THE PRICE-INCREASING EFFECTS OF DOMESTIC CODE-SHARING AGREEMENTS FOR NON-STOP AIRLINE ROUTES

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ABSTRACT
This article assesses the impact of domestic code-sharing agreements on prices of non-stop flights in the United States. The article finds a positive and significant correlation between code-sharing agreements and the level of airfares, and considers this to be the outcome of two anticompetitive effects: (1) a “round table” effect, produced when the exchange of commercially sensitive information among code-sharing partners facilitates coordination and collusion; and (2) a “double marginalization” effect, produced when carriers use code sharing to add a mark-up over their marginal costs. The article identifies an increase in airfares charged by code-sharing partners of more than 5 percent attributable to the “round table” effect. On top of this, the article finds further price hikes attributable to the “double marginalization” effect: ticketing carriers involved in code-sharing flights charge fares more than 4 percent higher than fares set by their code-sharing partner and almost 10 percent higher than other airlines in the same market.

JEL: L41; L93; K21

I. INTRODUCTION
A code-sharing agreement (CSA) is a marketing arrangement among two or more airlines whereby one or more carriers (ticketing carriers) sell tickets on a flight that is operated by a different carrier (operating carrier).¹ This sort of agreement represents one of the most basic forms of cooperation among airlines. At times, such cooperation may trigger cost efficiencies and enable


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additional flights and destinations, by allowing carriers to exploit economies of traffic density without additional investment.2

Nevertheless, from a competition law perspective, code sharing is an agreement between competitors and, as such, may harm competition. It might lead to higher airfares by enabling collusion through the exchange of commercially sensitive information.3 In addition, the operating carrier can add to the costs of the ticketing carrier by charging fees for seats that the ticketing carrier sells on the operating carrier’s flights. These fees can further raise prices due to a double marginalization problem, which further harms consumers.4 For this reason, CSAs may attract the scrutiny of competition authorities and may be forbidden when their anticompetitive effects outweigh their procompetitive effects.5

The procompetitive effects of CSAs are most pronounced in the case of “interline flights.” In these cases, the parties to the CSA do not compete over passengers but rather offer them complementary services: one carrier takes the passenger from destination A to destination B, and the second offers the continuing flight from destination B to destination C. Anticompetitive effects may emerge, however, with “non-stop flights”—flights for which the two carriers are competitors on a given route.

This article assesses the price-increasing effects of CSAs among direct or potential competitors in non-stop routes for domestic flights in the United States. Our focus on non-stop flights allows us to attend exclusively to the anticompetitive effects, as opposed to the procompetitive effects that accompany interline flights. This article also only considers flights in the first quarter of the year, a period that is for the most part off-peak. In periods of low demand, factors facilitating collusion are easier to identify, since the excess capacity that accompanies such periods (absent collusion or relaxed competition) typically reduces prices and intensifies competitive pressure. Robustness checks are also performed to corroborate the results of the empirical analysis. While heteroskedasticity is addressed by adopting the weighted least square (WLS) regression method suggested by Jan Brueckner,6 endogeneity issues are tackled by controlling for market-specific effects as is done by Harumi Ito and Darin Lee.7

The remainder of the article is divided into three main parts. The first part states the two hypotheses tested in the empirical analysis. The second part describes the methods and data used to estimate a regression equation that relates non-stop airfares to the presence of CSAs. The third part reports and discusses the results.

II. HYPOTHESIS DEVELOPMENT

The analysis performed in this article identifies two price-increasing effects due to domestic CSAs on non-stop routes: (1) a “round table” effect, produced when cooperation between code-sharers facilitates coordination and collusion; and (2) a “double marginalization” effect, which reflects the transfer fee that the operating carrier extracts from the ticketing carrier. This part states the two hypotheses to be tested empirically and discusses briefly the most relevant literature.

A. “Round Table” Effect

The effects of CSAs on airfares have been broadly investigated in the economic literature. Analytical models suggest that CSAs may decrease fares of interline flights but increase fares for non-stop flights. The latter effect reflects collusive behavior facilitated by the CSA. CSAs can offer convenient frameworks for exchanging commercially sensitive information and coordinating prices and frequencies (tacitly or explicitly). Code-sharing airlines may also have more opportunities to “punish” a company deviating from a collusive price. As a result, CSAs may ease collusion both on code-sharing flights and on flights independently operated by each signatory company for the non-stop route on which they cooperate. Hence, the following hypothesis is tested:

H1: Code-sharing partners raise airfares of all flights they operate for non-stop routes on which they cooperate.

Although several studies have been conducted with regard to the impact of CSAs on interline flights, empirical studies that consider the effects of CSAs on non-stop flights are less common and have led to inconclusive results.

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Brueckner and Tom Whalen\textsuperscript{10} attempted to capture this effect using 1,300 observations on trans-oceanic routes, in the third quarter of the year. However, the price increase that they identified was not statistically significant. Philip Gayle\textsuperscript{11} concentrates on the domestic effect of the Delta/Continental/Northwest code-sharing alliance by comparing data pre-alliance (third quarter of 2002) and post-alliance (third quarter of 2003). His study shows that the creation of the alliance is associated with an increase both in fares and in traffic for specific kinds of flights—those in which passengers remain on a single operating carrier’s plane (or planes) for the entire trip but acquire their ticket for that trip from a partner carrier. But Gayle’s is an event study that does not single out the effect of CSAs on behavior in non-stop routes, whereas we conduct a full-blown econometric analysis focused only on non-stop flights. William Gillespie and Oliver Richard\textsuperscript{12} focus on the anticompetitive effect of alliances that constitute a broad form of cooperation enjoying immunity from antitrust law. Using data from non-stop flights on all trans-Atlantic routes with non-stop service between the twenty largest cities in the United States and the European Union from 2005 to 2011, they show that an additional competitor leads to an average decrease in fares of 4.7 percent, unless the new competitor is in the same alliance as an incumbent airline. Our article focuses on the price effects of code-sharing cooperation that does not enjoy immunity from antitrust law. Accordingly, we analyze cooperation of a narrower scope than Gillespie and Richard.

\textbf{B. “Double Marginalization” Effect}

Double marginalization occurs when two companies involved in a vertical supplier-customer relationship both enjoy some market power in their respective market—that is, both companies are able to set prices above their marginal costs. As a result, the final price paid by consumers in the downstream market is higher than the price that would be set by a vertically integrated company. Although this concept was originally developed to analyze the vertical relationship between two monopolists, it applies to any pair of vertically related markets that are not perfectly competitive.\textsuperscript{13}

In the case of a CSA between competitors on a non-stop route, the operating carrier typically charges the ticketing carrier a transfer fee. In this sense, the two code-sharing partners are vertically related: the operating carrier is the upstream firm selling an input to the ticketing carrier, which is the downstream

\textsuperscript{10}Brueckner & Whalen, supra note 8.


firm. If this transfer fee is above the operating carrier’s marginal costs, and the ticketing carrier has some market power, double marginalization emerges, as shown formally by Yongmin Chen and Gayle. The ticketing carrier’s marginal costs, and therefore the final price it charges, are inflated. Thus, airfares for code-sharing flights may be influenced not only by collusion between code-sharing partners but also by double marginalization. The double mark-up that follows when both conditions inhere harms consumers and is potentially anticompetitive. Accordingly, the following hypothesis is also tested:

H2: Airfares of code-sharing tickets are higher than airfares of tickets marketed and operated by the same airline.

Gayle tests double marginalization by focusing on code sharing between airlines that operate flights to complementary destinations. In particular, the ticketing carrier sells tickets for two-leg itineraries—for instance from city A to city C with a stop in B—and operates flights on one leg of each itinerary—say from city A to city B—while the operating carrier operates the other leg—from city B to city C. In addition, in the routes examined by Gayle, the operating carrier always offers direct or indirect online flights on the entire itinerary—from city A to city C, with or without a stop in an intermediate city. He shows that, given this route structure, the fees levied on the ticketing carrier by the operating carrier create a double marginalization problem that inflates prices by 20 percent. Gayle concludes that operating carriers act this way to soften competition between the code-sharing service and their own online service on the entire itinerary. Some of this softened competition is indirect: between direct flights and flights via an intermediate airport. Our article excludes this vector of competition by concentrating specifically on code sharing over non-stop routes. We find that pricing in such cases is also influenced by double marginalization.

III. MATERIALS AND METHODS

This part introduces the basic regression model describing the effects of CSAs on prices for domestic non-stop routes; sets out the data sources and variables involved in the empirical analysis; and reports summary statistics.

A. Basic Regression Model & Data

In order to test the two hypotheses stated above, we estimate a regression equation relating airfares to existing CSAs on non-stop routes in the U.S. domestic


market. The basic regression model, which also includes additional independent variables, takes the following form:

\[
\text{Airfares} = (\text{airport features, market features, route features, carrier features, ticket features, code – sharing agreements}).
\]

Data for the empirical analysis comes from the database “Airline Origin and Destination Survey (DB1B),” compiled by the U.S. Department of Transportation (DoT).\textsuperscript{16} DB1B has been collecting information from a random sample comprising 10 percent of U.S. domestic flights since 1993 on a quarterly basis. We focus on data from the first quarter of 2012, which yields a total of 29,528 observations.

The online version of DB1B provides data for each U.S. domestic itinerary surveyed within three different tables: (1) DB1B Coupon, which includes coupon-specific information;\textsuperscript{17} (2) DB1B Market, which includes directional market-specific information;\textsuperscript{18} and (3) DB1B Ticket, which includes itinerary-specific information.\textsuperscript{19} For DB1B Ticket, the regression data set includes only itineraries described by the following characteristics: (1) flight tickets are round-trip tickets with two coupons (that is, are non-stop round-trip itineraries);\textsuperscript{20} (2) fare values are considered credible by the U.S. DoT; (3) fare values are higher than $20 and thus are not eligible for special discounts (such as those enjoyed by air carrier employees, frequent flyer program participants, and so forth); and (4) fare class is known (in other words, can be classified in a given booking class). We complete information on selected itineraries by adding further details reported in DB1B Coupon and DB1B Market. The following information is provided: (1) origin airport, that is, the airport where the round trip starts (International Air Transport Association (IATA) code); (2) destination airport, that is, the airport where the first leg of the round trip ends (IATA code); (3) origin city market, that is, the catchment area of the airport where the round trip starts; (4) destination city market, that is, the catchment area of the airport where the first leg of the round trip ends; (5) ticketing carrier, that is, the company selling the flight ticket (IATA code); (6) outbound operating carrier, that is, the company operating the first leg of the round trip.


\textsuperscript{17} Considering a round trip from A to C with an intermediate stop in B, DB1B Coupon includes a different observation for each of the 4 legs included (A–B, B–C, C–B, B–A).

\textsuperscript{18} Considering a round trip from A to C with an intermediate stop in B, DB1B Market includes a different observation for each directional market included (A–C, C–A).

\textsuperscript{19} Considering a round trip from A to C with an intermediate stop in B, DB1B Ticket includes one single observation for the whole itinerary (A–B–C–B–A).

\textsuperscript{20} One-way non-stop itineraries are excluded from the empirical analysis because pricing strategies for this kind of flight sharply differ from those adopted for round trip flights.
(IATA code); (7) inbound operating carrier, that is, the company operating the second leg (return flight) of the round trip (IATA code); (8) miles flown, that is, the total distance flown including both outbound and inbound flights; (9) fare class (6 classes); (10) airfare in U.S. dollars; and (11) number of passengers who have paid the same airfare. All itineraries that are characterized by the same origin airport, the same destination airport, the same ticketing carrier, the same outbound operating carrier, the same inbound operating carrier, and the same fare class are collapsed into a single observation by computing a passenger-weighted average airfare. Our resulting data set consists solely of tickets for U.S. domestic non-stop round-trip itineraries.

B. Variables

As indicated by the basic regression model introduced above, we group independent variables other than CSAs into six categories based on the flight features they summarize. This part provides qualitative information regarding all variables included in the econometric analysis—both dependent and independent—and describes the additional data sources used to complete the main data set.

1. Dependent Variable

The dependent variable (\( \ln \text{fare} \)) adopted in the regression equation is the natural logarithm\(^{21}\) of the weighted average airfare paid by passengers purchasing tickets for non-stop round-trip itineraries in the U.S. domestic market during the first quarter of 2012.

2. Airport Feature Variables

The vast majority of airports in the U.S. domestic market do not allocate slots in a way that raises significant barriers to entry.\(^{22}\) Nonetheless, the effects of the so-called “airport dominance” are empirically tested in this article. The literature indicates that serving a dominant share of traffic at a given airport is a source of competitive advantage for carriers, as manifested in higher fares.\(^{23}\) For each airport and for each company, an “airport dominance” variable is measured by computing the market share of each ticketing carrier that uses the airport. This market share is based on all observations included in DB1B Ticket (first quarter of 2012) and is calculated by dividing the total number of

\(^{21}\) Log transformation for this variable is consistent with all previous empirical studies on the topic.

\(^{22}\) In the United States, slot allocation is coordinated only in 4 airports: New York JFK (fully coordinated, level 3); Newark EWR (fully coordinated, level 3); San Francisco SFO (slot controls only at peak times, level 2); Chicago ORD (slot controls only at peak times, level 2). Therefore, only two U.S. airports (and only the New York city market) feature barriers to entry for newcomers.

passengers enplaned by a given ticketing carrier in a given airport by the total number of passengers enplaned in the same airport. Two independent variables are considered in the regression analysis: the “airport dominance” market share of the ticketing carrier at the origin airport (orairdom100) and at the destination airport (destairdom100).

3. Market Feature Variables

Features of market demand and supply may influence pricing strategies and are incorporated into the empirical analysis in the form of independent variables corresponding to each directional city-pair market. A directional market includes all non-stop round-trip itineraries between two particular city markets.24 City markets are geographic zones defined by the U.S. DoT as including all airports whose catchment areas overlap.25

On the demand side, statistical data for city markets as of 2010 are sourced from the Interactive Data Application database,26 compiled by the U.S. Bureau of Economic Analysis, and are complemented with data provided by the U.S. Census Bureau.27 To capture demand effects, we add four variables to the regression equation: the natural logarithm (lnorpop) of the origin city market population (orpop), the natural logarithm (lndestpop) of the destination city market population (destpop), the natural logarithm (lnorpinc) of the origin city market per capita income (orpinc), and the natural logarithm (lndestpinc) of the destination city market per capita income (destpinc).

On the supply side, we capture the impact of fare competition in a city-pair market by adding three additional independent variables. The first two are the number of ticketing carriers (ticketing_competitors) and operating carriers (operating_competitors) that provide non-stop round-trip service in a given directional city-pair market. While the variable ticketing_competitors accounts for the number of companies that sell tickets in the market—that is, the number of different suppliers among which consumers can actually choose—the operating_competitors variable includes also regional carriers. We also compute the Herfindahl Hirschman Index (HHI) in each city-pair market (routeHHI). The share of passengers transported by a given ticketing air carrier in a directional city-pair market is adopted as the market share in order to calculate the HHI.

24 Round-trip itineraries from A to B (A–B–A) and round-trip itineraries from B to A (B–A–B) are part of different directional markets.
25 In the selected sample, there are 318 origin city markets, 317 destination city markets, 341 origin airports, and 340 destination airports. On average, each city market comprises 1.07 airports.
Other differences across markets may affect airfares. These differences might also influence the decisions of airlines to sign a CSA, thus leading to endogeneity problems. To capture market-specific effects (fixed effects), we perform a robustness check\textsuperscript{28} by adding to the regression equation a dummy variable for each directional market included in the data set, as is done by Ito and Lee.\textsuperscript{29} This approach also solves potential endogeneity issues stemming from the inclusion of the HHI as a regressor.

4. Route Feature Variables
Because longer itineraries are usually associated with higher fares, we include the natural logarithm \((\ln\text{distance})\) of the miles flown \((\text{distance})\) in the analysis as a route-specific independent variable. Routes included in the same directional city-pair market can differ in distances flown;\textsuperscript{30} therefore, this variable can be kept in the regression equation even when using dummies for directional markets.

5. Carrier Feature Variables
Differences in cost structures and company features among airlines may influence pricing policies. To capture these airline-specific effects (fixed effects), previous empirical analyses adopted dummy variables for each air carrier included in the sample.\textsuperscript{31} We follow the same approach in this article by including dummies not only for each ticketing carrier but also for each outbound and inbound operating carrier. Doing so generates 93 additional variables: a dummy (from \(a1\) to \(a18\)) for each ticketing carrier included in the sample, a dummy (from \(b1\) to \(b37\)) for each outbound operating carrier, and a dummy (from \(c1\) to \(c38\)) for each inbound operating carrier.\textsuperscript{32}

6. Ticket Feature Variables
The data set includes tickets from 6 different booking classes: restricted coach class (X), unrestricted coach class (Y), restricted business class (D), unrestricted business class (C), restricted first class (G), and unrestricted first class (F). Business and first class tickets are few in number, and so in order to more easily capture the impact on airfares of improvements in service level, we

\textsuperscript{28} When running this robustness check, all other market feature variables are excluded from the regression equation to avoid perfect collinearity. The selected sample includes 4,372 directional markets.
\textsuperscript{29} Ito & Lee, supra note 7.
\textsuperscript{30} As mentioned above, city markets include all the airports whose catchment areas overlap. Round-trip routes from airport \(x\) (included in city market \(A\)) to airport \(y\) (included in city market \(B\)) and round-trip routes from airport \(x\) (included in city market \(A\)) to airport \(y\) are part of the same directional market, but can be characterized by differences in the distance flown.
\textsuperscript{31} See Brueckner, supra note 8; Brueckner, supra note 6; Ito & Lee, supra note 7.
\textsuperscript{32} The sample includes 18 ticketing carriers, 37 outbound operating carriers, and 38 inbound operating carriers. Hence, to avoid perfect collinearity, 17 dummies for ticketing carriers, 36 for outbound operating carriers, and 37 for inbound operating carriers are used in the regression.
classify the observations into 4 groups: restricted coach class (recoach), unrestricted coach class (uncoach), business class (busin), and first class (first). A dummy variable for each group is generated. Consequently, 3 additional variables have been included in the regression analysis (uncoach, busin, first); we omit the dummy variable for restricted coach class (recoach), which is taken as the base group category.

According to Benny Mantin and Bonwoo Koo’s definition, rather than separating economy class demand from business/first class demand, time-sensitive passengers are better identified by focusing on the demand for unrestricted tickets. Therefore, to account for consumer types, another dummy (timesensitive) has been generated that is equal to 1 for all unrestricted tickets regardless of the fare class. This variable is adopted to perform an additional robustness check.

7. Code-Sharing Agreement Variables

The database DB1B provides IATA codes of ticketing carriers, outbound operating carriers, and inbound operating carriers for each itinerary. In cases where the ticketing carrier differs from the operating carrier, a CSA usually exists. Nevertheless, in the U.S. market, so-called regional airlines are either affiliated to or wholly owned by full-service airlines, such that they operate flights as subcontractors. This arrangement creates a potential problem. Even when the ticketing and operating carriers are different companies, if they are affiliated or jointly owned, they cannot be included in the basic definition of CSA, which is supposed to take place between independent companies. To account for this problem, we have specified the affiliation/property schemes of all regional airlines included in the selected sample to provide a more accurate identification of code-sharing flights. Thus, in accordance with the definitions provided by Brueckner and by Brueckner, Lee, and Ethan Singer, an itinerary is classified as code sharing only if (1) the ticketing carrier differs from the outbound and/or the inbound operating carrier and (2) at least one of these operating carriers is not affiliated to or owned by the ticketing carrier. As a result, only flights operated by a given company and marketed by a different and independent company are deemed code-sharing flights in this article.

Two different dummy variables (csaroundtab and csadoublem) are included in the regression equation to capture the effects of CSAs on airfares. The first variable, csaroundtab, equals one for all flights marketed on a given directional market by a carrier that is involved in at least one code-sharing flight on the same market. This dummy is able to reveal the “round table” effect. The second

35 Brueckner, supra note 6, at 110.
36 Brueckner, Lee & Singer, supra note 9, at 582.
variable, $csadoublem$, equals one only for code-sharing flights—in other words, when the ticketing carrier and the operating carrier are different and independent companies. $Csadoublem$ is able to capture the “double marginalization” effect.

C. Summary Statistics

Table 1 reports the summary statistics of all variables included in the analysis. While the regression equation includes natural logarithms for some of the variables, this table gives these variables as they were before log transformation, so as to provide more valuable information.

The selected data set includes 29,528 observations. The bulk of the observations are coach class itineraries (64 percent are restricted coach class and 26 percent are unrestricted coach class). First class itineraries are approximately 9 percent of the total and business class approximately 1 percent. Focusing on code-sharing variables, 1,106 itineraries (4 percent) out of 29,528 are code-sharing flights ($csadoublem$), while 7,073 itineraries (24 percent) are offered for a given directional market by carriers involved in at least one code-sharing flight on that same market.

IV. EMPIRICAL EVIDENCE

This part presents and discusses the results stemming from the main econometric analysis performed to capture the price effects of domestic CSAs on non-stop routes. It further conducts robustness checks that corroborate the findings.

Table 1. Summary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
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<td>362.50</td>
<td>20.00</td>
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<td>0.13</td>
<td>0.00</td>
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<td>18,900,000</td>
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</tr>
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</table>

*Source: Authors’ own calculations.*
A. Main Analysis

The main regression equation is of the following form:

\[ \ln \text{fare}_j = \beta_0 + \beta_1 \times \text{uncoach}_j + \beta_2 \times \text{busin}_j + \beta_3 \times \text{first}_j + \beta_4 \times \ln \text{orpop}_m + \beta_5 \times \ln \text{orpinc}_m + \beta_6 \times \ln \text{indestpop}_m + \beta_7 \times \ln \text{indestpinc}_m + \beta_8 \times \text{indistance}_j + \beta_9 \times \text{competitor} \times \text{ticketing}_m + \beta_{10} \times \text{operating} \times \text{competitors}_m + \beta_{11} \times \text{route} \times \text{hi}_m + \beta_{12} \times \text{orairdom}100_k + \beta_{13} \times \text{destairdom}100_k + \beta_{14} \times \text{csadoublem}_j + \beta_{15} \times \text{csaroundtab}_j + \beta_{16} \times \text{a1}_j + \ldots + \beta_{32} \times \text{a17}_j + \beta_{33} \times \text{b1}_j + \ldots + \beta_{68} \times \text{b36}_j + \beta_{69} \times \text{c1}_j + \ldots + \beta_{107} \times \text{c37}_j + \varepsilon_j, \]

where \( j \) identifies a given itinerary, \( m \) a given directional market, and \( k \) a given airport.

The empirical results of this model specification are shown in Table 2. Column I displays coefficients estimated by adopting the ordinary least squares (OLS) method with robust standard errors.

The \( \text{csaroundtab} \) variable coefficient equals 0.052 and is significant at the 1 percent level. In other words, airlines signing a CSA on a given directional market are able to increase airfares for all of the flights (both online flights and code-sharing flights) they operate on that market by 5 percent (the “round table” effect). This outcome supports hypothesis H1. Another interesting result is provided by the \( \text{csadoublem} \) variable coefficient, which is equal to 0.047 and significant at the 1 percent level. Code-sharing flights, in particular, are associated with airfares that are approximately 5 percent higher than other fares set by partner airlines in the same market (the “double marginalization” effect). This outcome supports hypothesis H2. Hence, by summing the two effects, code-sharing causes a price increase of almost 10 percent relative to tickets sold in the same market by companies not involved in CSAs. This confirms our prediction that CSAs among actual and potential competitors lead to a general increase in non-stop fares set by signatory airlines. In addition, the results show that a double mark-up problem exists in CSAs between airlines that compete over non-stop itineraries. For all other variables within the equation, coefficient signs are in line with expected results. Service level improvements are positively associated with airfares. Likewise, fares for unrestricted coach class (\( \text{uncoach} \)), business class (\( \text{busin} \)), and first class (\( \text{first} \)) tickets are 9, 33, and 70 percent higher than fares for restricted coach class (the base category).

As for market-specific features, the size of the origin market population (\( \ln \text{orpop} \)) has a positive and significant effect on fares that is slightly higher than the one estimated for the destination market population (\( \ln \text{indestpop} \)). Similarly, the impact of the per capita income of the origin market (\( \ln \text{orpinc} \)) on airfares is positive, significant, and higher than the impact of the per capita income of the destination market (\( \ln \text{indestpinc} \)).
The coefficients of the variables capturing airport features confirm the role played by airport dominance. As expected, larger market shares in the origin (orairdom100) or destination (destairdom100) airport for ticketing carriers are associated with higher airfares.
While an additional ticketing competitor (ticketing_competitors) is associated with a 5.4 percent drop in fares, and more concentrated markets (higher HHI, routehhi) correlate with higher prices, an additional operating competitor (operating_competitors) is associated with a very small but significant increase in airfares (0.9 percent). A closer look at the data set reveals that the number of operating carriers is greater than the number of ticketing ones in the markets where regional carriers operate, markets whose itineraries are usually characterized by narrow demand. In these markets, given the existence of narrow demand and the high number of operating carriers, it is likely that the entry of an additional operating competitor triggers a reduction in load factors and an increase in marginal costs for all companies that operate in the same market, thus potentially leading to an increase in price.

B. Robustness Check

Columns II and III repeat the analyses provided in column I but adopt clustered (robust) standard errors and a WLS regression method, respectively. The second estimation links each cluster to a particular directional market, to capture the effects of those independent variables (market features and competition measures) that vary only across directional markets. This regression provides the same values for coefficients of code-sharing variables, thus corroborating the robustness of the outcomes examined above. For the third estimation, we assume that selecting passenger-weighted average airfare as the dependent variable may lead to heteroskedastic error terms; we address the issue by using the number of passengers included in each observation as a weight in a WLS regression. Here, again, coefficients are comparable to the ones stemming from the original OLS regressions, and code-sharing variables are still positive and significant. This result further corroborates the robustness of the regression outcomes.

In order to deal with potential endogeneity within the code-sharing variables, Column IV includes in its regression equation dummy variables for directional markets, thus capturing the impact on fares of all existing differences across markets, as is done by Ito and Lee. Under this model specification, the csaroundtab variable coefficient equals 0.056 and is significant at the 1 percent level, and the csadoublem variable coefficient equals 0.044 and is significant at the 1 percent level; even here, then, CSAs still correlate positively with airfares.

One can argue that changes in the csaroundtab variable reflect not only collusion and reduced competition, but also improvements in quality. In particular, code-sharing partners might offer a wider combination of flights on a given

37 Forbes & Lederman, supra note 34.
38 Brueckner, supra note 6.
39 Ito & Lee, supra note 7.
directional market, giving them latitude for fare hikes. If quality were the main
driver in the increase in price, fare increases would be sharper for those consumers
who are willing to pay a premium for quality — in particular, time-sensitive
passengers who benefit to a greater extent from a frequency expansion.
Accordingly, an additional robustness check is provided in column V by adding
the timesensitive variable and by interacting this dummy with the csaroundtab vari-
able (csaroundtabXtimesensitive).40 This robustness check shows that the roundta-
ble effect leads to a 7 percent increase in fares for non time-sensitive passengers
and to a 3.5 percent increase for time-sensitive ones. This result considerably
weakens the quality improvement thesis and underscores the anticompetitive
effects of CSAs.

V. CONCLUSION
This article has estimated the effects of CSAs on fare levels for non-stop
round-trip itineraries in the United States. Signatory airlines are able to in-
crease airfares for all flights (both online and code-sharing) in markets where
they cooperate by more than 5 percent (the “round table” effect). Furthermore,
ticketing carriers involved in code sharing charge fares more than 4 percent
higher than fares set by their code-sharing partner and almost 10 percent higher
than other airlines in the same market (the “double marginalization” effect).
The positive and significant correlation between CSAs and the level of fares
emerges from collusion facilitated by CSAs and from double marginalization.
These results provide new insights for competition authorities in assessing the
overall anticompetitive impact of CSAs.

For cases in which CSA partners both compete on non-stop routes and
offer complementary services on interline routes, competition authorities can
compare the anticompetitive effects of the kind identified by us with the pro-
competitive effects inherent in the interline services. Future research, using
samples involving both kinds of CSAs (among direct competitors and between
airlines offering complementary services), can aim at comparing these two
effects empirically. Furthermore, most of the literature on this topic, including
this article, has not distinguished among the anticompetitive effects of different
kinds of arrangements that are included in CSAs (“free sale,” “hard block,”
“soft block,” and so forth).41 Future research should focus on these contrac-
tual arrangements to assess degrees of anticompetitiveness among different
types of CSAs.

40 Owing to the relatively small number of unrestricted business and first class tickets, uncoach and
timesensitive might be collinear; hence, the uncoach dummy is dropped.
41 European Competition Authorities, supra note 3.