

International Airfares in the Age of Alliances: The Effects of Codesharing and Antitrust Immunity

by

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Abstract

This paper provides empirical evidence on the effect of airline cooperation on the level of interline fares paid by international passengers. The analysis focuses on two measures of cooperation: codesharing and antitrust immunity. The results show that the partial effects of codesharing and immunity are both negative. The presence of codesharing on an international interline itinerary reduces the fare by 8–17 percent, with the exact number depending on the sample used and the estimation method. Moreover, the presence of antitrust immunity reduces the fare by 13–21 percent. Codesharing and immunity are substitutes, however, in the sense that their combined effect is smaller than the sum of their partial effects. Recognizing this difference, which is captured by an interaction variable in the regressions, the combined effect ranges between 17 and 30 percent. These results provide strong evidence that airline cooperation in the fare-setting process generates substantial benefits for interline passengers.

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1. Introduction

As international airline traffic has expanded in recent decades, a new development has swept the industry: extensive cooperation among international carriers in the provision of service. The most visible form of cooperation is found in the international airline alliances that link U.S. carriers to partners in other countries. These alliances are designed to offer the international passenger a “seamless” travel experience by minimizing some of the inconveniences of a traditional interline (multi-carrier) trip. Schedule coordination by the alliance partners along with gate proximity at hub airports eases passenger connections between the carriers, and these conveniences are typically reinforced by a merger of the partners’ frequent flier programs. In addition, in those cases where the alliance partners enjoy antitrust immunity, cooperation extends into the realm of pricing. With immunity, the partners can collaborate in the determination of fares for interline trips in a fashion that was impossible under traditional pricing arrangements.

Cooperation is also widespread among carriers that are not formal alliance partners. Such cooperation arises through a web of international codesharing arrangements, which are common among alliance partners but also link many nonallied carriers. With codesharing, a trip is ticketed as if it occurred on a single carrier, even though some of the route segments are operated by the codeshare partner. In support of a codesharing agreement, the carriers may adjust schedules and take other steps to foster seamless travel, just as if they were formal alliance partners. In addition, codeshare trips are usually priced with greater flexibility than under traditional arrangements. However, outright collaboration in pricing is not allowed in the absence of antitrust immunity.

Given the increasing globalization of the world economy, and the consequent growth in in-

ternational air travel, it is important to quantify the impact of the new patterns of cooperation among international carriers. Although quantifying the effect on passenger convenience is likely to be difficult, the impact of cooperation on international airfares is more easily measured. The purpose of the present paper is to carry out such an exercise. The paper measures the separate impacts of codesharing and antitrust immunity on the fares charged for interline trips in a large sample of international city-pair markets. The empirical results show that codesharing leads to a substantial reduction in interline fares, and that antitrust immunity has an even larger negative effect. Thus, the results show that cooperation among international carriers generates substantial fare benefits for passengers, over and above any convenience gains they may enjoy.

Because the extent of cooperation between carriers is determined in part by government regulatory decisions, the above findings have policy relevance. The Department of Transportation (DOT) is the agency that grants U.S. antitrust immunity to alliance partners, and the present analysis identifies substantial benefits to interline passengers that might be considered when DOT acts on an application for immunity. DOT also must approve codesharing arrangements, and the present results point to significant benefits that could also help guide its decisions in these cases.

The paper's results extend the earlier empirical findings of Brueckner and Whalen (1998), who showed that international alliances lead to lower fares. Both studies use data from the Passenger Origin-Destination survey compiled by the DOT, which shows fares for thousands of individual itineraries (i.e., route/carrier combinations), both domestic and international. However, the 1999 data used in the present study provide key additional information that was not available in the 1997 data used by Brueckner and Whalen (BW). In particular, the 1999 data indicate both the operating carrier and the ticketed carrier for each route segment of an itinerary, with the two being different if the segment involves codesharing. As a result, the effect of codesharing on fares can be measured at the city-pair level.

Lacking such market-level data, BW constructed a broader measure of airline cooperation. In particular, they assumed that carrier pairs appearing on DOT's 1997 list of codeshare partners, who had codeshare authority in particular city-pair markets, would behave cooperatively

in *all* the markets they serve. Carriers with a codesharing agreement were thus identified as “alliance” partners, even though their codeshare activity may be limited to a narrow set of markets. The resulting set of alliance partners included the major 1997 alliance pairings, such as Northwest-KLM and United-Lufthansa, but it also included linkups between less well-known codeshare partners. Using this codeshare-based alliance definition, BW found that alliance service was associated with lower international fares. Their results also showed that antitrust immunity had a further negative effect beyond that associated with codesharing, as in the present study.

As shown in section 2 of the paper, economic theory supports these findings by predicting that airline cooperation should have a beneficial impact on international fares. The discussion, which draws on previous analysis by Brueckner (1997) and BW, shows that noncooperative pricing of an interline trip by the two carriers leads to an excessively high fare, which does not maximize joint profit. Cooperative pricing, by contrast, internalizes the negative externalities from the pricing decision, which arise because an interline trip is a joint product, and leads to a lower fare. The analysis thus predicts that antitrust immunity, which fosters cooperative pricing, should lead to lower interline fares. Focusing on institutional factors, the discussion also explains why codesharing should reduce fares, even in the absence of antitrust immunity.

Before proceeding to this analysis, a review of the sparse literature on airline alliances is useful. In addition to the analysis provided by Brueckner (1997) and BW, theoretical models of airline alliances are presented by Park (1997), Park and Zhang (1998), Park, Zhang and Zhang (2000), and Pels (2000). Other empirical studies include Oum, Park and Zhang (1996) and Park and Zhang (1999). A useful case study is offered by Walleed and Hansen (1994), and excellent institutional overviews are presented by Gellman Research Associates (1994) and U.S. General Accounting Office (1995). Finally, Whalen (1999) provides a simulation analysis of the effects of potential domestic U.S. alliances.

Following the theoretical discussion in section 2, section 3 of the paper discusses the empirical model and the data. Section 4 discusses the construction of the explanatory variables, section 5 presents the regression results, and Section 6 offers conclusions.

2. Theory

2.1. Model

To develop a theoretical prediction regarding the effect of airline cooperation on fares, consider the simplest possible model. More realistic and complex frameworks are developed in Brueckner (1997) and BW. In particular, consider the airline routes shown in Figure 1, which represents part of a larger network structure. Airline 1 (a U.S. carrier) provides service between cities A and B, while airline 2 (a foreign carrier) operates between cities B and C. Airline 1 carries passengers in city-pair market AB, airline 2 serves market BC, and together, the airlines provide interline service in market AC, which is served by no other carriers.

To impose symmetry, let the route segments AB and BC have the same length. In addition, suppose that the airline technology exhibits constant returns to scale, with the cost per passenger on a route segment equal to a constant c for both airlines. This assumption means that fares within any given network can be set independently across city-pair markets, a simplification that would vanish if increasing returns (i.e., economies of traffic density) were present.¹ Focusing on market AC, let q_{AC} denote total traffic in the market, which consists of round trips originating at A plus round trips originating at C. Letting p_{AC} denote the interline fare for travel in market AC, traffic satisfies $q_{AC} = D(p_{AC})$, where $D(\cdot)$ is the travel demand function.

Two types of fare setting behavior are possible in market AC: cooperative and noncooperative. In the noncooperative case, airlines 1 and 2 choose “subfares” s_{AB} and s_{BC} in noncooperative fashion, with the total fare p_{AC} equal to the sum of the subfares, $s_{AB} + s_{BC}$. The subfare s_{AB} gives airline 1’s revenue from carrying an interline AC passenger between A and B, while s_{BC} gives airline 2’s revenue from carrying the passenger between B and C. As seen in Brueckner (1997) and BW, the optimal subfares are less than the fares in city-pair markets AB and BC, which are set independently. If this were not true, the passenger would be better off purchasing separate AB and BC tickets to travel between A and C.

Airline 1’s profit in the noncooperative case is given by

$$(s_{AB} - c)D(s_{AB} + s_{BC}). \tag{1}$$

The airline chooses s_{AB} to maximize (1), viewing s_{BC} as parametric in Nash fashion, and the first-order condition can be written

$$\frac{D}{D'} + s_{AB} = c. \quad (2)$$

Because of symmetry, the airlines' subfares will be the same in the Nash equilibrium, with both equal to $p_{AC}/2$. Using this fact, and substituting the inverse-demand slope $\partial p_{AC}/\partial q_{AC} = 1/D'$, (1) can be rewritten as

$$2q_{AC} \frac{\partial p_{AC}}{\partial q_{AC}} + p_{AC} = 2c. \quad (3)$$

Alternatively, suppose that the airlines behave cooperatively, setting the overall fare in the market to maximize their total profit. Recognizing that the carriers split the interline fare, their combined profit equals

$$2 \left(\frac{p_{AC}}{2} - c \right) D(p_{AC}). \quad (4)$$

Using (4), the first-order condition for choice of p_{AC} is

$$q_{AC} \frac{\partial p_{AC}}{\partial q_{AC}} + p_{AC} = 2c. \quad (5)$$

This condition says that marginal revenue from an additional passenger in market AC should equal marginal cost, which is the cost of carrying the passenger along two route segments.

A comparison of (5) and (3) reveals the difference between the interline fares in the cooperative and noncooperative cases. Since the negative part of marginal revenue in (5) (the first term) is multiplied by two in (3), it follows that the left-hand side of (3) is smaller than the LHS of (5) at any given traffic level q_{AC} . Assuming satisfaction of the second-order condition, this fact in turn implies that (3) is satisfied at a smaller traffic level than (5). But since a smaller q_{AC} implies a higher p_{AC} , it follows that the interline fare is higher in the noncooperative case. The intuitive reason is that, with noncooperative behavior, each airline

ignores the negative effect on the other airline's profit from an increase in its own subfare. This effect arises because a higher subfare raises the overall fare, depressing traffic in the market. Because of the resulting externality, each subfare is set too high, leading to an overall fare that is excessive. Cooperative behavior, however, internalizes the externality, so that a lower fare is chosen. Recognizing that an interline trip is a joint product of the two airlines, the inefficiency of noncooperative pricing echoes standard results for such a market setting (see Tirole (1988)).

2.2. Applying the model to actual pricing behavior

While this abstract analysis is suggestive, applying its lessons to the study of actual airfares requires discussion of the institutional setting in which airline decisions are made. The first observation is that the cooperative case outlined above corresponds well to the situation of alliance partners operating with antitrust immunity. Immunity allows full collaboration in the choice of interline fares, which the carriers would set so as to maximize joint profit from the various markets where they provide interline service.

At the other extreme of the cooperative spectrum lies the traditional pricing method for interline trips. This method, which was used exclusively prior to the emergence of alliances and codesharing, relies on fares generated by the International Air Transport Association (IATA). IATA convened periodic fare "conferences," where carriers met to set fares for a multitude of international city-pair markets. The fare charged for a given interline trip would then be set automatically at the IATA level, and total revenue would be split between the collaborating carriers according to a distance-based "prorate" formula. Because the adoption of an IATA fare for a particular market required unanimous agreement among the airlines participating in the conference, IATA fares tended to be set high enough to cover the costs of the least efficient carriers (see Doganis (1985) and O'Connor (1989)).

From one perspective, the IATA fare-determination process corresponds roughly to the noncooperative case analyzed above, with carriers specifying the revenue they require to carry interline passengers, conditional on the revenue demands of their potential collaborators. However, the unanimity requirement appears to skew the outcome, putting a relatively high floor under IATA fares.

An intermediate type of pricing arrangement, which is now widely used, may correspond

better to the pure noncooperative case. This arrangement involves use of a “special prorate” agreement between two carriers. Such agreements underlie most codesharing pacts while also governing alliance pricing in the absence of antitrust immunity. Under a special prorate agreement, each of the two carriers specifies the revenue it requires to carry a passenger along its portion of an interline trip ticketed by the other carrier. The ticketing carrier then sets the overall fare for the trip, recognizing that the required amount must be paid to the collaborating carrier. It is easy to see that this process, which occurs within each fare class, is formally equivalent to the noncooperative choice of subfares, as outlined above.² As a result, the theory suggests that the fares emerging from a special prorate agreement will be higher than those chosen under antitrust immunity. Moreover, because such agreements are bilateral rather than multilateral in nature, the resulting fares are likely to be lower on average than IATA fares. To see this, observe that, under IATA’s unanimity requirement, a low proposed fare can be vetoed by a high-cost carrier, who cannot make a profit using it. By contrast, two cost-efficient carriers with a special prorate agreement, who are not bound by IATA procedures, can exploit their low costs to charge relatively low fares.

It should be noted that, even though outright collaboration in the fare-setting process is not meant to occur in the absence of antitrust immunity, carriers might tacitly cooperate to some degree under the guise of a special prorate agreement. If this happens, then such an agreement may produce fares not much higher than those observed under antitrust immunity.

This discussion suggests that the lowest interline fares will be charged by alliance partners operating with antitrust immunity. Higher fares will be charged by carriers who lack antitrust immunity and rely instead on special prorate agreements. Such carriers include codeshare partners, either allied or nonallied, as well as unimmunized alliance partners who choose not to codeshare. Finally, the highest fares should be observed when all these forms of cooperation (immunity, codesharing, alliance membership) are absent, with the resulting fares corresponding to IATA fares.

3. Empirical Model and Data

To test the above hypotheses, the empirical analysis estimates regression equations that

relate interline fares to measures of airline cooperation and to other explanatory variables. The regressions are of the following form:

$$\text{Fare} = \Psi(\text{Distance, Market Size, Competition, Regional and Directional Effects, Fare Category, Airline-Specific Effects, Cooperation Measures}) \quad (6)$$

This equation is estimated using fare data for individual airline itineraries, as explained above. An itinerary's fare depends on the total distance travelled; on the size of the city-pair market, as measured by endpoint populations (a demand variable); on the level of competition in the market; on the world region containing the non-U.S. endpoint, as well as the direction of travel; on a variable controlling for fare category (business class vs. coach); on airline-specific effects, reflecting operating-cost differences across carriers; and on the cooperation measures discussed above.

The construction of these variables is discussed in section 4 below, but it is helpful to first explain how the data set is generated. The data are drawn from database DB1B of the DOT's Passenger Origin-Destination Survey. This database comes from a quarterly 10 percent sample of all airline tickets where at least one route segment is flown on a U.S. carrier. A record in the database shows an itinerary, which consists of a sequence of airports together with the identities of the carriers providing service from one airport to the next. The operating carrier for each segment is indicated along with the ticketed carrier, allowing codeshare itineraries to be identified. The dollar fare for the itinerary is shown, along with the number of passengers observed paying the given fare during the quarter. While many different fares are observed in thick city-pair markets, only a single fare (perhaps associated with just a single passenger) may be observed in thin markets. The fare class for the itinerary is indicated, and turn-around points in the itinerary are shown by directional breaks, which can be used to identify the destination airport.³

To focus on the months of high international travel, the data are drawn from the third quarter of 1999. For this quarter, the DB1B contains slightly more than 3 million records, and about 750,000 of these represent itineraries involving at least one non-U.S. airport. In order

to focus on common types of interline trips with foreign endpoints, a number of restrictions are applied to this large subsample. First, itineraries must represent round trips, with same starting and ending airports. Second, to avoid trips with multiple destinations, itineraries with more than one directional break are deleted (the break point for the remaining trips identifies the destination). Third, the itinerary’s origin must be inside the U.S. and the destination outside the U.S., or vice versa. Fourth, itineraries with less than 3 or more than 6 route segments are dropped. Two-segment itineraries (with one segment outbound and one inbound) cannot involve interline travel in the sense of Figure 1, and itineraries with 7 or more segments (which are very infrequent in the data) represent complex trips that may involve multiple destinations. Fifth, in order to focus on itineraries that are reasonably symmetric (again limiting the likelihood of multiple stops), only those 4 and 6-segment trips with the same number of outbound and inbound segments (2 and 3, respectively) are selected, and 5-segment trips must have 2 inbound and 3 outbound segments or the reverse. To focus on typical interline travel, the sixth restriction requires that the itinerary’s service is provided by exactly two airlines, with one being a non-U.S. carrier.⁴ Finally, itineraries involving first-class travel are deleted.⁵

The resulting data set has multiple observation for itineraries in thick markets, with each observation corresponding to a different fare. The final step is to collapse this replication by computing a passenger-weighted average fare for each distinct itinerary. Note that itineraries that differ only in their codesharing pattern (with differences appearing only in the identities of ticketed carriers) are treated as distinct under this averaging process. The resulting data set has 54,687 observations, consisting of itineraries in 17,518 different international city-pair markets.

4. Construction of Variables

The log of the average fare for the itinerary, denoted LFARE, is used as the dependent variable for the regressions. The total round-trip distance for the itinerary is computed by summing the segment distances appearing in the DB1B, and it is denoted LDIST. The effect of a greater distance on the fare is obviously positive. Market size is measured by population

potential, denoted POPPOT, which equals the geometric mean of the endpoint populations (with each expressed in thousands).⁶ As seen in the literature, the high demand associated with large city populations tends to raise fares (see, for example, Brueckner and Spiller (1994)).⁷ Dummy variables are included to capture the world region of the non-U.S. endpoint, and they are denoted EUROPE, CENTAMER, CARIBB, SOAMER, AFRICA, MIDEAST, FAREAST, AUSTOCN, and CANADA. The second-to-last dummy represents Australia and Oceania, while the remainder are self-explanatory (Europe is the default region). In addition, a directional dummy variable, USDEST, indicates whether the itinerary’s destination lies in the U.S.

Following BW, airline-specific effects are measured by “carrier variables,” which are generated by interacting airline dummies with distance flown. For example, if the two carriers for an itinerary are United and Lufthansa, then United’s variable is set equal to the log of the distance flown on United, while Lufthansa’s variable is equal to the log of the distance flown on Lufthansa. The carrier variables for all other airlines are set equal to zero for the itinerary (American Airlines is the default carrier, with its variable always set to zero). For computational reasons, individual carrier variables are generated for the 74 carriers that appear most frequently in the data set. The remaining 136 airlines, which are relatively small, are represented by a single carrier variable. Because they are not of direct interest, the coefficients of the carrier variables are not reported below.

The average fare computed for a given itinerary may include both coach and business-class fares. To control for the presence of the costlier business-class trips, the following method is used. First, prior to the fare-averaging computation, the fraction of an itinerary’s route segments that are designated business class is computed. For example, if 2 out of 6 segments are business class, with the remainder coach, this fraction equals 0.33. Then, when the passenger-weighted average fare is computed, the passenger-weighted value of the business-class share is also computed. The resulting variable, denoted BCLASS, represents the passenger-weighted fraction of segments for the given itinerary that are business class.

An additional variable, COUPON, equals the number of ticket coupons for the itinerary (which corresponds to the number of route segments). On the one hand, more circuitous

routings should require a fare discount for the passenger. On the other hand, an itinerary with many coupons may involve intermediate stops, which are likely to raise the overall fare (such stops cannot be identified from the data). Therefore, the predicted effect of COUPON on the fare is ambiguous.

The main focus of the empirical analysis is on the airline cooperation measures. As explained above, these represent codesharing, antitrust immunity, and alliance membership. The presence of codesharing on an itinerary is represented by the dummy variable CODESHR, which takes the value one if the operating and ticketed carriers differ for at least one of the itinerary's route segments, equalling zero otherwise.

The dummy variable ALLY, which measures alliance membership, equals one if the itinerary's two carriers are alliance partners, belonging to one of the four major alliances in existence in the summer of 1999. Using the detailed survey of Gallacher (1999) to precisely identify alliance membership for this period, the relevant alliance groupings are as follows. The WINGS alliance (whose name has not yet been officially adopted) consists of Northwest, KLM, Alitalia, and Continental. The STAR alliance consists of United, Lufthansa, SAS, Air Canada, Varig, Thai Airways, Ansett Australia, and Air New Zealand. The ONEWORLD alliance consists of American, British Airways, Canadian, Qantas, and Cathay Pacific. The ATLANTIC EXCELLENCE alliance consists of Delta, Swissair, Sabena, and Austrian Airlines. Note that later in 1999, Delta withdrew from this alliance, linking instead with Air France.

The dummy variable IMMUNITY, which measures antitrust immunity, equals one if the itinerary's two carriers enjoy antitrust immunity, equalling zero otherwise. The following carrier pairs, all of whom are alliance partners, enjoyed immunity in the third quarter of 1999: Northwest-KLM, United-Lufthansa, United-SAS, United-Air Canada, American-Canadian, Delta-Swissair, Delta-Sabena, and Delta-Austrian. Note that while all of the Atlantic Excellence pairings enjoyed immunity, only a single Oneworld pairing had immunity. Note also that, because a nonzero value for IMMUNITY is associated with a nonzero value for ALLY, these variables have a high correlation coefficient, equal to 0.87.

Antitrust immunity is granted by the DOT, following an advisory recommendation from the U.S. Department of Justice. Immunity is granted to individual carrier pairs and not to

alliances generally, as can be seen from the fact that only three of the STAR alliance pairings enjoy it. Immunity has often been granted as a component of an open skies agreement between the U.S. and the country of the foreign partner airline. Immunity for United-Lufthansa and Northwest-KLM, for example, followed from the open skies agreements with Germany and the Netherlands, respectively. To be effective, U.S. antitrust immunity must be accompanied by similar authority from the foreign government. Although requests for antitrust immunity are usually approved, the case of American-British Airways shows that the immunity issue can be controversial. Their immunity application was denied by the DOT in 1999 on the grounds that collaboration between the carriers would seriously reduce competition on nonstop routes between major cities in the U.S. and the U.K. (see below for further discussion).

A last cooperation variable is computed, using the approach of BW. For each U.S. carrier, a list of all its different codeshare partners (as observed in the data) is created. All carriers on the list are deemed to be alliance partners of the given U.S. carrier, using the BW definition. Then, if an itinerary's two carriers are alliance partners (as defined), the variable `ALLY_BW` is set equal to one, equalling zero otherwise. Because codesharing by carriers may be limited to a subset of the markets they serve, `ALLY_BW` can equal one even when `CODESHR` equals zero.

Finally, the measurement of competition follows an approach similar to that used by BW. The procedure is to return to the large 750,000-record data set of international itineraries, and use the evidence on service patterns in that data to infer all the service that is available for city-pair markets in the smaller regression data set. For example, carriers X and Y may be observed in this larger data set providing interline service that includes the route segments JFK-CDG-BUD-ATH (i.e., New York-Paris-Budapest-Athens). However, a single itinerary for the JFK-BUD city-pair market might be appear in the regression data set, with service provided, say, by carriers W and Z. Looking just at smaller data set, it would appear that no other carriers serve the JFK-BUD market, while X-Y service is in fact available given the information in the large data set.

To exploit such additional information, the procedure looks across all itineraries and subsets of itineraries in the large data set to construct, for each possible international city-pair market

with a U.S. endpoint, a list of carriers providing service in the market. The lists generated consist of carriers providing online (single carrier) service in each market, as well as carrier pairs providing interline service. Service that requires more than two carriers is not counted.

The variable TOTCOMP, which is a total competition measure, is based on a simple count of the number of other airlines competing with the itinerary's carriers in the given city-pair market. Because most competing service is provided by interline carrier pairs, each counted carrier is worth one-half point, a convention that applies also to carriers offering online service. Since online service is more attractive, however, the additional variable ONLNCOMP counts the number of carriers captured in TOTCOMP that provide such service, with each competitor again worth one-half point. The variable ALLYCOMP equals the number of alliance pairs (from among the carriers counted in TOTCOMP) that provide competing interline service in the market, with an alliance pair counted only if both members differ from each of the itinerary's carriers. Each competing alliance pair is worth one point. Note that TOTCOMP always takes the same value for different itineraries in the same city-pair market (equal to total carriers serving the market, minus the itinerary's two carriers, all divided by two). However, the values of ONLNCOMP and ALLYCOMP depend on the identities of the itinerary's carriers, which affect the count of competitors.⁸

The means of the variables, along with their definitions, are presented in Table 1. The average fare in the sample is \$1242, and the average round-trip distance is 10,376 miles. The non-U.S. endpoint of the itinerary lies in Europe for 48.2 percent of the sample, with the Far East and Canada accounting for 13.7 and 12.9 percent of the non-U.S. endpoints, respectively. The passenger-weighted segment share for business class is 4.0 percent, indicating that one out of 25 segments in the sample involve business-class travel. The average number of ticket coupons (segments) is slightly less than five. Codesharing occurs on 40 percent of the sample itineraries, while the carriers on 41.6 percent of the itineraries enjoy antitrust immunity. Alliance partners provide service on 48.3 percent of the itineraries. The carriers on 65.7 percent of the itineraries have a codesharing agreement in some city-pair markets, although not necessarily for the given itinerary (this is the ALLY_BW variable). The average value of TOTCOMP is 3.47, indicating that the number of competing carriers providing either online or interline

service is nearly 7 on average (recall that each counts for one-half). ONLNCOMP averages 1.32, indicating that slightly less than 3 online competitors are present on average, while the average value of 1.22 for ALLYCOMP indicates that the carriers on the typical itinerary face one competing alliance pair.

Table 2 provides evidence on patterns of codesharing in the sample. Among nonalliance itineraries, which account for 51.7 percent of the sample, only 23 percent involve codesharing. The pattern is similar among alliance itineraries where the carriers do not enjoy antitrust immunity. Among such itineraries, which make up 6.6 percent of the sample, 27.7 percent involve codesharing. The codeshare proportion among alliance itineraries where the carriers have immunity is dramatically higher, equal to 63 percent. Thus, codesharing occurs on about a quarter of the itineraries where antitrust immunity is absent (with the carriers allied or nonallied), but it occurs on almost two-thirds of those where immunity is present.

It should be noted that, since carriers with immunity already have the ability to cooperate fully in pricing, a codesharing agreement between them may not indicate a substantial additional element of cooperation. Such an agreement may serve mainly as a marketing device, solidifying the advantage already secured through cooperative pricing and other types of coordination. However, for carriers lacking immunity, especially those who are not alliance partners, the presence of a codesharing agreement may reflect a significant enhancement in cooperation relative to a situation where one does not exist. As seen below, the regression equation can be specified to reflect this difference.

Codesharing patterns within the major alliances also show notable differences. While each of the ATLANTIC EXCELLENCE pairings exhibits a high level of codesharing, which occurs on around 80 percent of their itineraries, two of the ONEWORLD pairings (American-British Airways and American-Cathay Pacific) show no codesharing at all. Codesharing is extensive for Northwest-KLM, the dominant WINGS pairing, occurring on 60 percent of their itineraries, while codesharing for United-Lufthansa, the major STAR pairing, is observed only about 38 percent of the time. Both of the linkups with Canadian carriers (United-Air Canada and American-Canadian) show a high level of codesharing.⁹

Regulatory factors help determine codesharing patterns in the data. In particular, in order

for a U.S. carrier to offer codeshare service to a given country on flights operated by a partner airline, the U.S. carrier must typically have its own route authority to that country (so that, in principle, it could operate its own service). Route authority is, of course, not an obstacle if an open skies agreement exists with the given country. While this restriction partly governs codesharing, the observed patterns are also the result of conscious choices by the carriers. For example, despite formation of the ONEWORLD alliance, American and British Airways chose to not codeshare initially, although this omission was remedied by their recent application for codeshare authority in a host of city-pair markets. This belated request was presumably connected to the denial of the carriers' request for antitrust immunity.

5. Empirical Findings

5.1. Main results

The main empirical results are presented in Table 3. The discussion focuses first on the ordinary-least-squares regressions presented in the first three columns of the Table. Then, attention turns to results from several alternative estimation methods, which are designed to address a number of potential econometric problems, including heteroscedasticity, unobserved heterogeneity, and potential endogeneity of CODESHR.

To begin, consider the results shown in the first column of Table 3, and focus first on the variables other than the cooperation measures, which are discussed below. The significantly positive coefficient of LDIST shows, unsurprisingly, that longer trips have higher fares. Since both distance and the fare are in logs, the coefficient represents an elasticity, indicating that a one percent increase in distance raises the fare by one-third of a percent. POPPOT's significantly positive coefficient shows that fares are higher in markets with large endpoint cities, indicating a positive fare response to high travel demand. The coefficient of BCLASS is also significantly positive, indicating that the fare is high when the itinerary has a high (passenger-weighted) share of business-class segments. The significantly negative coefficient of COUPON shows that, holding distance fixed, greater trip circuitry depresses the fare. Recall that while greater circuitry could impose an inconvenience upon the passenger, requiring compensation with a lower fare, circuitry may alternatively reflect the presence multiple stops, a benefit that

typical raises the cost of a ticket. COUPON's negative coefficient shows that the former effect dominates in the sample, with an extra ticket coupon depressing the fare by 2 percent. Note that since the fare is in log form, the coefficients of the discrete variables such as COUPON give the percentage reduction in the fare associated with a unit increase in the variable. This point also applies to the dummy coefficients.

The regional dummies show that, after netting out the longer distance involved, trips to and from Africa, the Mideast, the Far East, and Australia/Oceania are 30–40 percent more expensive than trips to and from Europe, the default region. Trips to the Caribbean, which represent mostly leisure travel, are 7 percent less expensive. Moreover, trips whose destinations lie in the U.S. are 13 percent cheaper than trips with a U.S. origin.¹⁰

Increasing the number of competing carriers by one, which raises TOTCOMP by 1/2, reduces the fare by about one-half percent ($0.0083/2$). However, if the added carrier provides online service, ONLNCOMP also rises by 1/2, and the fare effect is 0.7 percent larger ($0.0138/2$), for a total effect of about 1.1 percent. This shows a relatively small fare impact from competition, a finding that is consistent with the results of BW. Finally, the insignificant coefficient of ALLYCOMP shows that alliance membership among interline competitors has no effect on the fare.

The coefficients of the cooperation measures in the first regression, CODESHR and IMMUNITY, are of paramount interest, and the results show that both are significantly negative. If an itinerary involves codesharing, then the fare is 7 percent lower on average than in the absence of codesharing. If the itinerary's carriers enjoy antitrust immunity, then the fare is 20 percent lower than in the absence of immunity. Combining these effects, the fare for an itinerary with codesharing where the carriers also enjoy immunity is 27 percent lower than in the absence of both cooperation measures. This finding strongly supports the hypothesis that airline cooperation leads to a reduction in interline fares.¹¹

As noted above, codesharing may signal a substantial increase in cooperation for carriers operating without antitrust immunity. But for carriers that enjoy immunity, codesharing may not significantly enhance the level of cooperation, which is already high. This suggests that the effect of codesharing on fares should depend on whether or not antitrust immunity is

present. To capture this possibility, an interaction variable equal to CODESHR*IMMUNITY is introduced into the regression, with variable denoted INTERACT. Then, the relevant portion of the regression equation's RHS can be written $\alpha * \text{CODESHR} + \beta * \text{IMMUNITY} + \gamma * \text{INTERACT}$, where α , β and γ are the coefficients. In the absence of immunity, the effect of codesharing on LFARE is equal to $\alpha < 0$, while its effect in the presence of immunity is given by $\alpha + \gamma$. If $\gamma > 0$ holds, then the second effect is less negative than the first, as hypothesized.

The same argument suggests that the effect of antitrust immunity should depend on whether codesharing occurs. In other words, if codesharing is present, then the added cooperation from immunity is likely to be smaller (and the fare effect less pronounced) than if codesharing were absent. From above, the fare impact of immunity in the presence of codesharing is given by $\beta + \gamma$, while the impact in its absence is equal to β , a larger absolute effect when $\gamma > 0$.

The second column of Table 2 gives the results when INTERACT is added to the regression. The effect on the non-cooperation coefficients is negligible. But as hypothesized, INTERACT's coefficient is positive and significant, indicating that the fare impact of codesharing is less pronounced when antitrust immunity is present. Without immunity, codesharing reduces the fare by approximately 10 percent (-0.0968). But when immunity is present, codesharing lowers the fare by only an additional 5 percent ($-0.0968 + 0.0504$). Conversely, immunity reduces the fare by 21 percent in the absence of codesharing, but only reduces it by 16 percent ($-0.2146 + 0.0504$) if codesharing is already present.¹² Thus, the two types of cooperation, codesharing and immunity, are substitutes in the sense that their combined effect is smaller than the sum of their partial effects. This combined effect equals 26 percent ($-0.0968 - 0.2146 + 0.0504$), while the sum of the partial effects corresponds only to the first two terms. Note that this combined effect is almost the same as the combined 27 percent effect from the regression without INTERACT.

As seen in Table 2, the sample contains relatively few alliance itineraries where the carriers do not enjoy antitrust immunity. Despite this deficiency, it is possible to identify the separate effects of immunity and alliance membership on fares, as seen in the third regression in Table 3. This regression, which includes ALLY but not INTERACT, yields virtually the same

CODESHR coefficient as the first regression. In addition, the estimates show that alliance membership reduces the fare by 4 percent and that immunity leads to a further 16 percent reduction, yielding a total impact that matches the 20 percent immunity effect seen in the first column. This decomposition shows that, when used by itself, the immunity variable captures the combined effects of alliance membership and antitrust immunity. The regressions reported below maintain this approach, with ALLY not appearing and IMMUNITY representing both antitrust immunity and alliance membership. The reason for this approach is that the coefficient of ALLY is often insignificant in these equations, indicating that a separate effect of alliance membership cannot be identified.¹³

5.2. Addressing potential econometric problems

The OLS regressions in Table 3 are subject to a number of potential problems that may affect the estimates. First, because the original itineraries have different numbers of passengers, the passenger-weighted averaging that generates the sample fares may lead to a heteroscedastic error term for the regression, which biases the standard errors of the estimated coefficients.¹⁴ The remedy is to estimate a passenger-weighted regression, and the results of doing so are shown in the fourth column of Table 3. As can be seen, the results (which include INTERACT) are very close to those in the second column.

Another potential problem is unobserved market-level heterogeneity. Because the regression includes relatively few variables measured at the level of the city-pair market, many market characteristics that may affect fares are implicitly relegated to the error term in the equation. Correlation between the included right-hand variables and these omitted characteristics may lead to biased coefficient estimates. The remedy is to estimate a fixed-effects regression, which gathers the effects of the omitted variables in a market-specific intercept term. These intercepts are suppressed in the estimation by expressing all variables as differences from the city-pair-market means. A drawback is that the fixed-effects estimates rely only on observations from the 8,236 markets from among the total of 17,518 where more than one itinerary is observed (the total of such observations equals 45,405).

The fixed-effects results are shown in the fifth column of Table 3, with estimates absent for those variables that are constant within a city-pair market. The estimated coefficients for

CODESHR, IMMUNITY and INTERACT are virtually identical to those in column 2, showing that unobserved heterogeneity is not a source of bias in the main coefficients of interest. The coefficients of BCLASS and COUPON change slightly, while LDIST's coefficient drops dramatically, reflecting the difficulty of precisely estimating a distance effect with the limited intra-market variation in this variable (this variation arises solely through different routings between the endpoints).

The notable changes in the equation are the substantial increases in the competition coefficients.¹⁵ The estimates show that, holding TOTCOMP fixed, converting an interline competitor into an online competitor (i.e., raising ONLNCOMP by 1/2) reduces the fare by 1.85 (3.7/2) percent. Converting a nonallied interline pair into an alliance pair (raising ALLYCOMP by one) reduces the fare by 3.5 percent. Both effects are much stronger than those in column two. This change suggests that the competition variables are positively correlated with unobserved market characteristics that are associated with high fares. Such correlation makes sense given that carriers will be eager to offer service in markets whose attractions allow high fares to be charged. This correlation distorts the measured the effect of competition in column 2, and controlling for it via fixed effects generates a larger competitive impact.¹⁶

A third econometric problem is potential endogeneity of CODESHR. As seen in Table 2, even when a given carrier pair engages in extensive codesharing, the carriers do not codeshare in each and every market they serve. As a result, the presence of codesharing is likely to depend on market characteristics, making CODESHR an endogenous variable. To understand the implications of such endogeneity, it is helpful to formalize a model where fares and codesharing are jointly determined. Let f_i represent the log fare for observation i , and let c_i represent the CODESHR dummy. In addition, let x_i denote the vector of variables other than c_i that help determine fares, and let z_i denote the vector of variables that influence the codesharing decision. Then the model can be written as

$$f_i = \rho c_i + \theta' x_i + u_i \tag{7}$$

$$c_i^* = \delta' z_i + v_i \tag{8}$$

$$c_i = 1 \text{ if } c_i^* > 0; \quad c_i = 0 \text{ otherwise.} \tag{9}$$

In (8), c_i^* is a latent variable whose value determines whether codesharing occurs, ρ , θ and γ represent coefficients, and u_i and v_i are normal error terms with mean zero, unit variance, and covariance σ_{uv} . The expected value of f_i when $c_i = 1$ is given by $\rho + \theta'x_i + \sigma_{uv}\phi(\delta'z_i)/\Phi(\delta'z_i)$, where ϕ and Φ are the standard normal density and cumulative distribution functions, respectively (see Maddala (1983)). Similarly, the expected value of f_i when $c_i = 0$ is given by $\theta'x_i - \sigma_{uv}\phi(\delta'z_i)/[1 - \Phi(\delta'z_i)]$. Thus, the expected value of f_i can be written as $\rho c_i + \delta'x_i + \sigma_{uv}\lambda_i$, where λ_i is the Mills ratio, given by

$$\lambda_i = \begin{cases} \phi(\delta'z_i)/\Phi(\delta'z_i) & \text{if } c_i = 1 \\ -\phi(\delta'z_i)/[1 - \Phi(\delta'z_i)] & \text{if } c_i = 0 \end{cases} \quad (10)$$

Consistent estimates of ρ and θ can then be obtained in a regression that includes the Mills ratio along with c_i and x_i . Estimation uses predicted values of the ratio, which are generated from a probit regression based on (8) and (9). Consistent estimates can also be generated by two-stage least squares, where the fitted probabilities from the probit are substituted in place of c_i in (7), with OLS then run. However, results from the first method are reported.¹⁷

Note that if σ_{uv} is nonzero, then c_i is correlated with the error term in a regression where the Mills ratio is not included among the right-hand variables (the error term then contains $\sigma_{uv}\lambda_i$). This correlation, which is positive when $\sigma_{uv} > 0$ and negative otherwise (see (10)), leads to biased coefficient estimates. The bias vanishes, of course, if $\sigma_{uv} = 0$.

The probit model of the codesharing decision includes LDIST, POPPOT, COUPON, the regional and directional dummies, and the competition measures as right-hand variables. The instrument chosen to help explain codesharing is the ALLY-BW dummy, which equals one if an itinerary's carriers codeshare in *some* markets (but not necessarily on the given itinerary). This variable should be strong predictor of whether the carriers codeshare on any particular itinerary.¹⁸

The probit results are shown in Table 4. As expected, ALLY-BW has a positive coefficient that is strongly significant. In addition, the results show that codesharing is more likely on long-distance itineraries between large cities, but that, holding distance constant, additional ticket coupons reduce the likelihood that codesharing occurs. Codesharing is less likely on trips

with a U.S. destination, and it tends to be less likely when the non-U.S. endpoint is outside of Europe (exceptions are Central American and Caribbean endpoints). While greater online competition increases the likelihood of codesharing, as intuition would suggest, an increase in TOTCOMP makes codesharing less likely. An explanation for the latter effect is not apparent.

The results of a second-stage regression that includes the fitted Mills ratio among the right-hand variables are given in the last column of Table 3. INTERACT, which is based on the CODESHR variable, is also included since the estimation method remains appropriate in its presence. The estimated coefficients for the non-cooperation variables show little change relative to the results in the second column of the Table. However, the coefficients of CODESHR and IMMUNITY change substantially. Now, the partial effect of codesharing is to reduce fares by almost 17 (as opposed to 7) percent, while the partial effect of immunity is to lower fares by 15 (rather than 20) percent. The INTERACT coefficient (which is marginally significant) falls to 0.02, indicating that the combined effect of codesharing and immunity is 2 percent smaller than the sum of the partial effects. The combined effect leads to a fare reduction of 30 percent, which is 4 percent larger than the 26 percent effect from column two. The results also imply that the additional fare reduction from codesharing when immunity is already present is almost 15 percent, much larger than 5 percent effect in column two.

To see the reason for these changes, observe that the estimated coefficient of LAMBDA is significantly positive. Recalling that LAMBDA's coefficient equals σ_{uv} , its positive sign indicates that the error terms in the fare and codeshare equations, (7) and (8), are positively correlated, suggesting that unobserved factors causing fares to be high in a city-pair market also make codesharing more likely. Given the above discussion, a positive σ_{uv} implies that CODESHR is positively correlated with the error term in the second-column regression, causing both its coefficient and the coefficient of INTERACT to be upward biased. Eliminating this bias makes CODESHR's coefficient more negative and INTERACT's coefficient less positive, as seen in the results from Table 3. Even though the resulting coefficient changes do not substantially alter the combined effect of codesharing and immunity, the new estimates suggest that codesharing accounts for the majority (rather than a minority) of this combined effect.

5.3. Results for subsamples

It is interesting to see if the preceding results are robust across subsamples. The most important subsample, which accounts for almost half of the total, consists of itineraries where the non-U.S. endpoint lies in Europe. The first three columns of Table 5 show the regression results for the European subsample. Among the coefficients of the non-cooperation variables, notable changes common to all three columns include absolute increases in the coefficients of TOTCOMP and ONLNCOMP, which suggest that competition reduces fares more effectively for travel to and from Europe than in the full sample. In addition, the fare discount for travel to a U.S. destination doubles to 26 percent.

Comparing the European coefficients of CODESHR and IMMUNITY to the analogous estimates in Table 3, all the absolute magnitudes are smaller. In the two regressions containing INTERACT (second and third columns), CODESHR's coefficients show a partial effect in the 8–9 percent range instead of the 10–17 percent magnitudes seen in Table 3. IMMUNITY's coefficients show a partial effect of 13–14 percent, in contrast to the 15–21 percent magnitudes from Table 3. With the coefficient of INTERACT near 0.04 in both regressions, the combined effect of codesharing and antitrust immunity is 17–18 percent rather than the previous 26–30 percent. Finally, the additional fare reduction from codesharing when immunity is already present is also smaller, lying in the 3–5 percent range.¹⁹ Despite these differences, the European results give the same overall message as those in Table 3, namely that airline cooperation reduces interline fares. However, the magnitudes of the effects are somewhat smaller than in the full sample.

A noteworthy feature of the European results is that the two-stage estimates in the third column of Table 5 are not much different from the OLS estimates in column two.²⁰ The reason for this outcome, which differs from that in the full sample, can be seen in the now-insignificant coefficient estimate for LAMBDA. Recall that if this coefficient is zero, indicating $\sigma_{uv} = 0$, then the OLS coefficients are unbiased. In this case, the two-stage and OLS results should be similar.

The last three columns of Table 5 show results when the sample is restricted so that one or both endpoints lie “behind” the international gateway airports. The fourth column shows the

results when sample is restricted to include only those itineraries whose U.S. endpoint is not an international gateway, lacking nonstop service to any foreign airport. The resulting sample contains 15,516 itineraries. The fifth column shows the results when the sample is restricted to include only those itineraries where the non-U.S. endpoint has no nonstop service to the U.S. Non-U.S. gateways with direct U.S. connections are thus excluded, yielding a sample of 18,635 itineraries. The last column shows the results when both restrictions are applied, yielding a subsample of 4,384 itineraries where both endpoints lie behind the gateway airports. For each subsample, results for the basic OLS model without INTERACT are presented.²¹

In the fourth column, notable changes in the non-cooperation variables include a decline in the U.S. destination discount to 8 percent, which may reflect the relatively high cost of serving small U.S. endpoints behind the gateways. The effect of TOTCOMP rises, while the impact of online competition disappears, perhaps reflecting the lesser availability of such service. The cooperation coefficients are similar to those in the first column, although the impact of codesharing falls while that of immunity rises. In column five, the strong U.S.-destination discount reappears, the CODESHR coefficient drops further below the column-one value, and the IMMUNITY coefficient returns to its value in column one. In the last column, where both endpoints are behind the gateways, all the competition coefficients become insignificant, as does the coefficient for CODESHR. The IMMUNITY coefficient, however, remains significant, but its magnitude is lower than in the other samples, indicating a 10 percent fare reduction from antitrust immunity. Although the reason for the disappearance of the codesharing effect is not clear, it could be a result of the dramatically smaller sample size.

Overall, the subsample results continue to show the beneficial effects of airline cooperation on interline fares, although the sizes of the effects are muted relative to the full sample. By establishing that this key empirical regularity is quite robust across different samples, the results provide further support for the maintained hypothesis that cooperation leads to lower fares.

6. Conclusion

This paper has explored the effect of airline cooperation on the level of interline fares paid

by international passengers. The analysis focuses on two measures of cooperation: codesharing and antitrust immunity. The results show that the partial effects of codesharing and immunity are both negative. The presence of codesharing on an international interline itinerary reduces the fare by 8–17 percent, with the exact number depending on the sample used and the estimation method.²² Moreover, the presence of antitrust immunity reduces the fare by 13–21 percent. Codesharing and immunity are substitutes, however, in the sense that their combined effect is smaller than the sum of their partial effects. Recognizing this difference, which is captured by an interaction variable in the regressions, the combined effect ranges between 17 and 30 percent. These results provide strong evidence that airline cooperation in the fare-setting process generates substantial benefits for interline passengers.

One aspect of the results that is perhaps surprising concerns the magnitude of the additional fare impact of codesharing when antitrust immunity is already present. Because immunity facilitates full cooperation, the extra cooperative gains from codesharing would appear to be modest. However, the results show that, when immunity is already present, codesharing reduces fares by an additional 3–15 percent. One explanation for such a potentially large effect lies in the complex pricing problem faced by carriers operating with antitrust immunity, who must set joint fares in thousands of international markets without the benefit of a common yield management system. It is possible that, faced with such a task, carriers devote most of their effort to setting fares for codeshare itineraries, which then exhibit a price discount relative to non-codeshare trips. Further exploration of this issue is needed, however.

As noted in the introduction, the results of the paper are relevant to regulatory policy. The estimates show that, when the DOT grants antitrust immunity, substantial benefits arise for an alliance’s interline passengers. Using the estimates from the third column of Table 3, Brueckner (2000) offers some illustrative calculations that indicate the magnitude of such benefits for STAR alliance passengers, providing a gauge of the potential welfare impact of the DOT’s regulatory power. To measure benefits from existing immunity, the approach is to compute the consumer-surplus loss from withdrawal of immunity, which arises because of higher interline fares. This loss is computed for each market served by the immunized STAR partners (United-Lufthansa, United-Air Canada, and United-SAS) under several assumed values of the

demand elasticity, and the losses are summed across markets. This calculation shows that the aggregate loss from withdrawal of immunity ranges between \$17 and \$22 million per quarter, suggesting that the annual gain to the STAR alliance's interline passengers from the presence of immunity is on the order of \$80 million per year. A similar calculation shows the surplus gain from extension of immunity to those STAR partners that did not enjoy it as of the summer of 1999 (see Table 2 for a list). This surplus gain, which again applies to interline passengers, is on the order of \$20 million per year.

A final point concerns the impact of airline cooperation on fares for a different type of itinerary than the one considered in the present paper. This is an itinerary involving nonstop travel on a single carrier between international gateway airports. On such routes, alliance partners often provide overlapping service, and in this situation, cooperation may result in collusive behavior, which leads to a higher rather than a lower fare. This outcome contrasts with the interline case, where the pursuit of higher profit leads cooperating carriers to reduce the fare. BW studied gateway fares using 1997 data, and they failed to find a statistically significant fare increase from overlapping alliance service in these city-pair markets. However, such an anticompetitive effect remains a concern of regulators, especially in evaluating requests for antitrust immunity, and it provides a potential counterweight to the substantial benefits enjoyed by interline passengers as a result of airline cooperation.

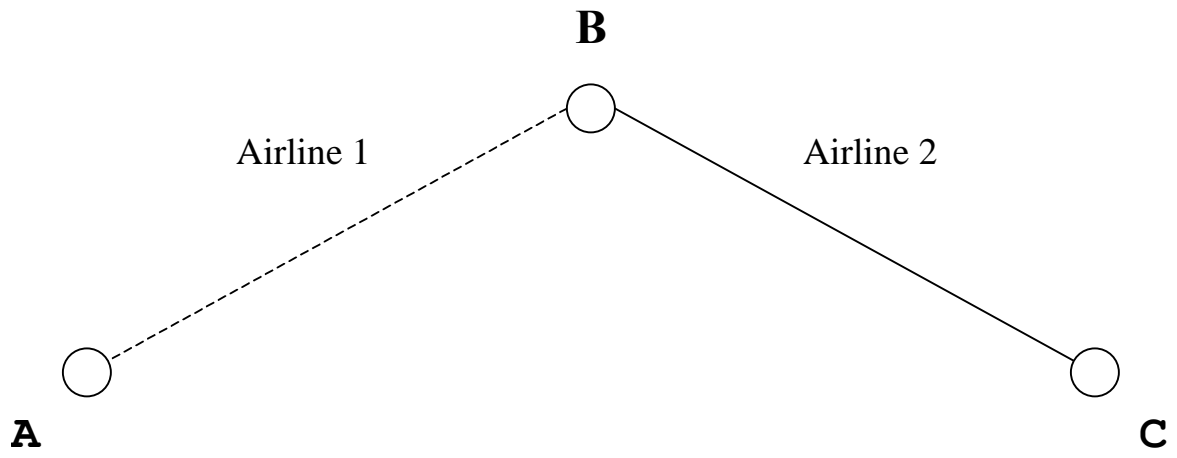


Figure 1.
Interline Route

Table 1.
Variable Definitions and Means

<u>Variable</u>	<u>Mean</u>	<u>Definition</u>
FARE	\$1,242	Round-trip fare
DIST	10,376	Round-trip distance in miles
POPPOT	1,280	Population potential, equal to geometric mean of itinerary's endpoint populations
CENTAMER	0.064	–
CARRIB	0.024	–
SOAMER	0.046	–
EUROPE	0.482	–
AFRICA	0.036	Regional dummies
MIDEAST	0.046	–
FAREAST	0.137	–
AUSTOCN	0.037	–
CANADA	0.129	–
USDEST	0.466	U.S. destination dummy
BCLASS	0.040	Passenger-weighted fraction of business-class segments for itinerary
COUPON	4.83	Number of ticket coupons
CODESHR	0.400	Codeshare dummy, equal to one if itinerary has at least one codeshare segment
IMMUNITY	0.416	Immunity dummy, equal to one if itinerary's carriers enjoy antitrust immunity
ALLY	0.483	Alliance dummy, equal to one if itinerary's carriers are formal alliance partners
ALLY_BW	0.657	Brueckner-Whalen alliance dummy, equal to one if itinerary's carriers codeshare in some markets
TOTCOMP	3.47	Total competition measure, equal to count of other carriers providing interline or online service in market (each worth 1/2)
ONLNCOMP	1.32	Online competition measure, equal to count of other carriers providing online service in market (each worth 1/2)
ALLYCOMP	1.22	Alliance competition measure, equal to count of alliance pairs providing service in market (each pair worth 1)

Table 2.
Codesharing Patterns

<u>Itinerary Type</u>	<u># Itineraries</u>	<u>[% Total]</u>	<u>% Codeshare</u>
Nonalliance	28,294	[51.7]	23.0
Alliance w/o Immunity	3,615	[6.6]	27.7
Alliance with Immunity	22,778	[41.6]	63.0
WINGS	8,085	[14.8]	60.6
Northwest-KLM*	7,671		60.3
Northwest-Alitalia	9		0
Continental-KLM	36		0
Continental-Alitalia	369		74.0
STAR	10,116	[18.5]	48.3
United-Lufthansa*	4,771		37.7
United-Air Canada*	3,575		67.0
United-SAS*	642		34.9
United-Air New Zealand	390		36.2
United-Ansett Australia	334		73.1
United-Varig	253		28.5
United-Thai	151		6.0
ONEWORLD	4,664	[8.5]	57.5
American-Canadian*	2,591		93.4
American-British Airways	1,412		0
American-Qantas	458		57.4
American-Cathay Pacific	203		0
ATLANTIC EXCELLENCE	3,528	[6.5]	81.8
Delta-Swissair*	1,683		77.2
Delta-Sabena*	1,511		86.9
Delta-Austrian*	379		81.8

*Carriers have antitrust immunity

Table 3.
Main Regression Results

Variable	OLS		OLS		OLS		Weighted		Fixed Effects		Two-Stage	
INTERCEPT	3.9039	(53.7)	3.8999	(53.7)	3.9101	(53.8)	3.6244	(51.3)	–		3.8814	(53.3)
LDIST	0.3355	(39.8)	0.3356	(39.8)	0.3362	(39.9)	0.3738	(45.4)	0.0722	(2.0)	0.3382	(40.0)
POPPOT	8.72 E–6	(4.4)	9.01 E–6	(4.6)	8.86 E–6	(4.4)	1.04 E–5	(5.9)	–		1.00 E–5	(5.0)
BCLASS	1.4138	(130.0)	1.4142	(130.1)	1.4127	(129.9)	1.4606	(124.3)	1.3742	(108.3)	1.4134	(130.1)
COUPON	–0.0204	(8.8)	–0.0207	(8.9)	–0.0203	(8.7)	–0.0240	(10.5)	–0.0322	(8.6)	–0.0212	(9.1)
CODESHR	–0.0689	(14.5)	–0.0968	(13.7)	–0.0672	(14.1)	–0.0973	(14.5)	–0.0934	(10.8)	–0.1663	(13.7)
IMMUNITY	–0.1990	(19.5)	–0.2146	(20.2)	–0.1616	(10.9)	–0.2125	(18.9)	–0.2061	(14.9)	–0.1520	(11.0)
INTERACT	–		0.0504	(5.3)	–		0.0559	(6.1)	0.0536	(4.8)	0.0195	(1.9)
ALLY	–		–		–0.0407	(3.5)	–		–		–	
TOTCOMP	–0.0083	(5.1)	–0.0083	(5.1)	–0.0083	(5.1)	–0.0073	(4.8)	–		–0.0094	(5.7)
ONLNCOMP	–0.0138	(5.6)	–0.0137	(5.6)	–0.0138	(5.6)	–0.0182	(7.9)	–0.0372	(3.2)	–0.0116	(4.7)
ALLYCOMP	–0.0004	(0.2)	–0.0002	(0.1)	–0.0001	(0.0)	0.0020	(1.0)	–0.0348	(6.9)	0.0002	(0.1)
USDEST	–0.1312	(34.5)	–0.1306	(34.3)	–0.1308	(34.4)	–0.1276	(34.8)	–0.0988	(21.5)	–0.1327	(34.7)
CENTAMER	–0.0301	(1.0)	–0.0326	(1.1)	–0.0344	(1.2)	0.0187	(0.6)	–		–0.0311	(1.0)
CARIBB	–0.0727	(2.4)	–0.0735	(2.4)	–0.0758	(2.5)	–0.0286	(0.9)	–		–0.0815	(2.7)
SOAMER	–0.0283	(1.4)	–0.0294	(1.4)	–0.0307	(1.5)	–0.0137	(0.6)	–		–0.0362	(1.8)
AFRICA	0.4047	(32.4)	0.4050	(32.4)	0.4054	(32.4)	0.3988	(33.1)	–		0.3966	(31.5)
MIDEAST	0.3671	(32.6)	0.3680	(32.7)	0.3679	(32.7)	0.3835	(33.8)	–		0.3589	(31.6)
FAREAST	0.3056	(24.3)	0.3048	(24.2)	0.3060	(24.3)	0.3371	(28.7)	–		0.2858	(22.2)
AUSTOCN	0.2785	(10.8)	0.2802	(10.8)	0.2799	(10.8)	0.3319	(13.5)	–		0.2723	(10.5)
CANADA	–0.0090	(0.4)	–0.0113	(0.5)	–0.0110	(0.5)	0.0165	(0.8)	–		0.0035	(0.1)
LAMBDA	–		–		–		–		–		0.0613	(7.1)
R ²	0.5443		0.5446		0.5444		0.5784		–		–	

Dependent variable is LFARE; absolute t-statistics in parentheses; regressions include carrier variables; observations=54,687.

Table 4.
Probit Results

<u>Variable</u>	<u>Coefficient</u>
INTERCEPT	−3.7448 (13.5)
LDIST	0.1278 (4.1)
POPPOT	4.54 E−4 (6.3)
COUPON	−0.0170 (2.0)
ALLY_BW	2.9667 (65.0)
TOTCOMP	−0.0317 (5.3)
ONLNCOMP	0.0644 (7.3)
ALLYCOMP	0.0103 (1.4)
USDEST	−0.1109 (8.1)
CENTAMER	0.1445 (3.5)
CARIBB	0.1495 (2.1)
SOAMER	−0.3271 (6.9)
AFRICA	−0.3062 (8.2)
MIDEAST	−0.3280 (9.2)
FAREAST	−0.7922 (25.2)
AUSTOCN	−0.2930 (7.5)
CANADA	0.5241 (13.6)

Dependent variable is CODESHR; absolute z-statistics in parentheses;
observations=54,687.

Fraction of observations correctly classified: 66% for CODESHR=0,
90% for CODESHR=1.

Table 5.
Results for Subsamples

<u>Variable</u>	<u>OLS/Europe</u>	<u>OLS/Europe</u>	<u>Two-Stage/Europe</u>	<u>OLS/Behind-U.S.</u>	<u>OLS/Bhd-non-U.S.</u>	<u>OLS/Behind Both</u>
INTERCEPT	3.7320 (23.3)	3.7280 (23.3)	3.7291 (23.3)	4.0933 (29.9)	2.7931 (18.3)	2.3730 (6.5)
LDIST	0.3656 (19.8)	0.3656 (19.8)	0.3654 (19.9)	0.3231 (20.7)	0.4510 (25.6)	0.5046 (12.6)
POPPOT	5.35 E−6 (1.5)	5.30 E−6 (1.4)	5.16 E−6 (1.4)	6.54 E−6 (0.9)	−1.57 E−5 (3.5)	−1.03 E−4 (5.4)
BCLASS	1.6589 (111.6)	1.6592 (111.6)	1.6592 (111.7)	1.4013 (61.5)	1.3776 (80.1)	1.3334 (36.4)
COUPON	−0.0464 (14.0)	−0.0465 (14.0)	−0.0465 (14.0)	−0.0040 (0.8)	−0.0278 (6.8)	0.0004 (0.0)
CODESHR	−0.0629 (10.0)	−0.0884 (8.0)	−0.0766 (3.5)	−0.0539 (6.0)	−0.0374 (4.7)	−0.0107 (0.6)
IMMUNITY	−0.1260 (8.9)	−0.1290 (9.1)	−0.1403 (6.1)	−0.1674 (9.0)	−0.1271 (7.5)	−0.0956 (3.0)
INTERACT	−	0.0374 (2.8)	0.0422 (2.7)	−	−	−
TOTCOMP	−0.0105 (4.6)	−0.0105 (4.6)	−0.0104 (4.5)	−0.0236 (5.2)	−0.0166 (5.7)	−0.0067 (0.8)
ONLNCOMP	−0.0244 (7.4)	−0.0240 (7.3)	−0.0244 (7.3)	0.0041 (0.6)	−0.0013 (0.2)	−0.0644 (1.6)
ALLYCOMP	−0.0027 (1.0)	−0.0026 (1.0)	−0.0026 (1.0)	0.0009 (0.2)	0.0112 (2.7)	−0.0113 (0.8)
USDEST	−0.2628 (49.7)	−0.2623 (49.6)	−0.2613 (47.5)	−0.0767 (10.7)	−0.1950 (30.2)	−0.1741 (13.2)
CENTAMER	−	−	−	0.0055 (0.1)	0.1728 (3.2)	0.1822 (1.9)
CARIBB	−	−	−	−0.1451 (2.2)	0.1856 (2.6)	0.1079 (0.5)
SOAMER	−	−	−	−0.0364 (0.8)	0.0132 (0.4)	0.1201 (1.5)
AFRICA	−	−	−	0.4079 (17.4)	0.4410 (25.2)	0.4480 (13.0)
MIDEAST	−	−	−	0.3706 (16.8)	0.3728 (24.0)	0.3454 (11.4)
FAREAST	−	−	−	0.2654 (9.8)	0.2858 (16.9)	0.2123 (5.4)
AUSTOCN	−	−	−	0.3066 (4.8)	0.3917 (11.3)	0.4320 (4.9)
CANADA	−	−	−	−0.1226 (2.7)	0.3075 (5.1)	0.2636 (2.2)
LAMBDA	−	−	−0.0102 (0.6)	−	−	−
R²	0.4138	0.4140	−	0.5278	0.5519	0.5361
Observations	26,357	26,357	26,357	15,516	18,635	4,384

Dependent variable is LFARE; absolute t-statistics in parentheses; regressions include carrier variables.

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Footnotes

*This paper makes use of an empirical framework developed jointly by Tom Whalen and myself in previous work (Brueckner and Whalen (1998)). As a result, Whalen is effectively a coauthor of this paper even though his name is not explicitly listed. I also thank him for many helpful discussions while the present work was carried out. George Deltas also provided useful comments.

¹In this case, the cost of carrying passengers between cities A and C would depend on traffic levels in markets AB and BC, so that fare decisions become interlinked. For analysis of this case, see Brueckner (1997) and BW.

²In choosing the overall fare, the selling carrier effectively is selecting its subfare, which equals the overall fare minus the amount paid to the other carrier.

³In multiple-airport cities, each airport is treated as a distinct destination. Therefore, the city-pair markets referred to in the discussion in fact correspond to airport pairs. This approach follows the literature.

⁴In many cases, U.S. commuter airlines are listed in the data according to their own airline code rather than under the code of the major carrier they serve. In these cases, the commuters are reassigned the major carrier's code. In addition, a handful of itineraries are dropped because of an odd codesharing pattern, where the ticketed carrier for one or more segments is different from both the operating carriers for the itinerary.

⁵Itineraries with fares below \$100 are also deleted. These may represent frequent-flier award trips or discounted trips by airline employees.

⁶City populations are drawn from the U.S. Census and from the *Rand McNally World Atlas* and *Cities of the World*. See BW for further information.

⁷Brueckner and Spiller (1994) also use the income levels at the endpoints as a measure of demand, but city-level incomes for foreign cities are not easily obtained.

⁸The minimum values of these variables are all zero, while the maximum values are 17.5, 11, and 11 for TOTCOMP, ONLNCOMP, and ALLYCOMP, respectively. Alternative versions of ONLNCOMP and ALLYCOMP were also computed in order to adjust for alliance overlap. For example, if an online competitor belongs to the same alliance as one of the itinerary's carriers, then the competition it offers may be lessened. Adjustment of the competition

measures to account for such effects had little impact on the results.

⁹It should be noted that if the codeshare percentages in Table 2, which are computed with all itineraries counted equally, are recomputed with each itinerary weighted by its passenger total, the results are largely unchanged. Most of the codeshare numbers rise by a percentage point or two, but the general pattern in the table is unaffected.

¹⁰This directional differential could reflect price discrimination on the part of the airlines. With lower incomes outside the U.S. leading to more elastic travel demands, price discrimination would generate a fare discount for trips with non-U.S. origins.

¹¹A similar conclusion emerges if BW's cooperation variable, `ALLY_BW`, is used in place of `CODESHR` and `IMMUNITY`. A positive value of `ALLY_BW` is associated with a fare reduction of 11 percent. This impact is substantial but notably smaller than the 25 percent reduction estimated by BW using 1997 data.

¹²Both this effect and the analogous effect for codesharing are significantly different from zero. The same conclusion applies to the combined effect discussed below.

¹³It is interesting to note the connection between codesharing and alliances, on the one hand, and business-class travel on the other. While the mean of `BCLASS` for alliance itineraries is 0.037, the mean for nonalliance itineraries is 0.046. Similarly, the `BCLASS` means for codeshare and noncodeshare itineraries are 0.029 and 0.047, respectively. Evidently, business class passengers are less attracted to alliance and codeshare travel, perhaps because they are less fare-sensitive. Further insight comes from including another interaction variable in the regression, equal to `BCLASS*IMMUNITY`. This variable has a significantly positive coefficient, indicating that the fare reduction associated with antitrust immunity is smaller for business-class than for coach tickets. To avoid greatly complicating the empirical model, this variable is left out of the main specification.

¹⁴After passenger weighting, total passengers per itinerary ranges from 1 to 1016, with a mean of 1.6.

¹⁵Recall that online and alliance competition varies across the itineraries within a city-pair market as carrier identities change.

¹⁶The fact that the fixed-effects estimates come from the subsample of city-pair markets with more than one itinerary does not explain this difference in results. OLS results for this subsample (including the competition coefficients) are nearly identical to those in column two.

¹⁷The estimation is carried out using LIMDEP version 7.0, which generates appropriate corrections for the coefficient standard errors.

¹⁸The regulatory factors mentioned above are not fully taken into account in the probit equation, as follows. Recall that in order for a U.S. carrier to offer codeshare service to a given country, the U.S. carrier must typically have its own route authority to that country. Incorporating such restrictions into the probit equation is impractical, however, because doing so would require worldwide route authority information for each U.S. carrier (such information would be used to create a dummy variable indicating the feasibility of codesharing for each itinerary). In addition, because bilateral agreements do not always impose the route-authority condition for codesharing, use of such a variable would not be strictly correct in some cases. Alternatively, a dummy variable indicating that the non-U.S. endpoint lies in an open-skies country can be included in the equation to capture the absence of restrictions on codesharing to such countries. When this is done, however, the variable's coefficient has the incorrect sign, indicating that codesharing is *less* likely on interline itineraries to and from open-skies countries (an explanation for this result is not apparent). Although the effect of route authority on codesharing is thus not directly measured in the probit equation, its impact should be captured in part by the regional dummy variables.

¹⁹This effect is significantly different from zero, a conclusion that also applies to the analogous effect of immunity and to the combined effect.

²⁰The underlying probit results for the European subsample, which are similar to those in Table 4, are not reported.

²¹Gateways are identified using the DOT's T-100 database, which shows all nonstop routes between U.S. and foreign airports.

²²These numbers are based on the results from the full sample and the European subsample.