure that takes as given the market structure, i.e., the allocation of the number of flights among firms, as well as the departure time of each flight. We calculate the average time distance between flights scheduled by competitors by applying Eq. (1) to the subset of flight differences, $|d_i - d_j|$, where the carriers scheduling flights departing at d_i and at d_j are different. We refer to this variable as *BTWNDIFF*. We then normalize *BTWNDIFF* by the average time distance between *all* flights on the route, i.e., *AVGDIFF*. The resulting variable is *BTWNRATIO*, the ratio of the average time distance between flights scheduled by different carriers to the average time distance between all flights.²³ *BTWNRATIO* is an indicator of whether the observed between-firm differentiation is greater

²³ *BTWNRATIO* can be calculated in another manner as well. We can compare the between (or within) measures with that which would result if the same departure times were distributed differently among the firms. For example, consider a route with 3 flights, departing at (A1) 8 am, (B) 9 am, and (A2) 3 pm, with (A1) and (A2) flown by firm A and (B) flown by firm B. We compare the average of the two between-firm time difference measures, $|8 \text{ am} - 9 \text{ am}|^\alpha$ and $|9 \text{ am} - 3 \text{ pm}|^\alpha$, with the average between-firm difference that would result if firm B operated the 8 am or the 3 pm flight instead of the 9 am flight. This alternative interpretation of *BTWNRATIO*, the ratio of the *observed* between-firm average differentiation to the average between-firm measure for all possible allocations of the same flight shares across the same departure times, is also an indicator of whether between-firm or within-firm differentiation dominates on the route.

(ratio >1) or less (ratio <1) than the flight differentiation in the market as a whole.²⁴

Table 2 presents the average values of *BTWNRATIO* for the route structures on which both within- and between-firm differentiation exists. A value of *BTWNRATIO* less than one implies that the average between-firm differentiation is less than the average differentiation among all flights on the route and, therefore, less than the average within-firm differentiation on the route. In all market structures except 5–1 and 4–1–1, between-firm differentiation is significantly less than within-firm differentiation at the 5% level. Though the ratio does not immediately map to a particular flight schedule, the result on a four-flight route is

Table 2
Average *BTWNRATIO*¹, by sample and market structure 3-flight markets

3-flight markets							
Mkt Struc	2–1						
Obs	44						
Avg <i>BTWNRATIO</i> †	0.886						
S.E. of Avg							
4-flight markets							
Mkt Struc	3–1	2–2	2–1–1				
Obs	46	50	14				
Avg <i>BTWNRATIO</i> †	0.595*	0.691*	0.860				
S.E. of Avg	(0.023)	(0.006)	(0.021)				
5-flight markets							
Mkt Struc	4–1	3–2	3–1–1	2–2–1	2–1–1–1		
Obs	25	65	5	7	1		
Avg <i>BTWNRATIO</i> †	0.912	0.904	0.928	0.965*	0.937		
S.E. of Avg	(0.017)	(0.003)	(0.018)	(0.008)	–		
6-flight markets							
Mkt Struc	5–1	4–2	4–1–1	3–3	3–2–1	3–1–1–1	2–2–1–1
Obs	6	40	3	58	16	1	7
Avg <i>BTWNRATIO</i> †	0.924	0.907	0.999	0.921*	0.949*	0.972	0.968
S.E. of Avg	(0.041)	(0.004)	(0.066)	(0.003)	(0.008)	–	(0.012)

¹*BTWNRATIO* is the average time distance of flights scheduled by different carriers relative to the average time distance between all flight pairs on a route.

†*BTWNRATIO* for all market structures is significantly less than 1 at the 5% level, except 5–1 and 4–1–1.

* Indicates the mean is significantly different than that of the neighbor to the right at the 5% level.

²⁴A similar ratio can be calculated for the within-firm differentiation, but it is redundant: a ratio less than one for between-firm differentiation necessarily implies a ratio greater than one for within-firm differentiation, since the average differentiation between all flights, *AVGDIFF*, is the same for all possible allocations of the given departure times across carriers.

more consistent with two firms each having one morning and one evening flight than with one firm having two morning flights and the other having two evening flights. In other words, on average, firms schedule their flights more closely to competitors' flights than to their own flights. However, it is not clear whether this scheduling occurs for strategic reasons or due to constraints such as network consideration. To more thoroughly investigate the effect of competition on differentiation of departure times, we must also control for other factors that affect flight scheduling.

5. An econometric model of departure-time differentiation

In the regression analysis, we seek primarily to estimate the effect of competition on departure-time differentiation. We measure competition with *COMP*, which is equal to the inverse of the Herfindahl index calculated by shares of nonstop flights.²⁵ Based on Hotelling's conjecture and the preliminary results, we would expect that as competition on the route increases, holding constant the total number of flights, product differentiation is lessened. Another category of variables that is likely to significantly affect departure time differentiation is demand patterns. As demonstrated by Eaton and Lipsey, demand patterns will influence the scheduling of flights, causing flights to be less crowded together on routes where the MPDTs of the potential customers are more diffuse. We employ two variables to capture such demand-driven crowding, reflecting the distribution of MPDTs and the cost to passengers of deviating from their MPDT. First, the distribution of MPDTs tends to be more concentrated on routes where certain normal hours of departure time, not in the middle of the night, would result in arrivals in the middle of the night. If demand is substantially less for flights that either depart or arrive during the early morning hours, then MPDTs and actual departure times will be more concentrated on long flights and on flights from the western to the eastern U.S., due to the associated time change. Flights from San Francisco to New York, for instance, involve a nine-hour time loss including the time change. For such a route, few passengers will want to depart between 3 pm and 10 pm local San Francisco time, as they would arrive in New York in the very early morning hours. In contrast, flights from New York to San Francisco effectively take only three hours, so that passengers can leave New York as late as 9 pm and still arrive in San Francisco before midnight. We control for this MPDT

²⁵This variable exhibits much better explanatory power than the Herfindahl index. We have also estimated the model with separate dummy variables for each market structure. The qualitative results are unchanged and the additional variables are not a statistically significant improvement over the more parsimonious model.

distribution effect with a travel time variable, *TRVTIME*, the average scheduled nonstop time of travel on the route plus the effect of any time zone changes.²⁶

Another factor in flight scheduling involves the cost to passengers of flying on an inconvenient flight. Theoretical work has tended to assume that this cost is identical across consumers. In a homogeneous setting with elastic demand, as the cost to passengers of inconvenience rises, *ceteris paribus*, the airline will have an incentive to increase differentiation in order to avoid losing customers at the ends of the market. Of course, in reality this cost differs over passengers. Though we are not able to analyze the effect of heterogeneity in delay costs among customers on a single route, we attempt to control for differences in average delay costs of passengers on different routes. We attempt to control for differences in delay costs between tourists and business travelers. Business travelers probably differ from others in at least two important ways: they place a higher cost on deviating from their MPDTs and their MPDTs are probably more concentrated into a few hours of the day. The second factor clearly suggests that there will be less departure time differentiation on business-oriented routes. The first factor, however, suggests that tourist travelers have weaker preferences among flights. This could mean that competitive scheduling is both less costly to consumers and less effective in attracting them. Airlines would be more free to schedule flights strategically, whether that means greater or less differentiation, because they are less constrained by consumer demand. Thus, the effect could be to increase or decrease differentiation compared to a business route with the same demand pattern. We measure the proportion of customers on a route who are on vacation or other nonbusiness matters using the variable *TOUR*.²⁷

The degree of departure-time crowding also will be affected by supply-side considerations other than the spatial competition that is our primary focus. The cost to an airline of rescheduling a flight for competitive purposes will depend on the degree to which the flight is integrated into the network of the airline. For instance, if TWA's flight from Philadelphia to St. Louis carries mostly passengers who switch planes at St. Louis in order to continue their trips westward, then TWA will schedule this flight to coincide with its other flights from the east coast that arrive at St. Louis at nearly the same time and then depart 30–60 minutes later for various points to the west (which is known in the industry as a "bank" of flights). It would be quite costly for TWA to reschedule this flight in order to compete with another airline for local Philadelphia–St. Louis passengers, since rescheduling may

²⁶We also tried including a variable indicating flights that were sufficiently long, over six hours of travel time, that they could be scheduled on a red-eye basis. Including this variable did not affect the other results, and was significant only in the 3-flight sample.

²⁷Borenstein, 1989, explains the construction of this variable. Briefly, it is an estimate of the proportion of total city income derived from hotel expenditures of tourists. To construct the variable at the route-level, we weight the tourist index at each endpoint city by the proportion of tickets originating at the other city.

make layovers too short or too long, so that TWA would lose connecting passengers. Thus, scheduling rigidities caused by integration of a flight into the carrier's network would tend to dampen the effect of strategic scheduling incentives. We attempt to capture this effect with a dummy variable, *HUB*, equal to one when either endpoint of the route is a hub for one of the carriers.²⁸ If carriers desire to locate their flights near competitors', then the additional logistical costs of doing so at a hub would lead to increased departure time differentiation relative to a situation without network considerations. Conversely, if carriers prefer to locate their flights away from competitors', then logistical complexities of a hub would lead to decreased departure time differentiation.

Another consideration in strategic scheduling is capacity constraints. Even on a route with no connecting passengers and no flights integrated into the airlines' networks, the incentive to strategically adjust departure times may be lessened if demand is high relative to the number of flights or seats offered. If there is a tendency for carriers to locate flights near their competitors' in order to steal customers, that incentive would be reduced if most flights are nearly full. If there is an incentive to locate flights away from competitors' in order to reduce price competition, the threat of price competition would also be reduced if flights are near full, so this motivation for rescheduling flights away from competitors would decline. To capture this effect, we include the average load factor, which is the percentage of seats occupied, on nonstop flights on the route, *LOADFAC*.^{29,30} We expect that on routes with high load factors, carriers will be less likely to strategically schedule flights.

At some airports, congestion is controlled not by queuing, but by a system of property rights for take-off and landing clearance at different times of the day, known as slots. We posit that slots would impede attempts to schedule flights strategically in response to competition. *SLOT* is equal to one if one of the endpoint airports is slot controlled—Chicago O'Hare, Washington National, New York's Kennedy and La Guardia airports, Orange County, or Long Beach—and zero otherwise. If strategic scheduling results in a net attraction between different brands (less brand differentiation), then because *SLOT* impedes strategic schedul-

²⁸The following airport-carrier pairs are identified as hubs: Chicago O'Hare for American Airlines and United Airlines; Atlanta for Delta and Eastern; Dallas–Ft. Worth for American and Delta; Denver for Continental, United, and Frontier; St. Louis for TWA and Ozark; Miami for Eastern; Detroit for Republic; Minneapolis for Republic and Northwest; Phoenix for Southwest and America West; Pittsburgh for USAir; Houston Intercontinental for Eastern and Continental; Charlotte for Piedmont; Salt Lake City for Western; Memphis for Republic; Baltimore for Piedmont; and Kansas City for Eastern. In this analysis, we take the location and existence of hubs to be exogenous to the departure-time differentiation on individual routes.

²⁹*LOADFAC* may be endogenous, an issue we discuss below.

³⁰The issues of congestion, capacity, or increasing marginal cost are not addressed in the theoretical literature that we have reviewed because those models assume constant, usually zero, marginal costs.

ing, it would be expected to have a positive coefficient, i.e., *SLOT* constrains a carrier to schedule with more differentiation than desired. Likewise, if strategic scheduling results in a net repulsion between different brands (more brand differentiation), then *SLOT* would be expected to have a negative coefficient.

Finally, it is possible that profits per passenger will affect the tendency of firms to crowd near competing locations. The discussion above identifies the costs to airlines of strategically scheduling a flight. Whether an airline is willing to bear such costs depends on its gain from doing so. In particular, on a route with a high price/cost margin, a firm might have a greater incentive to schedule flights strategically to gain more local passengers on the route at the cost of poorer connections for passengers changing planes or poorer overall integration of the flight into the carrier's network schedule. On the other hand, high profits per passenger may increase the "repulsion" force, since carriers have more to lose by increasing price competition by moving flights more closely to competitors'. Because we cannot directly measure profitability, to capture this effect, we include *RELFARE*, a measure of the average fare on the route relative to the average fare on all other routes in the U.S. of similar distance.^{31,32} Because a high price/cost margin may strengthen the "attraction" and the "repulsion" forces, we cannot make a sign prediction.

All of the variables that we have discussed, other than *COMP*, are hypothesized to have a different effect as the level of competition on a route changes. A carrier with a monopoly on a route, for instance, will respond to demand- and supply-side conditions without worrying about losing passengers to competitors or increasing price competition. We address this issue by assuming a log–log relationship.³³

$$\begin{aligned} LDIFF = & \beta_0 + \beta_1 LCOMP + \beta_2 HUB + \beta_3 LTRVTIME + \beta_4 LTOUR \\ & + \beta_5 SLOT + \beta_6 LLOADFAC + \beta_7 LRELFARE + \epsilon. \end{aligned} \quad (3)$$

One econometric difficulty is that the degree of differentiation may affect the relative fare or the load factor. As the degree of differentiation declines, price competition increases, driving the fare down. We control for the effect of *DIFF* on *RELFARE* using instrumental variables. The instruments used in addition to the included exogenous variables are the share of flights served by non-majors on the route and carrier dummies indicating those carriers that serve the route.³⁴ Scheduling convenience may also affect the number of passengers who fly nonstop

³¹To be precise, we calculate the average fare for all routes in every 50-mile category (e.g., 200–249 miles, 250–299 miles, etc.) and compare the average fare on a route to the average for routes in its category.

³²*RELFARE* is almost certainly endogenous, as discussed below.

³³The primary results are robust to linear and log–linear functional forms.

³⁴The first stage fits well, with R^2 s over 0.55.

on the route relative to capacity. Specification tests, however, do not reject the hypothesis that *LOADFAC* is exogenous.³⁵ Because two-stage least squares results are substantially noisier, but not substantially different, we report results with *LOADFAC* treated as exogenous.

Recognition of the possible effect of location competition on entry also raises an issue due to the nonrandom nature of each sample. We have taken the factors that determine the number of flights on a route to be irrelevant to analysis of the degree of departure-time differentiation of those flights. It is possible, however, that the number of flights on a route, which dictates whether or not a route is in a given sample, is determined in part by variables that are effectively part of the residual in Eq. (3). Even if the right-hand-side variables would be orthogonal to the residual in a “complete” sample, they could be correlated with the residuals in this nonrandom sample, which would lead to inconsistent coefficient estimates. This concern is common in labor economics studies that use nonrandom population samples. In our case, the resulting truncation is incidental, rather than direct, because the dependent variable in our study is not the basis for sampling.

The truncation problem in this instance is somewhat more complicated than in a typical labor supply study, for instance. In this case, the basis for selection is that the number of flights be exactly equal to the selection criterion, no greater and no less. Furthermore, we do not have a sample of included and excluded observations that would allow us to estimate Heckman’s (1977) selection equation and then include the resulting $\hat{\lambda}$ as a right-hand-side variable in Eq. (3).

Instead, we consider the bias that might result from estimating (3) ignoring the sample selection issue. The most apparent source for selection bias is that *COMP*, which appears in (3), might also appear in the selection equation. In particular, for a given route demand, routes with more competition may have lower prices and more flights. Thus, one indication of possible bias would be a correlation across the observations in the sample between *COMP* and other variables that would be in a selection equation. The correlation one might then expect to find within an *n*-flight sample is lower demand on routes that have greater competition. In each of the samples, however, *COMP* is not significantly correlated with the total number of passengers on the route or with exogenous measures of market demand such as the size of the endpoint populations. In fact, *COMP* tends to show a weak positive correlation with market size. Therefore we conclude that the potential sample selection issue does not bias our results.

³⁵The specification tests were carried out first using measures of endpoint populations as identifying instruments, and then also using the ratio of endpoint populations to capacity on the route. Taking route capacity as exogenous is questionable, but it is not much different from our sample structure that takes number of flights on the route as exogenous. In the first case, exogeneity could not be rejected in any of the regressions at the 10% level. In the second case, exogeneity could be rejected at 10% for one of the four regressions.

A final econometric issue is possible correlation between the residuals of different observations. An observation in these datasets includes all nonstop flights from airport A to airport B. If the same number of daily flights take place from airport B to A, then that will be a separate observation in the same dataset. Between one-third and one-half of all observations in each dataset are on routes on which there are two included observations, one in each direction. In the 3-flight and 4-flight datasets, there is significant positive correlation between the residuals on routes from which two observations are drawn. On the other two, the correlation is positive, but not significant at the 10% level. We estimate the regressions using the Huber correction to estimates of standard errors when there is group correlation among the residuals, as implemented in the Stata statistical package.³⁶

6. Results

As indicated in Table 1, we effectively have four different data sets, those with three, four, five, and six daily flights in the same direction on a route. Descriptive statistics for each sample are shown in Table 3. The samples appear to be relatively similar in terms of means, and the null hypotheses of equal means and equal standard deviations across samples are not rejected for *HUB* and *RELFARE* for all samples, and for *TRVTIME*, *TOUR*, and *SLOT*, with the exception of the 6-flight sample. The null hypotheses that the means of *DIFF*, *COMP*, and *LOADFAC* are equal are rejected. Thus, it is not surprising that pooling of the data sets is rejected even when separate intercept terms are permitted for each category. Therefore, we present results from each of the four datasets separately.

The basic conclusions from Table 1 hold up in the regression results shown in Table 4. In all regressions, the coefficient estimates for *LCOMP* are negative and

³⁶The limited range of the differentiation index also presents a potential econometric problem, implying that the assumption of a normally distributed error term may not be tenable. Of course, the index is an ad hoc measure and a monotonic transformation of the index may be an equally reliable measure of differentiation. Recognizing this, we have estimated the equation with a logistically transformed index as well as the index presented in Eq. (2):

$$TDIFF = \ln\left(\frac{DIFF}{1 - DIFF}\right) \quad (4)$$

The result is an index with infinite range. The constant marginal effect of the right-hand side variables on *TDIFF* implies that as *DIFF* approaches either limit, the right-hand side variables have less and less impact on *DIFF*. The results, however, are not substantially affected by this transformation. Because interpretation of the coefficients is complicated by the transformation, we present the results using the untransformed differentiation index.

Table 3
Descriptive statistics

Variable	Mean	Std. dev.	Minimum	Maximum
3-flight markets—236 observations				
<i>DIFF</i>	0.850	0.136	0.114	0.995
<i>COMP</i>	1.234	0.486	1.000	3.000
<i>HUB</i>	0.492	–	0.000	1.000
<i>TRVTIME</i>	1.372	0.960	–0.550	8.283
<i>TOUR</i>	0.011	0.010	0.003	0.070
<i>SLOT</i>	0.140	–	0.000	1.000
<i>LOADFAC</i>	0.544	0.142	0.201	1.000
<i>RELFARE</i>	1.183	0.331	0.513	2.160
4-flight sample—222 observations				
<i>DIFF</i>	0.829	0.101	0.406	0.986
<i>COMP</i>	1.483	0.573	1.000	4.000
<i>HUB</i>	0.532	–	0.000	1.000
<i>TRVTIME</i>	1.400	0.936	–0.433	7.733
<i>TOUR</i>	0.011	0.010	0.003	0.070
<i>SLOT</i>	0.153	–	0.000	1.000
<i>LOADFAC</i>	0.567	0.140	0.227	1.000
<i>RELFARE</i>	1.216	0.423	0.516	2.942
5-flight sample—166 observations				
<i>DIFF</i>	0.868	0.061	0.640	0.983
<i>COMP</i>	1.561	0.525	1.000	3.571
<i>HUB</i>	0.536	–	0.000	1.000
<i>TRVTIME</i>	1.442	0.956	–0.483	5.650
<i>TOUR</i>	0.010	0.008	0.003	0.039
<i>SLOT</i>	0.187	–	0.000	1.000
<i>LOADFAC</i>	0.539	0.145	0.112	1.000
<i>RELFARE</i>	1.222	0.422	0.442	2.204
6-flight sample—152 observations				
<i>DIFF</i>	0.842	0.061	0.620	0.952
<i>COMP</i>	1.916	0.550	1.000	3.560
<i>HUB</i>	0.533	–	0.000	1.000
<i>TRVTIME</i>	1.591	1.246	–0.017	8.050
<i>TOUR</i>	0.014	0.012	0.003	0.070
<i>SLOT</i>	0.217	–	0.000	1.000
<i>LOADFAC</i>	0.570	0.127	0.149	1.000
<i>RELFARE</i>	1.132	0.405	0.490	2.942

statistically significant. For a given number of flights, product differentiation declines as competition increases. The coefficient estimate for the 3-flight sample indicates that, for a route with other variables at their sample means, going from a 3–0 market structure to a 2–1 market structure, which increases *COMP* from 1 to

Table 4
IV estimation of log–log specification dependent variable: *LDIFF*

Flight sample:	3-flight	4-flight	5-flight	6-flight
<i>CONSTANT</i>	–0.159 (0.171)	–0.052 (0.086)	–0.054 (0.046)	–0.149*** (0.051)
<i>LCOMP</i>	–0.450*** (0.120)	–0.206*** (0.034)	–0.117*** (0.019)	–0.075*** (0.027)
<i>HUB</i>	–0.028 (0.058)	–0.036 (0.033)	–0.017** (0.011)	–0.021* (0.013)
<i>SLOT</i>	–0.143* (0.078)	–0.071** (0.045)	–0.014 (0.014)	–0.018 (0.018)
<i>LLOADFAC</i>	–0.094 (0.060)	–0.068* (0.040)	0.001 (0.014)	0.005 (0.029)
<i>LIVTIME</i>	–0.075** (0.038)	–0.017* (0.010)	0.002 (0.006)	0.006 (0.010)
<i>LTOUR</i>	–0.010 (0.029)	0.020 (0.017)	0.006 (0.009)	–0.008 (0.010)
<i>LRELFARE</i>	–0.091 (0.103)	0.063 (0.054)	–0.021 (0.019)	0.012 (0.029)
Observations	231	220	170	153
R^2	0.40	0.30	0.26	0.07

***Significant at 1%. **Significant at 5%. *Significant at 10%.

1.8, causes the index to fall from 0.856 to 0.657.^{37,38} The former index corresponds to one flight at 8 am, one at noon, and one at 5:05 pm, while the latter would imply moving the third flight up to 2:30 pm if the first two remained at 8 am and noon. Moving from a 3–0 market to a 1–1–1 market structure causes the index to fall to 0.522, corresponding to 8 am, noon, and 12:09 pm flights.

While that conclusion might be interpreted as support for a Hotelling-like incentive to strategically locate brands near competitors', other interpretations are also possible. One might argue, for instance, that the observed effect results from the network integration problem that each carrier must solve. A single airline schedules its flights on a given route so that they make the most valuable or profitable links with the airline's other flights. This is likely to involve scheduling departure times so that the flights arrive or depart a hub airport at the same times as the carrier's other flights. It also involves scheduling equipment so that an aircraft is properly positioned to be used for a sequence of profitable flights. In comparison, even if two carriers on a route were not strategically positioning their flights to gain a larger share of traffic on the route, the fact that their other flights

³⁷ Continuous variables are evaluated at their means. For this example, we assume that this is a route that includes a slot-constrained airport ($SLOT=1$) and does not include a hub ($HUB=0$).

³⁸ Note that the change is quite large, 80% in this case, so the change in the log value is not a close approximation to the percentage change.

on other routes are not coordinated across airlines is likely to lead to more crowding of the airlines' flights on the observed route. Thus, while more competition is correlated with less product differentiation, it may not follow that competition causes a strategic attraction tendency between brands. Indeed, the results on the other variables suggest that may not be the case.

For example, two of the independent variables—*HUB* and *SLOT*—indicate the ease with which an airline can schedule its flights. The coefficients on these variables are all negative and half are statistically significant. When a route includes a hub or a slot-constrained airport, the airlines have less flexibility in scheduling. The negative coefficient indicates that, given the constraint, flights are scheduled with less differentiation than without the constraint. That is, firms would prefer more differentiation.

The estimated impact of *LOADFAC* is less robust, but its negative estimated coefficient for the 3- and 4-flight samples also can be interpreted as implying a sort of competitive “repulsion” rather than “attraction” among carriers.³⁹ When load factors are high, we argued that firms have less desire to engage in strategic scheduling, of either the attraction or the repulsion type. The negative coefficient estimates indicate that this decline in strategic scheduling is associated with a decline in product differentiation, implying that strategic scheduling causes increased product differentiation.⁴⁰

The impact of travel time (*TRVTIME*) is generally negative as predicted. The longer the travel time, the more airlines are constrained by passengers' MPDTs. Routes with longer flights as measured by travel time tend to exhibit less product differentiation, probably due to the increased difficulty of scheduling arrival and departure times that are both at times that travelers consider reasonable.

The results on *LTOUR* and *LRELFARE* are not robust; the coefficients on both variables alternate in sign, and neither is significant. The results on *LTOUR* may be due to the conflicting incentives tourist passengers offer airlines. We argued that the preferred departure times of tourists are more spread out over the day, which, *ceteris paribus*, would lead to more differentiation. However, the schedule delay cost to tourists is low, reducing the incentive to respond to these passengers and allowing the airline to continue to respond to the demands of business travelers. Also, business travelers are a source of considerably more profit than are tourists, so unless a route is primarily tourists, it may well pay for an airline to cater to business travelers, despite losing tourist passengers. The results on *LRELFARE* may similarly be due to the conflicting incentives arising from high price/cost

³⁹The estimated (positive) coefficients in the 5- and 6-flight sample are not close to conventional significance levels.

⁴⁰A referee points out an alternative interpretation: routes with higher *LOADFAC* may be those with more distinct demand peaks not captured by our demand variables, which would also be associated with less departure-time differentiation for reasons not related to strategic scheduling.

margins. While a high margin increases the attraction force, since there is more to be gained by stealing customers, it also strengthens the repulsion force, because there is more to lose from increasing price competition. It may be that, on average, these two forces offset each other.⁴¹

Overall, one might interpret our results as suggesting that airlines are inclined to schedule flights such that they are farther away from competitors, rather than succumbing to an incentive for minimal differentiation. The variables that measure constraints on scheduling indicate that constraints lead to less differentiation.

While these results are provocative, a possibly cleaner test of the basic Hotelling conjecture is available using data from the regulated period in the airline industry. In that era, the threat of price competition was absent, since fares were set by regulators. In such a situation, airlines can schedule their flights closer together without a fear of increased price competition.

7. Differentiation with exogenous prices: The airline regulation era

To gain some insight into the effect of price competition on the tendency of firms to differentiate their product, we also have gathered data for 1975, a period in which airlines were subject to fare and entry regulation. Because data on airlines and departure times must be gathered by hand from the Official Airline Guide, we only have data for three- and four-flight routes. During this period of regulation, fares were set exogenously by the Civil Aeronautics Board, based on the distance of the flight. In 1986, while an airline had an incentive to schedule its flight close to competitors' in order to steal customers, the downside to such a strategy was an increase in price competition due to reduced product differentiation. In 1975, this offsetting effect was considerably muted.⁴²

The variables for the 1975 analysis are calculated in much the same manner as described previously. The most notable change is the substitution of *FARE* for *RELFARE*. Recall that *RELFARE* is included as a proxy for the price/cost margin. Since the CAB set airfares using a distance-based formula, virtually all routes of the same distance had the same fare, and a relative fare measure such as we used for the 1986 data would not be useful in controlling for cost. However, it is widely recognized that longer routes with higher fares also had higher price/cost margins. That is, the marginal price per mile in the CAB fare formula was greater than the

⁴¹ It is also worth noting that *TOUR* and *RELFARE* are significantly negatively correlated, which could account for the large standard errors on their parameter estimates. However, *TOUR* and *RELFARE* are also jointly insignificant.

⁴² Firms were still able to compete on service quality and other factors, including flight frequency. In fact, service-quality competition led to much lower load factors and greater excess capacity on routes prior to deregulation. Thus, the sample of routes with a given number of flights could be quite different in 1975 than in 1986. For example, the 4-flight routes in 1975 have fewer total passengers.

actual marginal cost of flying a longer route. We therefore use *FARE* to control for the effect of profitability on differentiation, since higher fares are generally associated with higher price/cost margins. The 1975 data also differ from the 1986 approach in that the route structure under regulation was a point-to-point system, rather than a hub-and-spoke system. Thus, there is no hub variable in this sample.⁴³ Finally, only four airports were slot-constrained in 1975: Chicago O'Hare, New York's Kennedy and LaGuardia airports, and Washington National. The means and standard deviations for all variables are very similar across the two time periods, as can be seen by comparing Tables 3 and 5.

We begin by examining the same descriptive statistics as before. An examination of the average differentiation index across various market structures, as presented in Table 6, reveals the same pattern as in the deregulation-era data. What does differ is the correlation between the degree of product differentiation and the Herfindahl index. Surprisingly, the two variables are correlated at a much lower level during the regulated period.⁴⁴ Absent the threat of price competition,

Table 5
Descriptive statistics

Variable	Mean	Std. dev.	Minimum	Maximum
3-flight markets—267 observations				
<i>DIFF</i>	0.847	0.116	0.462	0.998
<i>COMP</i>	1.202	0.408	1.000	3.003
<i>TRVTIME</i>	1.284	1.168	−0.367	8.000
<i>TOUR</i>	0.014	0.017	0.002	0.070
<i>SLOT</i>	0.090	–	0.000	1.000
<i>LOADFAC</i>	0.523	0.138	0.142	0.839
<i>FARE*</i>	68.62	44.20	26.45	260.18
4-flight sample-150 observations				
<i>DIFF</i>	0.844	0.090	0.556	0.978
<i>COMP</i>	1.232	0.384	1.000	2.667
<i>TRVTIME</i>	1.334	1.398	−0.367	8.100
<i>TOUR</i>	0.011	0.013	0.002	0.070
<i>SLOT</i>	0.173	–	0.000	1.000
<i>LOADFAC</i>	0.519	0.134	0.062	0.838
<i>FARE*</i>	63.62	40.28	23.92	219.47

*Real 1986 dollars.

⁴³The tourist variable is also slightly changed from 1986. For about a quarter of the sample, we do not have data on ticket originations by city, which is necessary to compute a weighted average of the tourist variable for each city. For these routes we use the simple average across the two cities.

⁴⁴A large proportion of this difference is driven by the 1–1 observations in the deregulated era, which exhibit an exceedingly low degree of differentiation. When these ten observations are omitted, the correlation between the differentiation index and the Herfindahl index drops from 0.520 to 0.389. Nonetheless, the correlation is lower in the regulated era.

Table 6
Average differentiation index by sample and market structure¹

3-flight markets—267 observations (<i>DIFF/HERF</i> correlation: 0.280)					
Mkt Struc	3–0	2–1	1–1–1		All
Obs	207	55	5		267
Avg <i>DIFF</i> ‡	0.865*	0.786	0.789		0.847
SE of Avg	(0.007)	(0.020)	(0.007)		(0.007)
4-flight markets—150 observations (<i>DIFF/HERF</i> correlation: 0.328)					
Mkt Struc	4–0	3–1	2–2	2–1–1	All
Obs	105	29	14	2	150
Avg <i>DIFF</i> ‡	0.862*	0.811	0.773	0.829	0.844
SE of Avg	(0.007)	(0.018)	(0.030)	(0.121)	(0.007)

¹The market structure indicates the number of flights by each carrier, e.g., 4–2 means one carrier schedules four flights and one carrier schedules two flights.

*Indicates the mean is significantly different than that of the neighbor to the right at the 5% level.

‡The mean value of the differentiation index is significantly different than 1 at the 5% level, for all market structures, except 2–1–1.

concentration appears to have a weaker, not a stronger, (negative) association with departure time differentiation. The comparison of *BTWNRATIO* across market structures in Table 7 gives similar results as under the deregulated period, indicating that the degree of differentiation between flights of different carriers is less than the average degree of differentiation for all flights.

Table 8, using 1975 data, parallels the regressions reported in Table 4 for 1986 data, with the changes noted above. Results with the regulation-era data indicate that competition exerted a negative influence on the degree of product differentiation. However, the magnitude of the effect is considerably smaller than estimated

Table 7
Average *BTWNRATIO*¹, by sample and market structure

3-flight markets				
Mkt Struc	2–1			
Obs	55			
Avg <i>BTWNRATIO</i> †	0.916			
S.E. of Avg	(0.014)			
4-flight markets				
Mkt Struc	3–1	2–2	2–1–1	
Obs	29	14	2	
Avg <i>BTWNRATIO</i> †	0.606*	0.712	0.948	
S.E. of Avg	(0.030)	(0.033)	(0.076)	

¹*BTWNRATIO* is the average time distance of flights scheduled by different carriers relative to the average time distance between all flight pairs on a route.

†The mean *BTWNRATIO* is significantly less than 1 at the 5% level for all market structures except 2–1–1.

*Indicates the mean is significantly different than that of the neighbor to the right at the 5% level.

Table 8
IV estimation of log–log specification dependent variable: *LDIFF*

Flight sample:	3-flights	4-flights
<i>CONSTANT</i>	0.180 (0.159)	0.341* (0.177)
<i>LCOMP</i>	–0.133*** (0.045)	–0.074* (0.044)
<i>SLOT</i>	–0.039 (0.032)	0.011 (0.026)
<i>LLOADFAC</i>	0.078** (0.039)	0.056* (0.034)
<i>LTRVTIME</i>	0.022* (0.012)	–0.001 (0.013)
<i>LTOUR</i>	–0.012 (0.013)	0.006 (0.013)
<i>LFARE</i>	–0.077*** (0.028)	–0.101*** (0.034)
Observations	223	127
R^2	0.11	0.19

***Significant at 1%. **Significant at 5%. *Significant at 10%.

in 1986. As before, we examine the impact of changing from a 3–0 to 2–1 to 1–1–1 market structure on the degree of differentiation, assuming that the other variables are at their sample means. A movement from 3–0 to 2–1 decreases the differentiation index from 0.822 to 0.761. If two flights are scheduled at 8 am and noon, then the former implies that the third flight is scheduled at 4:21 pm, and the latter at 3:32 pm. A movement to a 1–1–1 market structure decreases the index to 0.711, which corresponds to the third flight moving to 2:18 pm. These changes are substantially smaller than implied by the results using deregulation-era data.

Recall that three variables measure how tightly constrained an airline is in strategically scheduling a flight—*HUB*, *SLOT*, and *TRVTIME*. *HUB* is irrelevant in the regulated time period; *SLOT* is insignificant; and, when significant, *TRVTIME* is positive. In the deregulated era, all three variables were generally negative and often significant, indicating that airlines preferred to differentiate their flights more when faced with competition, but could not due to scheduling constraints. In contrast, carriers do not appear to be affected by constraints in the regulated period; when competition changes, regulated carriers have more freedom to adjust schedules strategically, and respond by reducing differentiation. In other words, the appearance that competition reduced differentiation by a larger amount in the deregulated period may be an artifact of structural changes in network considerations (a move from a point-to-point system to a hub-and-spoke system).

It is also possible that airlines adjust to the absence of price competition by competing in quality dimensions: scheduling flights more responsively to passengers' preferred departure times. When airlines can adjust their prices, a passenger who deviates from her preferred departure time may be compensated with a lower

fare. When price is set by a regulator, this compensation is unavailable. The variables that we include to control for the distribution of preferred departure times, *TRVTIME* and *TOUR*, do not appear to add much explanatory power. In essence, the airline may be more worried about losing passengers at the “endpoints” of the day when they cannot adjust price.

The primary determinants of differentiation, apart from *COMP*, appear to be *FARE*, which, as explained above, indicates the profitability per passenger, and the load factor. Consistent with our earlier discussion of the airline’s tradeoff between attracting passengers and integrating the flight into its system, the fare appears to have a significantly negative impact on the degree of product differentiation. There was greater differentiation on routes with low price/cost margins, where airlines had less to gain by trying to steal customers from competitors. The coefficient on the load factor is significantly positive, indicating that routes with higher load factors exhibit more product differentiation. This too is consistent with expectations: if flights are relatively full, there is no point to trying to steal customers from competitors.

8. Conclusions and interpretations

Simple descriptive statistics show that on a route with a given number of daily flights, departure times are less differentiated if the route is served by competing airlines than if it is served by a single firm. In our econometric analysis we have attempted to control for the other factors that might affect departure-time crowding, and have found a negative relationship between competition and product differentiation that is significant, both statistically and in terms of the size of this effect. While these results might be interpreted as indication of a competitive tendency towards reduced product differentiation, as conjectured by Hotelling and others, we argue that this conclusion is difficult to square with the other estimated effects on differentiation.

Some of the other coefficient estimates could be interpreted as implying that carriers respond to increased logistical flexibility in scheduling by increasing their differentiation from competing brands. Furthermore, high capacity utilization, which decreases the incentives for strategic scheduling, is (weakly) associated with less product differentiation, also implying that strategic scheduling increases differentiation.

When prices are fixed, most models of differentiation predict that there will be a stronger tendency for firms to crowd their brands towards competitors’. While our results from the era of regulated prices show that an increase in competition is significantly associated with less product differentiation, the raw statistical correlation and econometrically estimated causal relationship is weaker in the regulated fixed-price era (1975) than in the unregulated period (1986). At the same time, however, the indicators we found in the 1986 sample that airlines respond to

greater scheduling flexibility by increasing differentiation are not evident in the 1975 sample. In the 1975 samples, a decrease of scheduling constraints does not appear to affect the degree of departure time crowding. Furthermore, low load factors, which seem likely to increase the incentive to schedule strategically are significantly associated with less differentiation in departure times. Overall, it appears that the predictions of location models with exogenous prices are supported by the results from the 1975 data.

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