Measuring Strategic Firm Interaction in Product-Quality Choices: The Case of Airline Flight Frequency

by

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Abstract

This paper investigates strategic interaction among airlines in product-quality choices. Using an instrumental variables approach, the paper estimates flight-frequency reaction functions, which relate an airline's frequency on a route to its own characteristics and to the frequencies of competing airlines. A positive reaction function slope is found in some cases, suggesting the presence of strategic interaction in the choice of frequencies. The paper also asks whether multimarket contact generates mutual forbearance in frequency competition, finding no evidence for such an effect.

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1. Introduction

A voluminous theoretical literature deals with product differentiation and the choice of product quality. Horizontal product differentiation, where products have no natural quality ordering, is usually analyzed in a spatial-competition setting in the Hotelling tradition, with important contributions by d'Aspremont et al. (1979) and Salop (1979). Alternatively, Gabszewicz and Thisse (1979), Shaked and Sutton (1982) and other authors study vertical product differentiation, where products are ordered by quality and consumers have different quality valuations.

Despite the existence of this large theoretical literature, empirical work on product-quality competition is scarce. The purpose of this paper is to remedy this shortage by providing an empirical analysis of quality competition between firms, with a focus on the airline industry. The analysis studies what is probably the most important dimension of the quality of airline service: flight frequency. The importance of frequency was first shown empirically in the work of Morrison and Winston (1995), who use a multinomial logit model to analyze airline choices by passengers. In addition to finding that choices are influenced by fares and other elements of service quality, Morrison and Winston show that frequent daily departures by a given airline on a route strongly influence travelers to choose it. More recently, the structural demand estimates of Berry and Jia (2010) again show that flight frequency is highly valued by consumers.[1]

Unlike existing empirical work on product-quality determination, which is structural in nature and is discussed below, the paper attempts to measure the strength of strategic interaction in quality choices by airlines. It does so by estimating flight-frequency reaction functions, which give a carrier's best frequency response to a competitor's frequency choice. The estimated reaction-function slope indicates the strength of any strategic interaction. However, the competitor's frequency, which appears on the right-hand side of the reaction function along with carrier and route characteristics, is an endogenous variable, being jointly determined along with the carrier's own frequency in a Nash equilibrium. Therefore, an instrumental variables approach is needed to generate a consistent estimate of the reaction function's slope.

Estimation of reaction functions is the focus of empirical work in a number of fields of economics. In public economics, the tax competition literature contains many studies that estimate reaction functions. Strategic interaction arises because tax rates in competing jurisdictions must be taken into account when a given jurisdiction chooses its own rate, recognizing that capital and labor migrate in response to tax-rate differentials. See Brueckner (2003) and Revelli (2005) for surveys of this literature, which relies on the methods of spatial econometrics. In addition, reaction functions are sometimes estimated in the literature on peer effects, where an individual's choice of the level of some decision variable depends on peer choices. See Manski (1993) for the conceptual framework and Dietz (2002) and Dujardin, Peeters and Thomas (2009) for detailed surveys of the empirical peer-effects literature. In both types of studies, the endogeneity of the peer's or the competing jurisdiction's choice must be taken into account in the estimation.

Estimation of reaction functions is, by contrast, somewhat less common in the industrial organization literature. Grabowski and Baxter (1973) and Cockburn and Henderson (1994) estimate what are effectively reaction functions for competing R & D investments among pharmaceutical firms, without labeling them as such (the endogeneity of the competitor's investment level is also ignored). Pinkse, Slade and Brett (2012) estimate price reaction functions for gasoline wholesalers using a nonparametric approach, while Kalnins (2003) and Henrickson (2012) estimate such functions (for fast-food restaurants and sports teams, respectively), using spatial-econometrics methods. Escobari and Lee (2012) estimate price reaction functions for the airline industry, viewing competing flights as those with close departure times. Reaction functions have also been estimated in some papers as part of a procedure for deriving conjectual variations, which give a rival firm's anticipated response when a firm changes its price or output (see Liang (1989) and Dhar et al. (2005)). Many studies estimating price reaction functions are also found in the marketing literature, with contributions by Lazzarini et al. (2007) (who focus on the auto insurance industry), Reimer (2004) (who studies the ready-to-eat cereal industry), Cotterill et al. (2000) (who analyze the market for private label and branded grocery products) and Vickner and Davies (1999) (who study the spaghetti sauce industry).[2]

Although distinguished by its focus on reaction functions, the present paper is related to a number of recent empirical studies analyzing the choice of product quality using structural models. The early structural literature (Berry (1994), Berry, Levinsohn and Pakes (1995)) treats product attributes as exogenous, but recent empirical models have portrayed firms as choosing product quality along with price. In the models of Crawford, Shcherbakov and Shum (2011) and Fan (2011), firms choose the levels of continuous measures of product quality (for newspapers and cable television, respectively), while firms in Draganska, Mazzeo and Seim (2009) choose which product varieties to offer (the empirical work focuses on ice cream flavors). In each case, the empirical exercise yields estimates of taste and cost parameters, which are used in the latter two papers to simulate the effects of mergers on product quality or variety.[3] By contrast, the estimated reaction functions in this paper do not identify underlying utility and production parameters, which are intermixed in the slope coefficient.[4] Instead, the goal of the paper is to measure the strength of strategic interaction, with the slope of the airline reaction function of interest in itself, not the values of the underlying parameters. The slope estimate can be used, for example, to compute the effects on equilibrium route frequencies of a parallel shift in one competing carrier's reaction function. As seen in section 6, such a shift could come from relaxation of a carrier's "scope clause," which allows greater use of small planes and hence higher frequencies.

To motivate the empirical analysis, the paper reviews the theoretical frequency-competition model of Brueckner and Flores-Fillol (2007). To avoid the complexity of the spatial-competition approach, which is used by Schipper, Nijkamp and Rietveld (2003, 2007) and Lindsey and Tomaszewska (1999) to study frequency competition, Brueckner and Flores-Fillol introduce assumptions implying that average flight frequency is what matters (along with the fare) in the choice between airlines, not the departure times of individual flights. Despite the resulting elimination of space, the model effectively involves horizontal competition in the

Hotelling tradition, with exogenous brand loyalty to individual carriers providing a choice friction analogous to the spatial friction in the Hotelling model. In contrast to this approach, Borenstein and Netz (1999) carry out an empirical analysis whose focus is the departure times of individual flights rather than overall frequencies, and they rely on a spatial competition model to motivate the analysis.[5]

Data for the estimation of flight-frequency reaction functions are readily available from government sources, which tabulate monthly airline departures on each nonstop route. Cross-sectional US domestic route data from a single quarter in 2010 are used for the estimation. Variables that shift a carrier's reaction function include route characteristics (distance, endpoint populations and incomes, a leisure-destination endpoint) as well as carrier characteristics, as captured by dummy variables indicating airline identities. The hub status of the route endpoints for the airline is another such characteristic. As noted above, the endogeneity of the competitor's frequency requires the use of instruments in estimating the reaction function, and the theoretical structure helps in choosing appropriate variables. The chosen instruments are the vector of carrier dummy variables for the competing carrier, which shift that carrier's reaction function and thus help determine its own frequency. Many of the reaction-function studies cited above similarly use competitor-characteristics variables as instruments, and carrier-identity dummies represent the most comprehensive way of capturing such characteristics. These variables are used in two-stage least squares estimation of the reaction function, with attention focusing on the second-stage slope coefficient.

The estimation is carried out for nonstop duopoly routes. With only two carriers present, interaction is more straightforward on such routes than on oligopoly routes. A pooled regression is carried out first, where LCCs (low-cost carriers) are not distinguished from legacy carriers. Since the coefficient of the reaction function might depend on the nature of the competitor, the pooled duopoly regression is supplemented with regressions focusing on legacy-legacy, LCC-LCC, and legacy-LCC duopolies.

In an extension of the basic model, the paper also asks whether multimarket contact shifts the frequency reaction function. Evans and Kessides (1994), Zou, Dresner and Windle (2011) and others study the effect of multimarket contact on fares, finding that airlines show mutual forebearance by pricing less aggressively on routes where multimarket contact with the competitors is high (fearing retaliatory behavior on other jointly contested routes). The question is whether such behavior extends to frequencies.[6]

Several conclusions emerge from the empirical analysis. First, the slope of the reaction function is positive when the two duopoly carriers are of the same type. That is, frequencies are strategic complements in duopolies involving two legacy carriers or two LCCs, with the size of the slope coefficients (around 0.7) suggesting that strategic interaction is strong. Second, on duopoly routes where carriers are of different types, weak performance of the carrier-dummy instruments prevents definitive conclusions from being reached. Therefore, while the empirical analysis suggests the presence of strategic frequency interaction *within* carrier types, no conclusion can be drawn regarding interaction *across* types. Third, analysis of the effect of multimarket contact suggests no evidence of mutual forbearance in the choice of flight frequencies within carrier types.

The remainder of the paper is organized as follows. Section 2 provides the theoretical framework. Section 3 presents the empirical model and discusses the data and construction of the variables. Section 4 presents the main results, and section 5 introduces multimarket contact. Section 6 illustrates how the results might be used to predict the frequency impacts of a change in one airline's operating environment, as mentioned above. Section 7 offers conclusions.

2. Theoretical Framework

This section of the paper serves to motivate the empirical work by deriving a flight-frequency reaction function like those estimated below from a theoretical model, drawing on the framework of Brueckner and Flores-Fillol (2007). The model focuses on a single transport market connecting two cities, which has a unitary mass of passengers. As in the empirical work, the market is served by two competing carriers, which are assumed for simplicity to have identical costs (the empirical model allows asymmetry). Carrier i operates f_i flights, $i = 1, 2$, that are evenly spaced around a circle representing departure times, a pattern that roughly matches actual practice. A crucial feature of the model is that a consumer chooses a carrier before knowing his preferred departure time, which is drawn from a uniform distribution on the circle. As a result, a carrier's flight frequency is all that matters, not the departure times of individual flights. Without this simplifying feature, the model would require development of an unwieldy spatial competition framework where carriers choose individual flight times, an approach that has had only limited success in transportation modeling.

Although this portrayal of consumer choice is not fully realistic, it may be accurate for business travelers, who have uncertain schedules and thus purchase fully refundable tickets that allow them to board the next flight upon arrival at the airport. Flight frequency, not individual flight times, is what matters for such passengers. In addition, a corporate travel department charged with signing an exclusive contract with a particular airline will look at overall frequency and price without focusing on individual flight times.

Letting T denote the circle's time circumference, the interval between carrier 1's flights is T/f_1. Since the largest gap between a flight and a preferred departure time is $T/2f_1$, the expected schedule delay (the difference between the preferred and nearest departure time) for a consumer choosing carrier 1 is $T/4f_1$. Letting v denote the cost per unit of schedule-delay time, $vT/4f_1 \equiv \gamma/f_1$ is the cost of schedule delay, where $\gamma \equiv vT/4$. With p_1 denoting the carrier's fare, the full price of travel on carrier 1 is then $p_1 + \gamma/f_1$. This full price depends on the fare, a price variable, as well as frequency, a quality variable chosen by the carrier.

The benefits of travel are large enough that all consumers choose to travel (making one trip), with their only choice being which airline to use. In the absence of other assumptions, passengers would then choose the carrier with the most attractive fare/frequency assumption, yielding the lowest full price. To avoid this outcome, passengers are assumed to exhibit brand loyalty to particular carriers, which allows the carrier with the higher full price to still attract some passengers (those most loyal to it). Brand loyalty to carrier 1 is captured by the factor a, which is passenger specific and is assumed to follow a uniform distribution with support $[-\alpha/2, \alpha/2]$ and density $1/\alpha$. Passengers with positive values of a favor airline 1, while those with negative values favor airline 2. With the support centered at zero, brand loyalties are symmetric.

A passenger's utility from travel on airline 1 equals $y - p_1 - \gamma/f_1 + b + a$, where y is income (with $y - p_1$ equal to nontravel consumption expenditure) and b is the travel benefit. Since utility from travel on airline 2 is given by the analogous expression with a suppressed, the passenger will choose airline 1 when

$$-p_1 \; - \; \gamma/f_1 \; + \; a \; > \; -p_2 \; - \; \gamma/f_2 \tag{1}$$

or when

$$a \; > \; p_1 \; - \; p_2 \; + \; \gamma/f_1 \; - \; \gamma/f_2. \tag{2}$$

With a uniformly distributed across passengers, the number preferring airline 1, which equals the airline's passenger volume, is given by

$$q_1 \; = \; \int_{p_1-p_2+\gamma/f_1-\gamma/f_2}^{\alpha/2} \frac{1}{\alpha} da \; = \; \frac{1}{2} \; - \; \frac{1}{\alpha}\left[p_1 \; - \; p_2 \; + \; \frac{\gamma}{f_1} \; - \; \frac{\gamma}{f_2}\right]. \tag{3}$$

Airline 2's passenger volume, denoted q_2, equals $1 - q_1$, an expression that given by (3) with the first minus sign replaced by a plus sign.

Letting s_1 denote seats per departure, cost per flight is given by $\theta + \tau s_1$, reflecting a fixed cost of θ and a marginal seat cost of τ. Note that aircraft size is a choice variable, being freely adjustable to match demand, and that size is assumed not to affect consumer utility, thus not being an element of service quality. Finally, note that the presence of the fixed cost θ provides a source of increasing returns at the individual flight level. Using this cost-per-flight expression, the carrier's total cost can then be written as

$$f_1(\theta \; + \; \tau s_1) \; = \; \theta f_1 \; + \; \tau q_1, \tag{4}$$

using the fact that total seats, $f_1 s_1$, must equal passenger volume q_1 (flights are assumed to be full). Using (3) and (4), profit is then given by

$$\begin{aligned} \pi_1 \; &= \; (p_1 - \tau)q_1 \; - \; \theta f_1 \\ &= \; (p_1 - \tau)\left(\frac{1}{2} \; - \; \frac{1}{\alpha}\left[p_1 \; - \; p_2 \; + \; \frac{\gamma}{f_1} \; - \; \frac{\gamma}{f_2}\right]\right) \; - \; \theta f_1. \end{aligned} \tag{5}$$

The carriers are assumed to play a two-stage game, with frequencies chosen in the first stage and fares chosen conditional on frequencies in the second stage, assuming Nash behavior in each stage. This assumption is realistic since airlines must commit to flight schedules months in advance while fares change hour by hour. Using (5), the first-order condition for p_1 is

$$\frac{1}{2} \; - \; \frac{1}{\alpha}\left[p_1 \; - \; p_2 \; + \; \frac{\gamma}{f_1} \; - \; \frac{\gamma}{f_2}\right] \; - \; \frac{1}{\alpha}(p_1 \; - \; \tau) \; = \; 0. \tag{6}$$

The first-order condition for p_2 is generated by replacing the first minus sign in (6) by a plus sign and replacing the last p_1 by p_2. Adding the two first-order conditions, the bracketed terms cancel, yielding $p_2 = \alpha + 2\tau - p_1$. After using this expression to eliminate p_2 in (6), rearrangement yields p_1 as a function of the two flight frequencies:

$$p_1 \; = \; \frac{\alpha}{2} \; + \; \tau \; - \; \frac{1}{3}\left[\frac{\gamma}{f_1} \; - \; \frac{\gamma}{f_2}\right]. \tag{7}$$

Thus, carrier 1's fare in the second stage is increasing in its own frequency and decreasing in its competitor's frequency. The solution for p_2 comes from replacing the first minus sign in (7) with a plus sign.

Substituting the p_i solutions into the profit function (5) yields

$$\pi_1 \; = \; \left(\frac{\alpha}{2} - \; \frac{1}{3}\left[\frac{\gamma}{f_1} \; - \; \frac{\gamma}{f_2}\right]\right)\left(\frac{1}{2} - \; \frac{1}{3\alpha}\left[\frac{\gamma}{f_1} \; - \; \frac{\gamma}{f_2}\right]\right) \; - \; \theta f_1. \tag{8}$$

Carrier 1 chooses f_1 to maximize (6) viewing f_2 as parametric. After rearrangement, the resulting first-order condition can be written as

$$\frac{3\alpha\theta f_1^2}{\gamma} \; + \; \frac{2\gamma}{3f_1} \; = \; \alpha \; + \; \frac{2\gamma}{3f_2}. \tag{9}$$

While (9) does not give a closed form solution for f_1 as a function of f_2, it nevertheless yields an implicit solution for carrier 1's reaction function. Totally differentiating (9), the reaction function's slope is given by

$$\frac{\partial f_1}{\partial f_2} \; = \; \frac{-2\gamma/3f_2^2}{6\alpha\theta f_1/\gamma \; - \; 2\gamma/3f_1^2}. \tag{10}$$

Since the denominator expression (which is the derivative of the LHS of (9)) must be positive in order for the second-order condition for choice of f_1 to be satisfied, the slope of the reaction function must be negative, indicating that frequencies are strategic substitutes. The dependence of this slope on parameter values can be seen by evaluating it at the symmetric equilibrium, which is found setting setting f_1 and f_2 in (9) equal to a common value f and solving. This solution is $f = \sqrt{\gamma/3\theta}$, and substituting in (10) and simplifying, the reaction function slope at the equilibrium is

$$\frac{\partial f_1}{\partial f_2} \;=\; \frac{1}{1 \;-\; \alpha\sqrt{3/\gamma\theta}} \;<\; 0. \tag{11}$$

The denominator (which must be negative to satisfy the second-order condition) becomes more negative, steepening the reaction function, when brand-loyalty parameter α increases or when the schedule-delay-cost parameter γ or the fixed-cost parameter θ decrease.[7]

The slope's negative sign is conditional on the particular structure of the current model and need not be general feature of models of frequency competition. To derive a general expression for the slope of carrier 1's reaction function, let $\pi_1(f_1, f_2, p_1, p_2)$ denote the carrier's profit as a function of frequencies and fares, and let $p_1(f_1, f_2)$ and $p_2(f_1, f_2)$ denote the second-stage fare solutions conditional on frequencies. Substituting, profit can then be written as

$$\widetilde{\pi}_1(f_1, f_2) \;\equiv\; \pi_1[f_1,\; f_2,\; p_1(f_1, f_2),\; p_2(f_1, f_2)]. \tag{12}$$

The first-order condition for choice of f_1 is $\partial\widetilde{\pi}_1/\partial f_1 = 0$, and totally differentiating this condition yields the slope of carrier 1's reaction function:

$$\frac{\partial f_1}{\partial f_2} \;=\; -\,\frac{\partial^2\widetilde{\pi}_1/\partial f_1\partial f_2}{\partial^2\widetilde{\pi}_1/\partial f_1^2}. \tag{13}$$

Since the denominator of (13) must be negative for the second-order condition to be satisfied, the slope will take the sign of the cross-partial derivative in the numerator. While one component of this derivative is $\partial^2\pi_1/\partial f_1\partial f_2$, which will normally be negative (indicating that an increase in f_1 is less beneficial the larger is f_2), the directions of the effects that operate through p_1 and p_2 are unclear a priori and could conceivably reverse this negative sign.

However, it can be shown that a negative reaction-function slope still emerges in Brueckner's (2010) generalization of the previous model, which endogenizes individual trip quantities (here fixed at unity). This finding suggests that upward-sloping reaction functions may be hard to generate in a theoretical model, requiring an unusual model structure. As a result, even though the sign of the reaction-function slope is ambiguous in general, the theory leans toward predicting the emergence of a negative sign in empirical work.

3. Empirical Model and Data

3.1. Empirical Model

The empirical analysis focuses on a cross-section of nonstop duopoly routes within the US. Flight frequency for connecting trips is a less straightforward concept (involving layover times), which justifies the nonstop focus. Estimation of the reaction function uses the following log-linear regression model:

$$lnFREQ_{im} \;=\; \alpha \;+\; \delta\, lnFREQ_{-im} \;+\; \sigma X_m \;+\; \eta Z_{im} \;+\; \epsilon_{im}, \tag{14}$$

where m denotes the route and i denotes the ith carrier serving it, with $i = 1, 2$ for the duopoly case. $lnFREQ_{im}$ is the log frequency of carrier i on nonstop route m and $lnFREQ_{-im}$ gives the log frequency of i's competitor, carrier $-i$. X_m is a vector of route-characteristics variables, which capture distance, endpoint incomes and populations, a leisure-destination endpoint, and a slot-controlled endpoint. Z_{im} represents carrier characteristics, which are mainly captured by a vector D_{im} of dummy variables representing carrier identities, with the variable corresponding to carrier i turned on and the rest set equal to zero. These dummies capture cost differences across carriers as well as other idiosyncratic factors that affect frequency choices. Note that changes in X_m and D_{im} shift the reaction function in a parallel fashion. Observe also that the log-linear model in (14) represents an approximation to a possibly more-complex functional form. As a robustness check, a linear version of (14) is also estimated.

To understand estimation of (14), consider the set of legacy-legacy duopoly routes, where two legacies alone compete with one another. Each legacy-legacy route has two observations, one for each legacy competitor, with the frequency values on the two sides of (14) switched between the observations but with the value of X_m common between them. To estimate the reaction function for legacy-legacy competition, the regression is run on this set of observations.

Eq. (14) and its counterpart for carrier $-i$ constitute the two structural equations of a simultaneous-equations system, which consists of the reaction functions for carriers i and $-i$. The solution to this system, which corresponds to the intersection of the two reaction functions, yields values for $lnFREQ_{im}$ and $lnFREQ_{-im}$. The right-hand-side variable $lnFREQ_{-im}$ in (14) is thus endogenous, which means that consistent estimation requires the use of instruments. Proper instruments, used to generate predicted values of $lnFREQ_{-im}$ in a two-stage least squares procedure, are the D variables that give carrier identities, but with values that pertain to i's competitor, carrier $-i$. Along with the dummies D_{im} for carrier i itself, the competitor dummies (D_{-im}) affect equilibrium frequencies for both carriers by determining the position of carrier $-i$'s reaction function. As a result, they are correlated with carrier $-i$'s frequency. Second, the competitor dummies are not likely to be correlated with unobservables that influence the position of carrier i's reaction function (components of ϵ_{im} from (14)). In other words, the identify of the other carrier competing in the market is not likely to be correlated with unobservables that affect a given carrier's frequency choice. This claim is further discussed and justified below. Note finally that, since the reaction function in (14) has one endogenous right-hand side variable while the excluded vector D_{-im} consists of more than one dummy variable, the equation is overidentified.

To better grasp the simultaneity issue, observe that the first-stage regression of two-stage least squares corresponds to the reduced-form equation for carrier $-i$, generated by the structural system in (14). Ignoring for the moment the other variables in Z (considering only the carrier dummies), this equation is

$$lnFREQ_{-im} \;=\; \zeta \;+\; \nu X_m \;+\; \rho D_{im} \;+\; \lambda D_{-im} \;+\; \xi_{-im}, \tag{15}$$

where

$$\zeta = \frac{\alpha}{1-\delta}, \quad \nu = \frac{\sigma}{1-\delta}, \quad \rho = \frac{\delta\eta}{1-\delta^2}, \quad \lambda = \frac{\eta}{1-\delta^2}, \quad \xi_{-im} = \frac{\delta\epsilon_{im} + \epsilon_{-im}}{1-\delta^2}. \tag{16}$$

Since the error term ξ_{-im} in (16) depends on ϵ_{im}, $lnFREQ_{-im}$ in (14) is correlated with the equation's error term, leading to simultaneity bias in the OLS estimates, as discussed above. Assuming $|\delta| < 1$, which is required for stability of the Nash equilibrium, this correlation is positive (negative), with the direction of bias upward (downward), as the reaction function slope δ is positive (negative). The OLS slope estimate is thus biased away from zero. In addition, if ϵ_{im} and ϵ_{-im} are positively correlated, as is likely given that unobserved route characteristics will be elements of both error terms, then (16) shows there is an additional source of (positive) correlation between $lnFREQ_{-im}$ and ϵ_{im}, which biases the OLS slope estimate upward.[8]

In addition to D_{im}, another carrier-characteristics variable, denoted H_{im}, measures the hub status of the route endpoints for carrier i. This variable equals the geometric mean of number of destinations served by the carrier from the route endpoints. A large value for this variable, which indicates that one or both of the endpoints is a hub for the carrier, should lead to high frequency on the route as the airline seeks to accommodate both passengers connecting at the hub and passengers terminating their trips at the hub endpoint.

The same hub-status variable is also computed for the other carrier on the duopoly route, and it might initially appear that it could serve as an instrument along with the competitor dummies. However, overidentification tests usually show that competitor hub status is not a valid instrument. In other words, the tests show that it is illegitimate to exclude this hub-status variable from the right-hand side of the own-carrier reaction function. The implication is that the position of the reaction function depends on endpoint hub status for both the given carrier and its competitor. This conclusion is, in some sense, natural since the division of traffic on a route will be skewed in favor of the airline that operates a hub at one endpoint. Failure to capture this traffic-division effect by excluding the other carrier's hub-status variable (measuring only own-carrier hub status) will give a false picture of the height of the own-carrier reaction function. With the hub-status variables for both carriers appearing in the reaction function, the variable Z_{im} then includes a vector $E_{im} \equiv \{H_{im}, H_{-im}\}$ along with D_{im}.

In addition to estimating the legacy-legacy reaction function, reaction functions involving low-cost carriers (LCCs) are also estimated. In an analogy to the legacy-legacy case, a reaction function is estimated for LCC-LCC duopoly routes, where two LCCs alone compete with one another. But in addition to studying frequency competition between carriers of the same type, asymmetric competition is also considered, with reaction functions estimated for duopoly routes where a legacy carrier competes with an LCC. In this case, the reaction functions are allowed to differ by the type of carrier, with an LCC's response to an increase in frequency by a legacy competitor allowed to differ from a legacy carrier's response to an increase in LCC frequency. Note that in estimating the LCC-legacy reaction function, the second-stage regression only uses the LCC observations for the sample routes. Correspondingly, the legacy-LCC reaction function is estimated using only the legacy observations in the second stage. Observations for the other carrier type are used in the first-stage regressions, with a separate regression run for each case.

Finally, a pooled model is estimated, where all three types of duopoly routes are intermixed without distinguishing between carrier types. This model, which serves as a kind of benchmark, assumes that carriers react in the same way to all competitors, independently of their own type (legacy or LCC) or the type of the competitor. This assumption may be incorrect, and if so, the validity of instruments is compromised. For the dummies to be valid instruments, they should be uncorrelated with the unobserved determinants of own-carrier frequency, as noted above. But with the carrier types mixed, the dummies indicate, for example, whether a legacy carrier faces an LCC competitor rather than another legacy competitor on a route. The position of the actual reaction function, however, might depend on the competitor's type, with a legacy carrier, for example, perhaps offering more flights when competing with an LCC. But with the reaction function's intercept constrained to be equal across cases, the effect of the competitor's LCC status would then be captured in the error term. The upshot is that the other-carrier dummies would be correlated with the reaction function's error term, leading to biased estimates.

By contrast, when routes are divided according to the types of competing carriers, this problem would appear not to be present. In the legacy-legacy case, for example, there is little reason to expect that the particular identity of the competing legacy carrier would be correlated with the unobserved determinants of own-frequency. In other words, United's preferred frequency on a duopoly route, other things equal, should not depend on whether its competitor is American or Delta. Similarly, conditional on an LCC's competitor being a legacy carrier, there is little reason to expect that the legacy's particular identity matters. While the same arguments may be valid in the LCC-LCC and legacy-LCC cases, it could be argued that Southwest, the largest LCC carrier, may play a different role than other LCCs. However, distinguishing among LCCs turns out to be impractical.[9]

It should be noted that, by conditioning on the presence of two carriers on a route, the empirical work abstracts from issues of entry or exit, which have received considerable attention in recent dynamic structural work in industrial organization, some of it devoted to airlines (see, for example, Aguirregabiria (2012) and Gayle and Wu (2011)). A dynamic structural model, while allowing estimation of entry costs, would also generate estimates of the parameters underlying static reaction functions, albeit in a more complex fashion than under the present approach.

3.2. Data

The data are for US domestic routes, and they come from the US Department of Transportation's T-100 service-segment data-base, which contains domestic nonstop flight-frequency data reported by US carriers, with the route endpoints being individual airports.[10] The data are used to compute quarterly frequency for the second quarter of 2010, a period after the completion of Delta/Northwest merger and prior to the approval of United/Continental merger. To ensure that flights are regularly scheduled, any carrier with less than 20 departures during each month of the quarter is not counted as being present on a route. This restriction is also extended to exclude routes with possible entry or exit during the quarter, a situation that would complicate the measurement of frequency interaction. With entry or exit, some months would have small or zero frequencies for a particular carrier while other months would exceed the 20-departure threshold. Any route with such a frequency pattern for a carrier serving it is excluded.[11]

Following Brueckner, Lee and Singer (2012), legacy carriers are American (AA), Alaska (AS), Continental (CO), Delta (DL), United (UA), US Airways (US) and Hawaiian (HA). LCCs are jetBlue (B6), Frontier (F9), AirTran (FL), Allegiant Air (G4), Spirit (NK), Sun Country (SY), Virgin America (VX) and Southwest (WN). Regional carriers are recoded as their corresponding mainline carriers.

Since a carrier's frequencies tend to be nearly equal in each direction on a route (with some differences due to flight cancellations), the frequency measure is computed in a nondirectional fashion. A carrier's monthly departures are summed over the second quarter of 2010 for each direction on a route, with the average across the two directions then computed. Among the route characteristics, distance in miles between the two airports is reported in the T-100 database. Since longer distances should yield lower frequencies, a negative shift coefficient in the reaction function is expected. The income variable is the geometric mean of the high-income shares of the two endpoint populations, with the share for an endpoint equal to the proportion of households in the MSA containing the airport with annual incomes greater than $75,000 (gathered from the 2010 State and Metropolitan Databook). The population measure is the geometric mean of the endpoint MSA populations from the 2010 US Census of Population and Housing Occupancy Status. Higher incomes and populations are expected to shift the reaction function upward. Following Pai (2010), the leisure-route variable takes on the value one when either endpoint is Las Vegas (LAS) or Orlando (MCO) and zero otherwise, and its coefficient is expected to be positive.[12]

The endpoint hub-status variable is computed for the first quarter of 2010 to avoid endogeneity. This variable, which equals the geometric mean of the number of destinations served from the route endpoints by the carrier (including international destinations), is computed using the T-100 database, and a positive coefficient for the own-carrier variable and a negative coefficient for that of the competitor are expected. Finally, a dummy variable is included indicating whether one or both route endpoints is a slot-controlled airport (these airports are New York-JFK, New York-LaGuardia, Washington Reagan National, and Newark).

Summary statistics for the data are presented in Tables 1–3. Table 1 shows the number of duopoly routes broken down by carrier mix, while also showing flight frequencies by carrier type. Note that legacy carriers offer higher frequencies on average than LCCs. Table 2 presents variable means and other statistics, while Table 3 shows airline presences on duopoly routes by tabulating the percentage of these routes on which a given carrier is present. These duopoly routes differ from oligopoly routes with three or more carriers (discussed briefly below) by having, on average, lower frequency, shorter distance, and a smaller geometric mean of the endpoint populations.

It is important to note that, given the nature of the instruments, a panel approach with route fixed effects is not workable, accounting for the cross-sectional approach used in the paper. To understand why, consider a set of duopoly routes observed over multiple quarters where the identities of two carriers on each route are constant over time. In this situation, the carrier dummies would be perfectly collinear with the route fixed effects, ruling out their use and thus precluding the paper's IV strategy. In reality, however, a panel of duopoly routes may contain a few routes with changes in carrier identities over time, but such limited variation would be insufficient to estimate the carrier-dummy coefficients. While data from multiple quarters could be used as long as time-varying route characteristics replace the route fixed effects, the only gain would be more observations, not the ability to control for unobserved route characteristics.

The absence of this ability, of course, raises the chance of finding spurious evidence in favor of strategic interaction. In other words, unobservable route characteristics that tend to generate high frequencies for both duopoly carriers will also generate correlation between their frequencies that can be mistaken for strategic interaction, as mentioned in the discussion following (16). The hope, however, is that by controlling for the most important determinants of travel demand (population, income, route distance, and leisure status) as well as endpoint hub and slot-control status, the remaining unobservables are relatively unimportant. With the carrier-dummy instruments then correcting for the standard simultaneity bias in (15) and (16), a consistent reaction-function slope estimate could emerge.

4. Main Empirical Results

This section present the main results. Several diagnostic tests are carried out for each model, including the Durbin-Wu-Hausman exogeneity test and the Sargan overidentification test. In addition, to appraise instrument strength, the first-stage F statistic for the instruments is computed and compared to rule-of-thumb value of 10 (see Stock, Wright and Yogo (2002), Stock and Yogo (2005)).[13] The discussion first considers a pooled duopoly model, where legacy and LCC carriers are not distinguished. Since estimation of this model is not successful, attention then turns to legacy-legacy and LCC-LCC duopoly routes, where the estimation of reaction functions is more successful. Mixed duopoly (legacy-LCC) and 3-carrier oligopoly routes, where estimation is again unsuccessful, are then described without detailed presentation of the results.

4.1. Results for the pooled duopoly case

To start, the pooled duopoly model, where LCCs and legacy carriers are not distinguished, is analyzed. The sample consists of 371 routes, with two carrier observations per route. Table 4 presents results for the pooled duopoly regression, with columns (1) and (3) showing the estimated coefficients for the OLS and 2SLS regressions, respectively. The OLS results are presented for comparison, and the regressions use clustered robust standard errors, with clustering by route. Such clustering is needed because omitted route-specific variables affect frequencies for both duopoly carriers, leading to error correlation within each route.

The central result in Table 4 is the estimate of the reaction function's slope, given by the coefficient of the competitor's frequency variable. Under the log specification, the slope shows the percentage in change in carrier i's frequency in response to a 1 percent increase in $-i$'s frequency. While the estimated OLS slope coefficient is positive and significantly different from zero, the 2SLS estimate is only half as large and statistically insignificant, a finding that appears to suggest the absence of strategic frequency interaction. However, the diagnostic tests on the instruments indicate that this conclusion may be unwarranted, as follows. The Durbin-Wu-Hausman test rejects exogeneity of the competitor's frequency at the 10 percent level (see the footnote to Table 4). In addition, the first-stage regression, shown in the first column of Table 5, yields an F statistic of 18.97 for the instruments, suggesting that they are not weak. But the Sargan overidentification test soundly rejects validity of the instruments, with a p value below 5 percent (see the footnote to Table 4). The test thus suggests that the second-stage error term is correlated with the competing-carrier dummies, a possibility that was recognized in the previous discussion.

This finding points to a need to distinguish between carrier types in attempting to estimate reaction functions. However, before turning to this task, it is useful to consider the estimated coefficients of the remaining variables in Table 4, even though these coefficients could be biased given the failure to properly correct for endogeneity of the competitor's frequency. As expected, an increase in endpoint populations and incomes shifts the reaction function up, while an increase in distance shifts it down. The reaction function is higher on a leisure route, and it shifts upward when the carrier serves more destinations from the route endpoints, shifting down when the competitor serves more such destinations. A slot-controlled endpoint shifts the reaction function downward, reflecting limited airport access.

The carrier dummy coefficients indicate, in percentage terms, frequency differences across carriers relative to American (the omitted carrier). For example, the US coefficient of 0.22 indicates that US Airways offers frequencies about 22 percent higher than American, holding the competitor's frequency and route characteristics constant.

Even though the results in Table 4 are not reliable, an understanding of the setup of first-stage regressions is needed for the subsequent analysis. Looking more closely at column (1) of Table 5, the IV prefix on the second set of carrier dummies indicates that they belong to the competing carrier. Recall that the first-stage regression gives the Nash equilibrium solution for carrier $-i$'s frequency, which corresponds to the intersection of reaction functions. Since both reaction functions appear to shift out for a shorter route, one with larger populations or high-income shares, or for a leisure route, equilibrium frequencies both rise, as seen in the estimated coefficients. The competitor hub-status coefficient indicates that a larger number of competitor destinations served from the endpoints leads to higher competitor frequency. The coefficient of the own hub-status variable, expected to be negative, is positive but insignificant, while the slot-control coefficient is significantly negative.

Predicted frequencies on a duopoly route served by, say, UA and DL are found as follows.

To find UA's predicted frequency, the IVUA dummy is set equal to 1 along with the DL dummy, and the competitor hub-status variables are set at UA's values while the own hub-status variables take DL's values. DL's predicted frequency is found by the reverse substitutions.

4.2. Results for the legacy-legacy duopoly case

The unsatisfactory results for the pooled regression show the need to distinguish between carrier types, and this section accordingly restricts the sample to the 166 duopoly routes served by two legacy carriers, yielding 332 observations. Table 6 shows the OLS and 2SLS results. The 2SLS slope coefficient is now statistically significant and positive, and it is considerably larger in magnitude than the OLS coefficient, which is also significant, an outcome that is discussed further below. The 2SLS estimate suggests that a carrier raises its own frequency by about 0.7 percent in response to a 1 percent increase in the competitor's frequency, showing that frequencies are strategic complements and that the strategic response is very strong.

This finding differs from the theoretical example in section 2, which generated a downward-sloping reaction function, with frequencies being strategic substitutes. Although the predicted sign of the reaction-function slope is ambiguous in general, the tendency of specific models to generate negative slopes may provide a cautionary note regarding the estimates in Table 6. However, matching the current results, the price reaction functions estimated in the earlier literature typically also have positive slopes, although this conclusion applies to a different strategic variable.[14]

To judge whether the resulting evidence of strategic interaction in Table 6 is credible, the diagnostic tests on the instruments must be checked. Exogeneity of the competitor's frequency is rejected at the 5 percent level, and the F statistic for the instruments is slightly above the rule-of-thumb value of 10, suggesting that they are not weak (see the second column of Table 5). In addition, the overidentification test indicates that validity of the instruments cannot be rejected, with a p value of 0.56. Therefore, all of the diagnostic tests are favorable, indicating that the existence of strategic frequency interaction among legacy carriers is a valid inference from the results.

Although the distance, income, population, and own hub-status variables shift the reaction function as before, the leisure-route and slot-control coefficients, though retaining their previous signs, are insignificant. However, the competitor's hub-status coefficient gains significance. Despite the relatively large F statistic, only the Continental carrier dummy coefficient is individually significant, showing that CO frequencies are about 25 percent greater than American's, other things equal.[15]

As a robustness check for the legacy-legacy case, a linear rather than log-linear reaction function was estimated. In addition to this functional-form change, the population, income, and hub-status variables were all computed using simple means of the endpoint values rather than geometric means. Although the F statistic for the instruments drops to around 8.5, the results are otherwise qualitatively similar to the log-log results.

4.3. Results for the LCC-LCC duopoly case

This section restricts the sample to the 35 duopoly routes served by two LCCs, yielding 70 observations. Since none of these routes has a slot-controlled endpoint, that dummy variable does not appear. Table 7 shows the OLS and 2SLS results for the log-linear specification. Although the reaction-function slope coefficient is insignificant in the OLS case, the 2SLS slope is significantly positive. Its magnitude of 0.76 is close to that in the legacy-legacy case, indicating that the strength of strategic interaction is similar within the two carrier types, being strong in both cases.

The diagnostic tests on the instruments are again fully satisfactory, as in the legacy-legacy case. Exogeneity of the competitor's frequency is soundly rejected, the value of the F statistic for the instruments is almost 18 (see Table 5), and the overidentification test fails to reject validity of the instruments (with a p-value of 0.72). Therefore, as in Table 7, the evidence of strategic frequency interaction is credible.

Since no LCC-LCC route has a slot-controlled endpoint, that variable is omitted from the regression. Among the other shift variables, the population, income, and leisure-route coefficients are insignificant, while the remaining coefficients are significant with the expected signs. With LCCs more oriented to nonbusiness passengers than legacies, the failure of the high-income shares to shift the reaction function may be plausible (recall that this variable's coefficient was significant in the legacy-legacy case). Also, with LCCs tending to serve leisure passengers on all routes (leisure or otherwise), the insignificance of the leisure-route coefficient may make sense. The one LCC with frequencies significantly different from those of jetBlue is Virgin America, with the difference being dramatic.[16]

As a robustness check, the linear specification was estimated for the LCC-LCC case. The F statistic for the instruments falls to 7.8, but the results are otherwise qualitatively similar to the log-log results.

4.4. Results for the legacy-LCC and LCC-legacy duopoly cases

With the previous results showing the presence of strategic frequency interaction *within* carrier types, the next step is to investigate interaction *across* types. Unfortunately, however, this investigation turns out to be unsuccessful. The reason is that, for both the legacy-LCC and LCC-legacy cases, the performance of the competing-carrier dummies as instruments is unsatisfactory. On the 170 duopoly routes where the carrier types are mixed, the competing-carrier dummies have little influence over the frequencies chosen by the competitor. Evidently, when paired with a carrier of the other type, a competing carrier's identity appears not to matter in determining its own frequencies. In other words, when it comes to frequencies, all legacies behave the same way when their competitor is an LCC, and vice versa, a pattern that has no obvious explanation.

The same obstacle arises for a sample of 87 oligopoly routes. Focusing on 3-carrier routes, and estimating reaction functions for a pooled model as well as for the 1-legacy/2-LCC and 1-LCC/2-legacy cases, the performance of the carrier-dummy instruments is unsatisfactory in each case.[17] The first-stage regressions yield unacceptably low F statistics, again indicating that flight frequencies do not vary significantly across carriers on such routes.

4.5. Overall lessons

The challenge in estimating reaction functions is to find instruments that help determine the level of the endogenous right-hand variable, in this case the competitor's flight frequency. Good choices for instruments are variables that shift the competitor's reaction function without being correlated with the unobservable determinants of the carrier's own frequency. Variables that, in principle, meet this requirement are measures of the competing carrier's characteristics. One such characteristics variable, which is actually both carrier- and route-dependent, is the endpoint hub-status measure, but it turns out to be invalid as an instrument since it directly determines own-frequency, as discussed above. A remaining choice is the vector of dummy variables indicating carrier identities. As long as these variables shift the flight-frequency reaction function, with carrier identities mattering in the choice of frequencies, these variables should perform successfully as instruments.

As the preceding discussion shows, the dummy variables meet this requirement for some types of routes but not others. On duopoly routes where the carriers are of same type (both legacies or both LCCs), carrier identities matter in the determination of frequencies. But on mixed duopoly and oligopoly routes, as well in the pooled oligopoly case, carrier identities do not exert enough influence on frequencies to be viable as instruments. Given this failure, one might wonder whether objective carrier-characteristics measures might do a better job. However, regressions using several such variables, including cost per seat mile and several measures of fleet size relative to network size (presumably a determinant of frequencies), did not yield better results for the problematic mixed-route cases. This outcome is no surprise, of course, since carrier dummies offer the most comprehensive way of capturing differences in carrier characteristics.

Another approach, which follows Berry et al. (1995), is to choose an instrument related to the other "products" offered by a carrier. The chosen instrument is the weighted average of the competitor's (logged) flight frequencies on the other routes it operates that do not share endpoints with the given route, with larger weights used on routes that have endpoint populations similar to those on the given route. This instrument, however, performs poorly by itself, and including it along with the carrier dummies does not substantially improve the results. Finally, appealing to a partial adjustment model, a one-quarter lag of frequency can be added to the reaction function, with the competitor's lagged frequency included as an instrument. However, the overidentification test shows that lagged frequency is invalid as an instrument.

With no other attractive instruments apparently available, the present results may offer the best that can be done in investigating strategic interaction in the choice of flight frequencies. Fortunately, it appears that the strength of interaction can be measured with some confidence for at least some types of routes.

As observed earlier, a note of caution regarding the results concerns the discrepancy between the negative reaction-function slope from section 2's theoretical example and the positive empirical slopes found in the legacy-legacy and LCC-LCC cases. Although the predicted slope sign is ambiguous in general, the tendency of specific models to generate negative slopes may be cause for suspicion regarding the estimates. Indeed, given that route-specific factors not captured by the route-characteristics variables may lead to upward bias in the estimated slope, it is conceivable that the true reaction function is downward sloping but that the estimated one slopes up. However, such a sign reversal would require the presence of unobserved factors whose effect on frequencies is strong and highly correlated across carriers on the route, an outcome that is not especially plausible given that the most important route characteristics are already captured in the regression, and that the instruments (which are meant to eliminate the resulting bias) pass the diagnostic tests.

Another cautionary note comes from recalling section 3's conclusion that, when the true reaction function slopes up, the OLS slope should be upward biased. The legacy-legacy and LCC-LCC estimates yield the opposite pattern, with the positive 2SLS slope estimates being larger, not smaller, than the OLS estimates. While this outcome could just reflect statistical noise, a broader explanation for this discrepancy as well as the slope sign anomaly may be that the Nash depiction of flight-frequency choices is somehow inappropriate, with another behavioral model applying instead. Further research could explore this possibility.

5. Multimarket Contact

Evans and Kessides' (1994) work on multimarket contact added an important innovation to reduced-form models of airline pricing by showing that extensive contact between competitors on other routes could soften price competition on a given route, with carriers fearing retaliation elsewhere when they cut fares. Evans and Kessides showed that airlines with high multimarket contact practice "mutual forbearance" by charging higher fares on routes they jointly serve.

With the view of airline competition broadened to include both fares and frequencies, a natural question is whether mutual forebearance exists in both the quality and price dimensions. In other words, do airlines with high multimarket compete less vigorously in frequencies on routes where they are both present? While this question could be addressed in a reduced-form fashion, it also can be addressed in the current, reaction-function context. The question is then whether multimarket contact shifts the reaction function downward, with carriers offering lower frequencies on routes where multimarket contact with the competitor is high.

To address this question, a contact variable is constructed following Evans and Kessides (1994), and the variable is then added to the previous legacy-legacy and LCC-LCC duopoly regressions. For a duopoly route, the contact measure is simply the total number of routes on which the two carriers are both present. Table 8 shows the matrix containing these route counts for all pairs of carriers.

Table 9 presents the results. To simplify the table, the dummy variables are omitted and only 2SLS estimates are displayed. With the coefficient of the contact measure insignificant in both regressions, the results suggest that multimarket contact does not shift the reaction functions in the legacy-legacy and LCC-LCC cases, a finding that contradicts the mutual forbearance hypothesis.[18] A possible explanation is that, with frequencies a less-prominent competitive tool than fares, airlines need not adjust their competitive behavior in the frequency dimension in response to high multimarket contact, letting mutual forebearance in prices do all the work.

In the present context, the reduced-form results of Evans and Kessides (1994) correspond the estimates of the first-stage regression. These results, which are not shown, provide a somewhat different picture. Although the coefficient of the contact variable is insignificant in the LCC-LCC first-stage regression, the legacy-legacy first stage shows a significant and positive coefficient, indicating that multimarket contact *raises* equilibrium frequencies. This outcome is a consequence of the positive reaction-function coefficient for contact, which indicates that both functions shift outward (although not in a statistically significant fashion) as multimarket contact increases, raising equilibrium frequencies. This conclusion is, of course, the opposite of what mutual forebearance would predict and is thus counterintuitive. Moreover, the failure of the contact effect to appear significantly in the reaction functions themselves casts some doubt on the conclusion. The lesson to be drawn is that the results definitely do not show evidence of mutual forebearance in frequency choices, with the effect of multimarket contact possibly running in the opposite direction for legacies, although not for LCCs.

6. Using the Estimates

The estimated reaction functions can be used to predict the effects on flight frequencies of changes in the airline operating environment, which may shift the positions of the functions for one or more carriers. Consider, for example, the impact of a change in an individual airline's "scope clause." A scope clause is now typically part of the collective bargaining agreement between a legacy carrier and its pilot's union, with the clause limiting the extent to which the airline's service can be operated by regional carriers. The goal is to limit the reliance on regional-carrier pilots in providing service under the airline's brand name, preserving jobs for the pilots who fly the mainline fleet. A scope clause often limits the number of regional aircraft that can be operated as well as their seat capacities, with both limitations serving to cap the number of non-mainline seats that the carrier can use in providing its service. Relaxation of a scope clause thus allows greater reliance on small planes, either by allowing a larger number to be used or by allowing the operation of larger regional aircraft (which remain smaller than mainline planes) in the provision of service. The mainline carrier therefore gains flexibility in matching aircraft to market conditions.

Scope clauses are relevant to the present analysis because, by limiting the use of small planes, they may constrain a carrier's ability to provide high flight frequencies. For example, carriers might be prevented from raising frequencies on high-volume routes by adding a few regional-jet flights each day to supplement mainline operations, a change that would require raising the share of such jets in the combined fleet. From the perspective of the current framework, the key observation is that relaxation of a carrier's scope clause may lead to an *upward shift in its reaction function*, with a higher frequency provided for any given level of the competitor's frequency. Concretely, this change would be reflected in an increase in the coefficient of the dummy variable identifying that carrier. The larger dummy coefficient, in effect, raises the carrier-specific intercept of the reaction function.

How will a relaxation of one carrier's scope clause affect flight frequencies? Consider the case of American Airlines (AA), which has recently negotiated a relaxation of its scope clause under bankruptcy proceedings, and consider a route where AA competes with another legacy carrier (call it YZ). The upward shift in AA's reaction function, which is shown in Figure 1, will lead to a new Nash equilibrium with higher frequencies for both American and carrier YZ. In addition, the figure shows that AA's frequency will rise by more than YZ's in moving to the new equilibrium. Analytically, let δ denote the reaction function's slope (as in (14)) and let η_{AA} denote AA's dummy coefficient (represented by the intercept α in (14) since AA is the omitted carrier). Then, letting η_{AA} change by $\Delta\eta_{AA}$ and using f's to denote frequencies (as in the theoretical model), the changes in frequencies on the route, Δf_{AA} and Δf_{YZ}, must satisfy

$$\Delta f_{AA} \;=\; \Delta\eta_{AA} \;+\; \delta\Delta f_{YZ} \tag{17}$$

$$\Delta f_{YZ} \;=\; \delta\Delta f_{AA}, \tag{18}$$

where (17) and (18) come from AA's and YZ's reaction functions. Solving yields

$$\Delta f_{AA} \;=\; \frac{\Delta\eta_{AA}}{1-\delta^2}, \quad \Delta f_{YZ} \;=\; \frac{\delta\Delta\eta_{AA}}{1-\delta^2} \tag{19}$$

Using the δ value of 0.558 from unreported results for the linear legacy-legacy specification, (19) shows that $\Delta f_{AA} = 1.452\Delta\eta_{AA}$ and $\Delta f_{YZ} = 0.810\Delta\eta_{AA}$. Therefore, f_{AA} increases by about half of the increase in the AA intercept, while the increase in f_{YZ} is a bit less than the intercept's increase. The ratio of the two changes is $1.452/0.810 = 1.792 = 1/\delta$. The lesson is that a relaxation of an legacy airline's scope clause (reflected, by assumption, in a larger dummy coefficient) raises equilibrium frequencies on all the duopoly routes where it competes with another legacy carrier, but that its own frequency rises by eighty percent more than that of its competitor. Although it is not possible to quantify the connection between AA's scope clause and the magnitude of η_{AA} or to validate the assumption that the clause only affects the intercept, these calculations show how the estimates from the model might be used to generate qualitative insights.

A final point is that the first-stage estimates, which correspond to the reduced-form of the structural model, could be used instead to generate analogous conclusions. However, because the first-stage estimates are derived statistically, not through algebraic manipulation of the reaction-function estimates, the answers from this method may be different.[19]

7. Conclusion

This paper has provided empirical evidence on product-quality competition in the airline industry. Focusing on a main element of quality, flight frequency, the paper has estimated reaction functions in a search for strategic interaction in the determination of frequencies. Regressions for duopoly routes where two competitors are of the same type (two LCCs or two legacy carriers) yield seemingly credible, significantly positive 2SLS slope estimates. Strategic interaction therefore appears to occur on such homogenous routes, and the slope estimates indicate that it is strong, with a carrier responding in almost one-for-one fashion to an increase in its competitor's frequency (a conclusion that applies on both legacy and LCC routes). But on duopoly routes where the competing carriers are of different types, the weak performance of the instruments, which are needed to identify strategic interaction, prevents a strong conclusion from being reached. Therefore, while the analysis shows the presence of strategic interaction *within* carrier types, the existence of interaction *across* types remains an open question. Regressions including a multimarket-contact variable show no evidence of mutual forbearance in frequency competition within carrier types.

Because the positive sign of the estimated reaction-function slopes contradicts the predictions of several theoretical models of frequency competition, the results of the paper should be viewed with some caution. It is conceivable that the true flight-frequency reaction function is downward sloping but that the paper's empirical procedures are not sufficiently discriminating to reveal this property. As a result, further work attempting to generate more-refined estimates could be worthwhile.

With little existing empirical work on product-quality competition in the industrial organization literature, this paper may point the way toward a possible new line of research. In other industries where substantial quality variation is observed, either cross-sectionally or intemporally, reaction functions could be estimated in an attempt to expose the nature of strategic interaction.

Table 1: Duopoly Route Structure

Route Structure	**Mean Frequency**		**Number of Routes**
	Legacy	**LCC**	
pooled	427.55	276.28	371
legacy-legacy	402.94	-	166
LCC-LCC	-	232.36	35
legacy-LCC	475.62	294.37	170

Table 2: Summary Statistics for Duopoly Routes

Variable	**Mean**	**Std.Dev.**	**Min**	**Max**
Frequency	378.622	249.396	78	1797
Distance	819.846	545.192	67	2918
Geometric Mean of Income above $75,000	34.783	4.392	23.769	51.327
Geometric Mean of Population (in hundred thousands)	30.079	15.266	5.670	95.529
Leisure Route	0.094	0.292	0	1
Slot-control	0.164	0.371	0	1
Geometric Mean of Number of Destinations	19.828	16.211	0	169

Table 3: Airline Presences on Duopoly Routes

Airline Code	**Airline**	**Airline Share**
AA	American	14.15%
AS	Alaska	3.50%
CO	Continental	6.87%
DL	Delta	16.44%
UA	United	15.09%
US	US Airways	11.05%
HA	Hawaiian	0.27%
B6	JetBlue	4.72%
F9	Frontier	2.43%
FL	AirTran	9.03%
G4	Allegiant Air	0.13%
NK	Spirit	1.21%
SY	Sun Country	0.13%
VX	Virgin America	0.27%
WN	Southwest	14.42%

Table 4: Pooled Regression for Duopoly Routes

	OLS		2SLS	
	(1)	**(2)**	**(3)**	**(4)**
Variables	**Coeff.**	**Std.Err.**	**Coeff.**	**Std.Err.**
Log Competitor Frequency	0.291**	(0.055)	0.136	(0.097)
Distance	-0.0004**	(0.0001)	-0.0005**	(0.0001)
Geometric Mean of Income above $75,000	0.023**	(0.005)	0.028**	(0.006)
Geometric Mean of Population	0.006**	(0.002)	0.008**	(0.002)
Leisure Route	0.163**	(0.055)	0.172**	(0.065)
Slot-control	-0.196**	(0.056)	-0.217**	(0.067)
Geometric Mean of Own # Destination	0.016**	(0.002)	0.016**	(0.002)
Geometric Mean of Competitor's # Destination	-0.004*	(0.002)	-0.001	(0.002)
AS	0.080	(0.117)	0.080	(0.113)
B6	-0.240*	(0.115)	-0.271*	(0.110)
CO	0.312**	(0.087)	0.307**	(0.085)
DL	0.063	(0.065)	0.049	(0.062)
F9	-0.039	(0.105)	-0.039	(0.096)
FL	-0.262**	(0.071)	-0.245**	(0.074)
G4	-0.722**	(0.095)	-0.857**	(0.121)
HA	0.097	(0.097)	0.142	(0.104)
NK	-0.176	(0.110)	-0.158	(0.106)
SY	-0.643**	(0.093)	-0.570**	(0.105)
UA	0.031	(0.063)	0.021	(0.059)
US	0.229**	(0.066)	0.218**	(0.065)
VX	0.493**	(0.167)	0.481**	(0.153)
WN	-0.230**	(0.066)	-0.226**	(0.065)
Constant	3.213**	(0.303)	3.908**	(0.477)
Observations	742		742	
R^2	0.537		-	

[1] ** p<0.01, * p<0.05.

[2] Standard errors are clustered robust, clustering by route.

[3] Dependent variable: Log Own Frequency.

[4] Tests of exogeneity: p = 0.092

[5] Tests of overidentifying restrictions: Sargan chi-squared(13) = 27.539 (p = 0.011)

Table 5: First-stage Regressions for Duopoly Routes

	Pooled	**Legacy-Legacy**	**LCC-LCC**
	(1)	**(2)**	**(3)**
Variables	**Coeff.**	**Coeff.**	**Coeff.**
Distance	-0.001**	-0.001**	-0.001**
	(0.0001)	(0.0001)	(0.0001)
Geometric Mean of Income above $75,000	0.035**	0.035**	0.012
	(0.006)	(0.009)	(0.027)
Geometric Mean of Population	0.009**	0.004	0.021**
	(0.002)	(0.003)	(0.005)
Leisure Route	0.175*	0.100	-0.050
	(0.082)	(0.178)	(0.123)
Slot-control	-0.204*	-0.222*	-
	(0.083)	(0.112)	
Geometric Mean of Own # Dest.	0.001	0.001	0.014
	(0.001)	(0.002)	(0.009)
Geometric Mean of Competitor's # Dest.	0.015**	0.018**	0.040**
	(0.002)	(0.003)	(0.008)
AS	0.154	0.081	NA
	(0.112)	(0.153)	
CO	0.050	-0.002	NA
	(0.108)	(0.118)	
DL	0.016	-0.405**	NA
	(0.073)	(0.095)	
UA	-0.034	-0.210	NA
	(0.113)	(0.127)	
US	0.105	0.103	NA
	(0.088)	(0.104)	
HA	0.285	-0.053	NA
	(0.247)	(0.190)	
B6	-0.164	NA	Omitted
	(0.112)		
F9	0.100	NA	0.453
	(0.150)		(0.250)
FL	0.260**	NA	0.421
	(0.095)		(0.219)
G4	-0.738**	NA	0.121
	(0.120)		(0.206)
NK	0.219	NA	0.796*
	(0.194)		(0.351)
SY	0.469**	NA	NA
	(0.124)		
VX	0.239	NA	1.039**
	(0.123)		(0.234)
WN	-0.002	NA	-0.00003
	(0.070)		(0.197)
Constant	4.557**	4.665**	3.859**
	(0.217)	(0.285)	(0.884)

Continued on next page.

Table 5: Continued from previous page

	Pooled	Legacy-Legacy	LCC-LCC
	(1)	(2)	(3)
Variables	Coeff.	Coeff.	Coeff.
IVAS	0.106	-0.052	NA
	(0.131)	(0.193)	
IVCO	0.287*	0.208	NA
	(0.119)	(0.132)	
IVDL	-0.050	-0.450**	NA
	(0.087)	(0.090)	
IVUA	-0.002	-0.184	NA
	(0.113)	(0.122)	
IVUS	0.198	0.228	NA
	(0.106)	(0.137)	
IVHA	0.133	-0.158	NA
	(0.144)	(0.232)	
IVB6	-0.382**	NA	Omitted
	(0.131)		
IVF9	-0.118	NA	0.467
	(0.109)		(0.239)
IVFL	-0.235*	NA	0.224
	(0.114)		(0.169)
IVG4	-1.229**	NA	-0.047
	(0.125)		(0.210)
IVNK	-0.153	NA	0.485**
	(0.132)		(0.175)
IVSY	-0.523**	NA	NA
	(0.144)		
IVVX	0.572**	NA	1.876**
	(0.197)		(0.228)
IVWN	-0.298**	NA	0.052
	(0.090)		(0.241)
Observations	742	332	70
R^2	0.508	0.449	0.711
F-statistic for the IVs	18.972	10.039	17.634

[1] ** p<0.01, * p<0.05.

[2] Standard errors are clustered robust, clustering by route.

[3] Dependent variable: Log Competitor Frequency.

Table 6: Legacy-Legacy Regression

	OLS		2SLS	
	(1)	**(2)**	**(3)**	**(4)**
Variables	**Coeff.**	**Std.Err.**	**Coeff.**	**Std.Err.**
Log Competitor Frequency	0.404**	(0.076)	0.685**	(0.111)
Distance	-0.0003**	(0.0001)	-0.0001*	(0.00005)
Geometric Mean of Income above $75,000	0.021**	(0.006)	0.010*	(0.005)
Geometric Mean of Population	0.003	(0.002)	0.002*	(0.001)
Leisure Route	0.100	(0.107)	0.035	(0.066)
Slot-control	-0.137	(0.071)	-0.081	(0.053)
Geometric Mean of Own # Destination	0.018**	(0.003)	0.017**	(0.003)
Geometric Mean of Competitor's # Destination	-0.007**	(0.002)	-0.012**	(0.003)
AS	-0.073	(0.200)	-0.111	(0.207)
CO	0.245*	(0.095)	0.250*	(0.105)
DL	-0.188*	(0.081)	-0.146	(0.092)
UA	0.019	(0.071)	0.038	(0.080)
US	0.184	(0.095)	0.169	(0.104)
HA	-0.149	(0.124)	-0.114	(0.173)
Constant	2.646**	(0.402)	1.409**	(0.524)
Observations	332		332	
R^2	0.505		-	

[1] ** p<0.01, * p<0.05.

[2] Standard errors are clustered robust, clustering by route.

[3] Dependent variable: Log Own Frequency.

[4] Tests of exogeneity: p = 0.015

[5] Tests of overidentifying restrictions: Sargan chi-squared(5) = 3.930 (p = 0.560)

Table 7: LCC-LCC Regression

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Variables	**Coeff.**	**Std.Err.**	**Coeff.**	**Std.Err.**
Log Competitor Frequency	-0.085	(0.226)	0.762**	(0.211)
Distance	-0.001**	(0.0002)	-0.0003**	(0.0001)
Geometric Mean of Income above $75,000	0.022	(0.031)	-0.006	(0.015)
Geometric Mean of Population	0.021**	(0.006)	0.005	(0.004)
Leisure Route	-0.066	(0.141)	-0.019	(0.072)
Geometric Mean of Own # Destination	0.049**	(0.010)	0.033**	(0.012)
Geometric Mean of Competitor's # Destination	0.004	(0.008)	-0.021**	(0.008)
F9	0.564*	(0.246)	0.212	(0.391)
FL	0.078	(0.229)	-0.194	(0.336)
G4	0.041	(0.191)	0.002	(0.194)
NK	0.366	(0.307)	-0.203	(0.432)
VX	1.489**	(0.356)	1.218**	(0.218)
WN	-0.015	(0.229)	0.093	(0.346)
Constant	4.271**	(1.218)	1.414	(0.839)
Observations	70		70	
R^2	0.630		-	

[1] ** p<0.01, * p<0.05.

[2] Standard errors are clustered robust, clustering by route.

[3] Dependent variable: Log Own Frequency.

[4] Tests of exogeneity: p = 0.0004

[5] Tests of overidentifying restrictions: Sargan chi-squared(5)= 2.875 (p = 0.719)

Table 8: The Number of Contact Points

	AA	AS	B6	CO	DL	F9	FL	G4	HA	NK	SY	UA	US	VX	WN
AA	309	4	32	26	85	4	12	0	4	6	0	192	33	12	8
AS	4	76	4	6	2	4	0	0	6	0	0	30	4	4	34
B6	32	4	122	10	54	0	16	0	0	8	0	20	14	12	18
CO	26	6	10	114	30	6	0	0	2	2	0	24	16	0	8
DL	85	2	54	30	347	13	100	0	8	22	2	43	55	8	48
F9	4	4	0	6	13	113	22	0	0	0	0	82	8	0	64
FL	12	0	16	0	100	22	180	2	0	6	0	8	14	0	42
G4	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0
HA	4	6	0	2	8	0	0	0	14	0	0	4	2	0	0
NK	6	0	8	2	22	0	6	0	0	38	0	2	2	2	6
SY	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0
UA	192	30	20	24	43	82	8	0	4	2	0	371	22	20	96
US	33	4	14	16	55	8	14	0	2	2	0	22	215	2	94
VX	12	4	12	0	8	0	0	0	0	2	0	20	2	26	4
WN	8	34	18	8	48	64	42	0	0	6	0	96	94	4	308

Table 9: 2SLS Multimarket-Contact Regressions

	(1)	(2)
Variables	**Legacy-Legacy**	**LCC-LCC**
Log Competitor Frequency	0.731**	0.762**
	(0.100)	(0.214)
Contact	0.001	-0.001
	(0.001)	(0.005)
Distance	-0.0001*	-0.0003**
	(0.00005)	(0.0001)
Geometric Mean of Income above $75,000	0.008	-0.007
	(0.0045)	(0.013)
Geometric Mean of Population	0.001	0.005
	(0.001)	(0.004)
Leisure Route	0.035	-0.025
	(0.057)	(0.056)
Slot-control	-0.058	-
	(0.045)	
Geometric Mean of Own # Dest.	0.017**	0.034**
	(0.003)	(0.013)
Geometric Mean of Competitor's # Dest.	-0.013**	-0.020*
	(0.003)	(0.009)
Constant	1.138*	1.426
	(0.447)	(0.816)
Observations	332	70
R^2	0.436	0.353

[1] ** p<0.01, * p<0.05.

[2] Standard errors in the bracket are clustered robust, clustering by route.

[3] Dependent variable: Log Own Frequency.

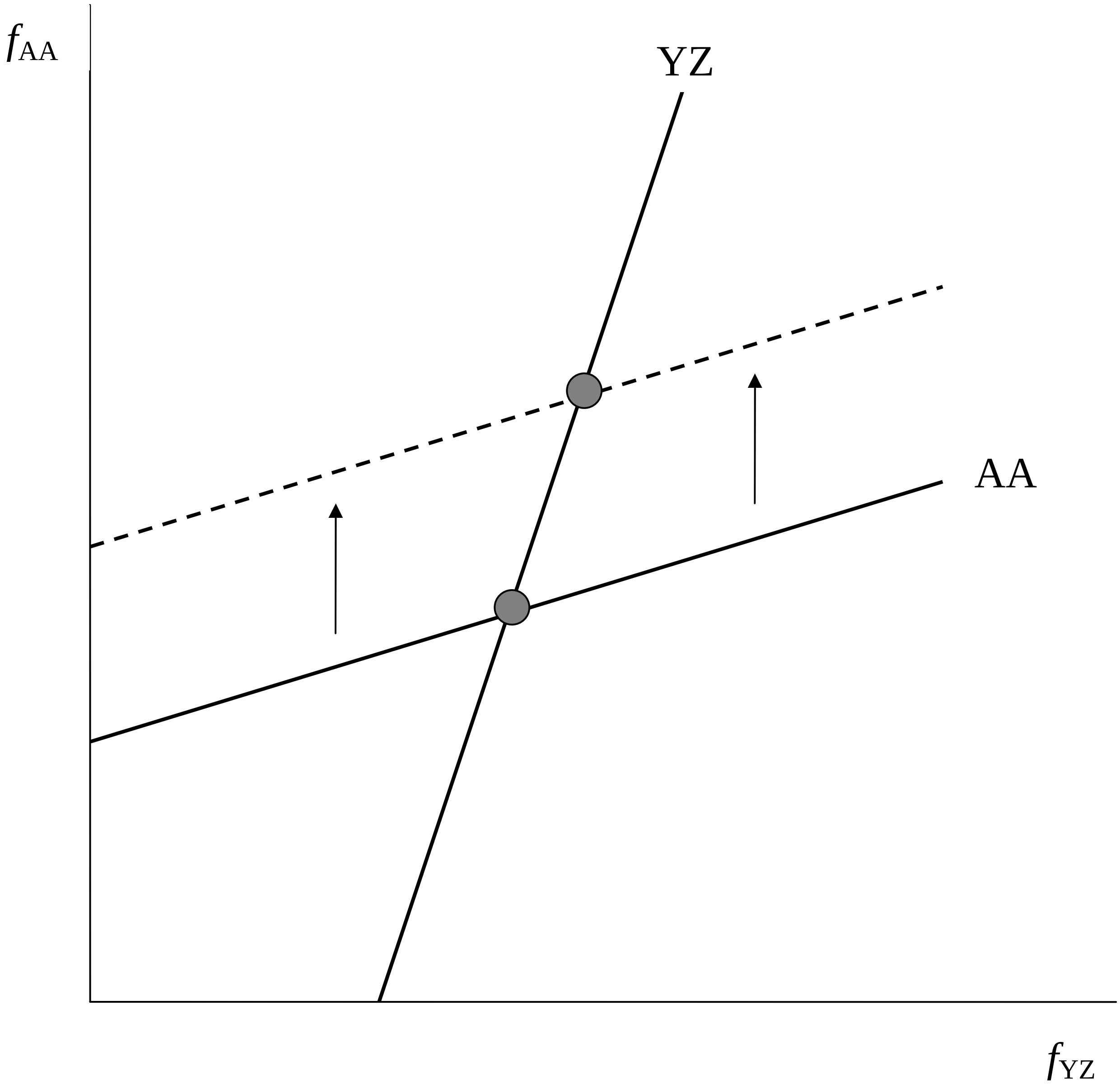

Figure 1: Shift of Reaction Function

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Footnotes

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[1]Prior to airline deregulation, when price competition was not allowed, airlines were viewed as competing excessively in flight frequency. Although deregulation enabled airlines to compete more vigorously in fares, airlines appear to still compete in flight frequency, and frequency has indeed increased since the hub-and-spoke system expanded airline networks (see Morrison and Winston (1995)).

[2]Most of these papers recognize the endogeneity issue in their estimation procedures.

[3]For earlier non-structural empirical work on product quality, see Mazzeo (2002) and Crawford and Shum (2007).

[4]This mixture of parameters can be seen in the reaction-function slope derived in the theoretical analysis below (eq. (11)).

[5]Their goal is to identify market characteristics that lead to greater clustering of departure times for different carriers. Other empirical papers on flight frequencies include Pai (2010), who explores the determinants of frequencies and aircraft sizes using a reduced-form approach, and Bilotkach et al. (2010), who focus primarily on the relationship between the frequency choice and trip distance, providing a theoretical model and empirical evidence.

[6]In work more closely related to the present exercise, Bilotkach (2011) studies the relationship between flight frequencies and multimarket contact in a reduced-form model, while Prince and Simon (2009) explore the impact of multimarket contact on flight delays and cancellations.

[7]It should be noted that, if aircraft size were fixed rather than flexible, then an airline's frequency and its passenger volume would be perfectly correlated. In this case, frequencies would no longer be choice variables, with the airlines competing only in fares. Estimating a frequency reaction function would then be an inappropriate exercise.

[8]Note that, in the legacy-legacy duopoly case, the first-stage regression is estimated using each of the two observations per route, with the values of the two carrier dummies switching between observations. Fitted values for the frequencies on the right-hand side of (14) are

then generated for both carriers on a route, with the values differing because the estimates of the coefficient vectors ρ and λ will be different. Note also that the particular identities of carriers on a route are taken to be uncorrelated with the error term. For this assumption to hold, large values for the unobservable factors associated with high flight frequencies should not elicit the presence of a particular carrier on the route.

[9]In particular, the need to exclude one LCC from among the competitor dummies in regressions where the competitors are LCCs (such as the LCC-LCC model) leaves only one instrument and an exactly identified equation, which cannot be subjected to the overidentification test (see footnote 16 below).

[10]An alternate approach would rely on city-pairs rather than airport-pairs. This approach could use the airport groupings for multiple-airport metro areas generated by Brueckner, Lee and Singer (2012). While the airport-pair approach is used for simplicity, this city-pair approach could be explored in further work.

[11]Frequency could still exceed the 20 threshold when entry or exit occurs midway through a month, creating a misleading quarterly frequency total, but this drawback cannot be addressed and thus creates a source of measurement error. Aside from entry and exit, most cases with 20 or fewer departures involve flight diversions or other irregular events, which lead to only a few flight operations.

[12]Smaller leisure destinations such as ski areas are not in the route sample.

[13]The precise F-statistic value depends on the number of instruments, and the values are somewhat over 11 in the current applications (see Table 1 of Stock and Yogo (2005)). However, since the F value is partly arbitrary in any case (depending on the target 2SLS bias relative to OLS), the familiar value of 10 will be used below.

[14]Like the present paper, one such study (Brueckner's (1998) study of strategic interaction in the choice of urban growth controls) contains a theoretical example with a downward-sloping reaction function but an estimated function that slopes up.

[15]It is important to note that, since the weak-instrument criterion hinges on the impact of the instruments as a group (as reflected in the F statistic), the insignificance of individual coefficients is not directly relevant.

[16]Observe that IVB6 (jetBlue) is also omitted from the list of intruments. With the competitor being an LCC by construction, the IV's would sum to one without such an omission.

[17]Routes with 3 legacies or 3 LCCs are too few in number for these cases to be investigated. In the regressions, the average of the log frequency of the two competitors appears on the right-hand side, as does the average of the competitors' hub-status measures. This specification follows from the assumption that the coefficients of the individual log frequencies and hub-status variables are equal across the two competitors.

[18]Allowing the contact variable to affect both the height and slope of the reaction function again yields insignificant effects.

[19]Solving for the reduced form, AA's dummy coefficient when it is carrier $-i$ in (15) (that is, the carrier whose frequency is being determined) is equal to $\eta_{AA}/(1-\delta^2)$, while its dummy coefficient when it is carrier i (that is, the other carrier in the market) is equal to $\delta\eta_{AA}/(1-\delta^2)$. The $1/\delta$ factor by which AA's frequency change exceeds that of its competitor (from the text) would thus be found by taking the ratio of the IVAA coefficient and the AA coefficients from the first-stage regression. Since AA is the default carrier, such coefficients are not estimated, but the same point would apply to any other carrier. As can be seen from sample calculations using the first-stage estimates in Table 5, the resulting value can differ substantially from the second-stage estimate of $1/\delta$.