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Abstract

This study provides further empirical evidence on pricing by international airline alliances. The paper covers a long sample period, which runs from 1997 to 2016, and it supplements the usual USDOT fare data with confidential fare data reported by the foreign alliance partners of US carriers. The empirical results for connecting service match earlier findings, with alliances charging lower fares than nonaligned carriers. The GTG results imply that, in the latter part of the sample period, granting antitrust immunity to two previously nonaligned carriers is equivalent to removing a competitor, with a consequent increase in fares (an effect seldom seen in previous work).

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Pricing by International Airline Alliances: A Retrospective Study Using Supplementary Foreign-Carrier Fare Data

by

Jan K. Brueckner and Ethan Singer

1. Introduction

Starting with the formation of the Northwest-KLM alliance in 1993, international airline alliances have come to dominate the provision of air travel between the US and other countries. Alliances represent the airlines' way of providing seamless international travel (like that on a single carrier) in the face of prohibitions on cross-border airline mergers. Currently, three large international alliances exist: the Star alliance, built around the original partnership of United and Lufthansa; the Skyteam alliance, built around the Delta-Air France/KLM partnership; and the oneworld alliance, built around the partnership of American and British Airways. Within the alliances, particular groups of carriers enjoy antitrust immunity (ATI), which allows them to coordinate pricing and scheduling decisions. In many cases, ATI has been replaced by a fuller degree of cooperation through joint-venture (JV) arrangements, under which revenues on particular routes are pooled and shared. JV agreements are typically required to be "metal-neutral", which makes the partners indifferent as to which carrier transports a given passenger (achieved by splitting revenue from a passenger regardless of which carrier is used). Under a JV, carriers are incentivized to behave as a single airline on the relevant routes.

Table A.1 in the appendix shows, for each alliance (including those that no longer exist), the groups of carriers within it that were granted ATI as well as the groups operating JVs. Table A.2 shows the dates at which individual carriers joined (and perhaps exited) alliances, and Tables A.3 and A.4 show the start (and possibly end) dates for ATI and JV status for individual carriers (all this information was provided to us by the DOT).

International alliances make interline trips (which involve multiple carriers) more convenient than traditional interline travel on nonaligned carriers, helping to achieve the goal of seamless travel. Greater convenience is achieved through schedule coordination by the alliance partners to shorten layovers, gate proximity at connecting airports, reciprocal lounge access, and a single check-in at which the passenger receives all boarding passes, benefits made possible by carrier cooperation under ATI or a JV agreement.

Alliances also affect fares for international travel, impacts that can be understood by referring to the network diagram in Figure 1. Travel between endpoints W or X in the US and Z or Y in a foreign country requires using both airline 1 (the US carrier) and airline 2 (the foreign carrier), with a connection at either H (the US hub and international gateway) or K (the foreign gateway). Economic theory predicts that the fare for this interline trip is cheaper when the two airlines are alliance partners than when they are nonaligned. Because each airline takes its partner's interests into account, the alliance reduces "double marginalization," an excessive markup over cost that each nonaligned carrier would apply for its portion of the interline fare, ignoring the negative impact on the other carrier (namely, lower traffic on its part of the trip due to a higher overall fare). Full integration of the carriers, as under a JV, should completely eliminate double marginalization, while it may be only partially eliminated with less integration, as under ATI, leading to a smaller fare reduction relative to the nonaligned case.

Despite lower alliance fares for interline travel, passengers whose trip is from one gateway city to the other, using just a single airline rather than two, may face a higher fare under the alliance. The ability to cooperate in fare-setting may lead the alliance partners, who provide overlapping service between the H and K gateways, to raise the fare in the HK market in anticompetitive fashion. The alliance would restrict seats for HK passengers at the same time that it expands seats for interline passengers flowing across the gateway route, whose volume rises in response to the lower fare they face.

These potential fare effects, which were analyzed theoretically by Brueckner (2001), have generated a sizable empirical literature.[1] The purpose of the present study is to extend this literature by analyzing the price effects of alliances over a longer time period than most previous studies, and by using a new data source to supplement the DOT fare data used in previous work. We study the effects of alliances on both gateway-to-gateway (HK) fares and on connecting fares over the 1997-2016 period, using empirical specifications familiar from some earlier studies. We supplement the usual DB1B international fare data from the DOT's Origin and Destination Survey (a 10% sample of tickets with at least one US-carrier route segment) with confidential DB1B-style data provided to the DOT, starting in 1997, by foreign carriers having an ATI or JV partnership with a US airline. While foreign-carrier trips to a US endpoint that lack a US carrier segment are unobservable in the DB1B data, this supplemental data source allows such trips to be included in an international fare study.

The first empirical study testing the hypotheses drawn from Figure 1 is by Brueckner and Whalen (2000). Because of the limitations of the 1997 DB1B data used in the study, they measured airline cooperation on interline itineraries by an "alliance" dummy variable indicating whether the two carriers had a codesharing agreement. The results showed that fares for alliance itineraries were 25% lower than fares for interline itineraries on nonaligned carriers. In addition, the results showed the absence of any anticompetitive alliance fare effects on gateway-to-gateway (hereafter "GTG") routes. In a follow-up study using more detailed DB1B data from 2000, Brueckner (2003) relied on three measures of increasingly integrated airline cooperation on interline trips: codesharing, alliance membership, and ATI, each of which was associated with a successive fare discount relative to nonaligned itineraries. Relative to these itineraries, codesharing reduced fares by 7%, alliance membership by an additional 4% and antitrust immunity by a further 16%, for a total fare reduction of 27% from the presence of all three types of cooperation (i.e., immunized codeshare service between alliance partners).

A limitation of both of these studies was the use of cross-section data from a single quarter, a drawback remedied by the panel-data study of Whalen (2007). Using DB1B data from the 1990-2000 period, Whalen's preferred model specification showed a 9% codesharing discount relative to nonaligned itineraries and a further 18% discount from ATI, for the same 27% total discount found by Brueckner (2003). The panel approach was also used by Willig, Israel and Keating (2009) in an unpublished study, which relied on DB1B data from the 2005-2008 period. Their results, which focused on U.S.-transatlantic city-pairs, again showed interline fare discounts from codesharing and ATI relative to nonaligned fares.

Brueckner, Lee and Singer (2010) focused on connecting fares (interline and online) using a longer DB1B panel data set covering the 1998-2009 period, and their results showed somewhat smaller interline fare effects than most previous work. The combination of codesharing, alliance membership, and ATI yielded a fare reduction of 11% relative to fares for nonaligned itineraries worldwide, although the reduction was a larger 16% for transatlantic travel. The authors conjectured that this smaller discount might reflect reductions in nonaligned interline fares themselves in attempt to limit traffic losses to alliances, a reduction that would narrow the alliance discount. Aside from Brueckner and Whalen (2000), none of these studies offered results on GTG fares.

Gillespie and Richard (2012), who used panel data for the period 2005-2010, focused on economy fares for U.S.-transatlantic travel, studying both connecting and gateway-to-gateway fares. In contrast to previous studies, the authors used individual fares rather than aggregating up to an average fare for each itinerary, and their results showed much smaller negative effects of airline cooperation on interline fares than previous studies. Alliance membership without ATI reduced interline fares by only about 1% relative to nonaligned fares, and the addition of ATI yielded at most an extra 1.8% reduction, for a total of about 3%. The study's gateway-to-gateway results showed the existence of an anticompetitive alliance effect. In particular, while adding a nonaligned carrier to a GTG route reduced fares, adding to the route an ATI partner of an existing carrier had no fare effect, showing that the two carriers do not compete.

In an unpublished paper, Brueckner, Lee and Singer (2016) used fare data provided by Air New Zealand to study the effects of JV agreements on ANZ's connecting fares. The use of ANZ internal data allowed the study to control for ticket characteristics not observed in the DB1B, such as the advance-purchase interval and the duration of the traveler's stay. The results showed that JV interline fares were lower than ANZ's fares with nonaligned carriers, and that pricing on such trips was indistinguishable from online (single-carrier) pricing, confirming that ANZ and its JV partners set fares like a single airline.

The most recent study in this tradition is Calzaretta, Eilat and Israel (2017), which used DB1B data to focus on both connecting and GTG fare effects in a long 1998-2016 panel like the one in the present paper. As in Brueckner et al. (2016), their results show that airline cooperation reduces interline fares and that JV trips again yielded the same reduction below nonaligned interline fares as did online trips (8%). However, like Brueckner and Whalen (2000), the study found no anticompetitive alliance effect on GTG routes.

In an earlier GTG study that did not rely on transaction-based fare data, Wan, Zou and Dresner (2009) used posted GTG fares for U.S. transatlantic routes collected from the website of Expedia, the online travel agency. Instead of counting competitors, they measured competition on GTG alliance routes using the Herfindahl (HHI) index, and the findings showed no HHI effect on fares, consistent with the results of Brueckner and Whalen (2000) and Calzaretta et al. (2017).[2]

This finding is repeated in a study by Gayle and Brown (2014) that again uses a different methodology, in this case a structural econometric approach. Using a model that captures both the demand and cost effects of alliances as well as potential collusion in fare setting between overlapping alliance partners, the paper finds no evidence of this phenomenon.[3]

The present study uses the approach of Brueckner, Lee and Singer (2010) to analyze alliance fare effects for connecting trips, and it uses the approach of Brueckner and Whalen (2000) to analyze fare effects in gateway-to-gateway markets. While the methodology is thus familiar, the paper differs from most of the literature by using data from a long 1997-2016 panel and by combining confidential foreign-carrier data provided to us by the DOT with data from the usual DB1B source. Relative to Calzaretta et al. (2017), who use a similarly long panel and a similar methodology, the paper's incremental contribution is reliance on the confidential supplementary data, which has never been used before in an international fare study.

Like all past studies, the paper finds evidence of fare reductions from alliance cooperation on connecting itineraries, with magnitudes that match those found in the most recent papers. The study also finds evidence of anticompetitive fare effects from overlapping ATI and JV service on GTG routes, effects that are confined to the later part of the sample period. This finding emerges for only the second time in the literature, and it is due to a regression specification that allows anticompetitive effects to change across the sample period. By constraining these effects to be constant across their sample period, Calzaretta et al. (2017) were unable to uncover the late-period effect identified in the paper.

The plan of the paper is as follows. Sections 2 and 3 present the data and the regression results for connecting trips, while sections 4 and 5 present the data and regression results for GTG trips. Section 6 uses the regression results in a simulation designed to measure the consumer welfare effect of removing JV status for two partner airlines. Section 7 offers conclusions.

2. Connecting-Market Data and Variables

The data set for the connecting-market analysis is constructed as follows. The focus is on round-trip itineraries (carrier/routing/fare-class combinations) between US and foreign cities that start and return to the same city, with "open-jaw" round trips thus omitted. These round trips can originate inside or outside the US, and they must contain no more than 8 route segments (ticket coupons). Following Brueckner et al. (2011), one-way trips are excluded. In addition, service must be provided by no more than two carriers.

Markets are defined as city-pairs, not airport-pairs, with airports in multi-airport cities grouped into a single endpoint, using the groupings of Brueckner, Lee and Singer (2014) for domestic cities and following the convention used in the Official Airline Guide (OAG) for foreign airports. The endpoint Tokyo (TYO), for example, thus includes both Narita and Haneda airports.

City-pair markets in the sample must have no nonstop service between the endpoints, so that a connecting trip is the only way to travel in the market. Itineraries with endpoints in Alaska, Hawaii or the US territories are excluded. In addition, because the connecting focus puts emphasis on trips of substantial length, itineraries involving travel between the US and Canada, Mexico or the Caribbean are excluded. Markets with potential service by carriers not present in the data are also deleted, given that such an omission precludes an accurate count of market competition.[4] In standard fashion, regional airlines are recoded with the airline codes of the major carriers to which they connect, both within the US and overseas.

As in Brueckner et al. (2011), itineraries with fares below $200 are excluded, and the fare credibility indicator contained in the data is used to exclude high fares that may represent coding errors (bulk fares are also eliminated). Following these exclusions, fares are aggregated up to the carrier-market-year-quarter level by computing a passenger-weighted average fare for each itinerary.

Several dummy variables indicate the extent of carrier cooperation in providing service on an itinerary. One case is an itinerary with service provided by two nonaligned carriers, who have no alliance relationship. These are "traditional interline" or simply "interline" itineraries, captured by the dummy variable **interline**. While in the traditional interline case, each of the two carriers on the itinerary are both operating and "marketing" carriers for their respective segments, the **interline** dummy also captures codesharing between nonaligned carriers. For example, the two outbound segments of a 4-segment round trip could be operated by the same carrier, with the second segment marketed by a different carrier that is not an alliance partner of the operating carrier (its airline code and flight number then appear on that segment). Alternatively, the two segments could be operated by different nonaligned carriers, but the second segment could be marketed by the first carrier. The common element in these cases and the traditional interline case is that the itinerary contains the airline codes of two nonaligned carriers, in either operating or marketing roles, a pattern that is captured by the **interline** variable.

While interline itineraries represent a polar case involving the absence of cooperation between two carriers, the other extreme is an online itinerary, where service is provided by a single carrier and cooperation across the route segments of the trip is by definition perfect. These itineraries are denoted by the dummy variable **online**.

Cooperation that potentially lies between the extremes of interline and online travel is captured by three additional dummy variables, which capture the current alliance, ATI and JV memberships of the airlines on two-carrier itineraries. **ALLY** is set equal to 1 if service on the itinerary is provided by two carriers who are alliance partners but who lack ATI or JV status (American and Cathay Pacific, for example; see Tables A1-A4). As in the case of the interline dummy, **ATI** is set equal to 1 if the itinerary's service is provided by two carriers who are immunized alliance partners (enjoying ATI) but who do not have JV status (for example, United and SAS). **JV** is set equal to 1 if service is provided by two carriers who are JV partners, thus also being immunized alliance partners (for example, Delta and Air France). As in the case of the interline dummy, the **ALLY**, **ATI**, and **JV** dummies also capture codesharing, with the difference being that codesharing is between alliance, ATI, or JV partners rather than nonaligned carriers.

Several additional features of the **ALLY**, **ATI** and **JV** variables should be noted. First, since the variables capture the evolution of alliances, they can vary with time for any given carrier pair. In addition, the variables can be route-specific since ATI or JV status is sometimes tied to particular routes (the relevant coverage was provided to us by the DOT). Note finally that **ALLY**, **ATI** and **JV** all equal zero for online itineraries and that interline itineraries have zero values for the three variables as well as for **online**.[5]

Since double marginalization is reduced or eliminated by carrier cooperation, thus reducing the fare for a connecting trip, the variables **ALLY**, **ATI**, **JV**, and **online** are expected to have negative coefficients. Moreover, since the extent of cooperation rises moving through this list from **ALLY** to **online**, the negative coefficients are expected to rise in absolute value, with **ALLY**'s coefficient being the smallest, **ATI**'s coefficient being the next largest, **JV**'s coefficient being larger still, and **online**'s coefficient being the largest in absolute value. Writing the regression equation as

$$\mathbf{log\_fare}_{ict} = \rho + \tau\,\mathbf{online}_{ict} + \sigma\mathbf{ALLY}_{ict} + \mu\mathbf{ATI}_{ict} + \nu\mathbf{JV}_{ict} + \mathbf{Z}_{ict}\omega + \xi_{ict}, \quad (1)$$

these relationships are written $\sigma, \mu, \nu, \tau < 0$ and $|\sigma| \leq |\mu| \leq |\nu| \leq |\tau|$. In (1), i denotes the city-pair market, c denotes the online carrier or carrier pair, t denotes time, ξ is an error term, and Z is a vector of additional covariates. Note that since JV status allows carriers to act like a single airline, the fares for online and JV itineraries could be indistinguishable, with the last inequality holding weakly and $\nu = \tau$.

Since the sample period is long, we might expect the effects of the carrier cooperation variables to differ across subperiods of the sample, as defined by one or more "break points." To allow such a change, the cooperation variables would be replaced by interaction terms between the variable itself and a time dummy. For example, to allow JV effects to differ between the early and late parts of the sample period, possibly in response to the substantial expansion of the number of JVs (see Table A.4), the dummy variable $\mathbf{D}_t$ would be set at 1 for t in the first part of the sample period and set at zero for t in the last part of the period. Then the $\mu\,\mathbf{JV}_{it}$ term in (1) would be replaced by

$$\nu_{early}\,\mathbf{D}_t\mathbf{JV}_{ict} \;+\; \nu_{late}\,(1-\mathbf{D}_t)\mathbf{JV}_{ict}, \tag{2}$$

with μ_{early} and μ_{late} giving the effects of **JV** in the two subperiods. Some connecting regressions presented in section 3 allow break points for both the **ATI** and **JV** coefficients, with the coefficients of **online** and **ALLY** constrained to be constant over the sample period.

The additional variables in the vector Z from (1) include total segment distances for the itinerary, denoted **dist**, which is used in log form (it includes both directions). Since previous work shows that the point-of-sale of a ticket (inside vs. outside the US) matters for the fare, two point-of-sale dummy variables are used: **EU_pos** indicates a European point-of-sale (EU is a shorthand), while **nonUS/EU_pos** indicates a point-of-sale outside the US but not in Europe.

Following Brueckner et al. (2011), the fare class for an itinerary is set equal to fare class pertaining to its longest route segment. Itineraries that are first class according to this definition are deleted, leaving economy and business-class itineraries. The default class is economy, with business class denoted by the dummy variable **business**, whose coefficient is expected to be positive. Note that some route segments of a business-class itinerary could be economy and vice-versa, with a common arrangment having business-class transcontinental segments combined with shorter economy-class domestic segments. An additional variable, **coupons**, counts the number of ticket coupons (or route segments) for the itinerary (in both directions). While passengers prefer fewer route segments, suggesting a negative coefficient for **coupons**, more segments are associated with higher carrier costs, implying a positive coefficient and thus an ambiguous overall effect.

The regressions also include a variable measuring competition in the itinerary's city-pair market, again following Brueckner et al. (2011). The variable, denoted **comps_connect**, is a count of competing online carriers or carrier pairs serving the market. To be counted as a competitor, an online carrier or a carrier pair must carry at least 5 percent of the traffic in the market. Each distinct carrier pair is usually counted as a separate competitor, even if the pairs include a common carrier. For example, if both American-British Airways and American-Air France service is present in a city-pair market (with an endpoint at, say, Toulouse), then both pairings are counted as competitors. However, if the pairings involve carriers that all belong to the same ATI or JV grouping, the treatment is different. For example, if both United-Lufthansa and United-SAS service is present in a city-pair market, the fact that both pairs are immunized Star alliance partners means that they count as only one competitor, not two. Similarly, if United online service were present in the same market as these two United pairings, it would also not count as an additional competitor. With additional competition reducing fares, the coefficient of **comps_connect** is expected to be negative.

The dummy variable **LCC_connect** indicates that one of the carriers on a two-carrier itinerary is a low-cost airline, which connects to a mainline carrier. This variable captures the presence of both foreign and US LCCs, and its coefficient is expected to be negative. Routes with LCC presence are expected to have lower fares. US LCCs are Southwest, JetBlue, Virgin America, AirTran, Frontier, Spirit, Allegiant, and Sun Country, and foreign LCCs are Ryanair, easyJet and many others.

Two additional variables are designed to capture demand effects based on the size of the city-pair market. The variable **mktpop** equals the geometric mean of the yearly endpoint city populations, and **mktinc** equals the geometric mean of the yearly per capita incomes of the US city and foreign country at the route endpoints (both variables vary across time and both are used in log form).[6] High demand due to large populations or incomes could raise fares in a city-pair market, but by leading to high passenger volumes, high demand could also reduce fares via economies of traffic density. Because of missing values for **mktinc**, not all connecting itineraries could be included in the sample.

Open-skies agreements have led to more airline service on the routes between the affected countries, and the impact of these agreements is captured by the dummy variable **open_skies**, which takes account of the starting points of the individual agreements using information available at a US Deparment of State website (`https://www.state.gov/e/eb/tra/ata/`). Since the number of carriers serving a route, which open-skies agreements are partly designed to raise, is already captured by **comps_connect**, it is not clear that the agreements will have any additional effect on fares.

The connecting regressions include city-pair fixed effects, which capture unobservable market characteristics that may affect fares (denoted "FEs" hereafter). The regressions also include year and quarter dummy variables along with carrier variables, which control for operating-cost differences across airlines. In the case of an online itinerary, the carrier variable is just the dummy variable for the single carrier. When the itinerary involves two carriers, the dummies for those carriers are turned on but multiplied by each carrier's share of the total itinerary distance. For example, if the first carrier accounts for 40% of the distance, its variable is set at 0.4 while the other carrier's variable is set at 0.6.

Summary statistics for the connecting data set are shown in Table 1 and in Table A.6. The average connecting fare $1704, the average number of sampled passengers per itinerary is 1.67, indicating the thinness of most connecting markets, and business-class trips account for 7.5% of the sample. The average number of coupons is just above 5, and LCCs provide service on about 2% of connecting itineraries.[7] Note that these means are across itineraries and not weighted by passengers.

Figure 2 plots the annual mean values of the **interline** variable as well as the four cooperation variables (these values indicate shares of connecting travel in the different categories). The JV share rises from less than 10% at the beginning of the sample period to near 30% at the end of the period, a change that is fueled in part by a decline in the interline share, from near 40% at the beginning of the sample period to around 10% at the end. In addition, the online share drops slightly starting in 2010 as passengers increasingly connect from one JV partner to another. A transatlantic version of this figure shows a larger increase in the JV share coupled with a large decline in the online share.

The foreign-carrier fares used to supplement the DB1B account for a relatively small part of the connecting sample. The sample share of these fare observations starts at 1% in 1998, when the fare data are first avaiable, and rises to around 2% by 2001, fluctuating around this value for the rest of the sample period. This small share partly reflects a tendency for connecting trips with a US endpoint to involve a US carrier, which makes them visible in the DB1B, but it may also be due to the absence of data on connecting trips solely on non-reporting foreign carriers.[8]

3. Connecting-Market Results

3.1. Main results

Table 2 shows connecting regressions with different possible break points for the **ATI** and **JV** coefficients, using the full sample of economy and business-class itineraries. The standard errors for these regressions and all subsequent ones are clustered at the city-pair level, and the regressions are unweighted. Consider the regression in the first column, which has no break point.[9] The **ATI** and **JV** coefficients in the regression are thus constant over the sample period, along with the **online** and **ALLY** coefficients. The **online** coefficient indicates that fares for online itineraries, where service is provided by a single carrier, are 7.4% lower than interline fares. The **ALLY** coefficient shows that, for two-carrier itineraries where the airlines are alliance partners without ATI or JV status, fares are only 0.7% below interline fares. Alliance partners with ATI but without JV status charge fares that are 6.4% below interline fares, as shown by the coefficient of **ATI**. The fares of JV partners are 7.2% below interline fares, as seen in the **JV** coefficient. While the online, ATI and JV fare effects are all similar in size, statistical tests indicate whether the effects are significantly different from one another, as seen in the continuation of the next table, Table 3, which shows the same regression in its first column. The first column of the continuation of Table 3 carries out tests of the hypotheses $\nu = \tau$ and $\mu = \tau$. In listing a test, the table shows the variable names along with the coefficients (following STATA's format). Equality of the **online** and **JV** coefficients cannot be rejected ($p = 0.4971$), showing that JV partners act like a single carrier in setting connecting fares. However, the **ATI** and **online** coefficients are significantly different from one another ($p = 0.0005$), indicating that ATI does not lead to full elimination of double marginalization, although it comes close.

The coefficients of the **Z** variables in the first column show that longer trips have higher fares, that tickets bought in Europe are 5.6% cheaper than those bought in the US, and that tickets bought outside both Europe and the US are 6.9% more expensive than US-bought tickets. These latter disparities could reflect some combination of directional income-based price discrimination, different passenger mixes, and issues related to currency conversion. The price discrimination explanation is discounted, however, because lower fares would then be observed for trips originating at almost all endpoints outside the US, given their typically lower incomes. Other coefficients show that business-class fares are substantially higher than economy fares (the default category), and that an increase in the number of ticket coupons raises the fare (with carrier cost effects thus dominating). Connecting competition in the market has a very mild effect on fares, with addition of another competing online carrier or carrier pair reducing fares by only 0.3%. A connection with a US or foreign LCC reduces the fare by 5.3%, and fares are lower in large or high-income markets, evidently indicating the effect of economies of density. Finally, when the city-pair market is covered by an open-skies agreement, fares are 6.7% lower than without such an agreement.

The fare effects for airline cooperation seen in first column of Table 1 are similar to those in Calzaretta et al. (2017), who find online fares to be 8.2% below interline fares, using almost the same sample period. This similarity emerges despite their lack of access to foreign-carrier fare data. Brueckner et al. (2011), however, find a larger online fare effect of 14.4%, a disparity that is presumably due to their different sample period, which runs from 1998 to 2009 (they also had no foreign-carrier data).

The remaining columns of Table 2 show the effects of allowing the **ATI** and **JV** coefficients to differ across a single break point. The second column shows results for a 2010 break point, with subperiods of 97-09 and 10-16. The third column shows results for a 2009 break point (subperiods of 97-08 and 09-16), and the fourth column shows results for a 2007 break point (subperiods of 97-06 and 07-16). Note first that introduction of the break points has little effect of the coefficients of the **Z** variables. In addition, changes in the **ALLY** and **online** coefficients are slight. Allowing the **ATI** coefficients to differ across early and late periods leads, however, to a modest divergence in the coefficient values. Compared to the single **ATI** fare effect of 6.4% in the first column, the 97-09 and 10-16 early and late effects in the second column diverge to 4.0% and 9.9%, respectively. The divergence narrows in the third column, with 97-08 and 09-16 early and late effects of 4.4% and 9.0%, and it narrows further in the fourth column, with with 97-06 and 07-16 early and late effects of 5.7% and 7.0%. Thus, the break points reveal a somewhat larger fare reduction from ATI in the later part of the sample period.

Allowing a break point also leads to divergence in the **JV** coefficients, although in less straightforward fashion. Compared to the single **JV** fare effect of 7.2% in the first column, the 97-09 and 10-16 early and late effects in the second column diverge slightly to 6.7% and 7.6% respectively. The divergence almost vanishes in the third column, with 97-08 and 09-16 early and late effects of 7.26% and 7.25%. But the divergence reverses itself in the fourth column, with 97-06 and 07-16 early and late effects of 8.5% and 6.9%. Thus, in contrast to the **ATI** case, whether the early or late period has a stronger **JV** effect depends on the location of the break point.

Although absence of a break point therefore masks a somewhat stronger late-period **ATI** effect, its absence does not hide an unambiguous trend in the strength of the **JV** fare effect. The insights provided by a break point are thus not substantial, and the presence of a break point can lead to counterintuitive estimates in some of the subsequent regressions. As a result, the remaining analysis of connecting fares will proceed without using a break point.

Table 3 divides the sample into economy and business-class itineraries, with the first column repeating the previous regression when the classes are combined (from the first column of Table 2; see also Table A.7 for the time dummy coefficients). As can be seen in the second column, the results for economy class alone are quite similar to the combined results, which is natural given that these itineraries make up the great majority of the combined sample (see the observation counts at the bottom of the table). One change, though, is that both the **JV** and **ATI** coefficients are now statistically indistinguishable from the **online** coefficient, indicating that the fares for ATI and JV itineraries are the same as online fares (see the continuation of Table 3). Thus, carriers with either ATI or JV status act like a single airline in setting connecting economy fares.[10]

The business-class results, shown in the third column, exhibit a number of differences from the economy estimates. A nonUS/EU point of sale or additional coupons now reduce rather than raise the fare, larger or higher-income markets are now associated with higher rather than lower fares, and an LCC connection raises rather than lowers fares. While connecting competition now has no fare effect, the open-skies effect is stronger than in the economy regression.

The economy and business-class coefficients for the carrier cooperation variables also exhibit different magnitudes, with online itineraries now 12.5% cheaper than interline business-class itineraries (vs. 7.0% for economy). ATI now only reduces fares by 2.0%, whereas the **ALLY** coefficient is now significantly positive, although this counterintuitive effect is relatively small at 2.7%. The JV fare effect is similar in size to the economy effect. In contrast to the economy-class results, both the **JV** and **ATI** coefficients are significantly different from **online** coefficient, a consequence of that coefficient's large size (see the continuation of Table 3). The main conclusion, therefore, is that online service leads to substantially lower business-class fares, while JV service is associated with a smaller but still appreciable fare reduction. Intermediate levels of airline cooperation (alliance or ATI) have mixed effects.[11]

3.2. Results for regional subsamples

Table 4 shows regression results for the subsample of transatlantic itineraries, which connect the US to Europe, Africa and the Middle East. The results for the combined fare classes, shown in column two, differ from the full-sample combined results (column one of Table 3) mainly in stronger fare effects from airline cooperation. The online fare effect is now 9.5% rather than 7.3%, the ATI effect is now 10.2% rather than 6.4%, and the JV effect is now 9.1% rather than 7.2%. The **ATI** coefficient is now significantly different from the (slightly smaller) **online** coefficient, while the **JV** and **online** coefficients remain statistically indistinguishable (see the continuation of Table 4).

Among the other coefficients, the only other noteworthy change is that the effect of a nonUS/EU point of sale (indicating a point of sale in Africa or the Middle East) is now negative. The economy results once again closely match the combined results, while the business-class estimates diverge. The online effect is much stronger than in the economy case (at 14.4%), while the effects of ATI and JV become weaker, with both being significantly different than the online effect. Therefore, for transatlantic business-class itineraries, airline cooperation through alliances is a poorer substitute for online service than in the full sample.

Table 5 shows the results of regressions using the subsample of transpacific itineraries. The economy-class results show online and JV fare effects similar to the estimates in the previous tables, although the ATI effect has a counterintuitive (and significant) positive sign. Airline cooperation on transpacific routes thus has beneficial fare effects only when it comes in the form of online or JV service. A similar conclusion again holds for business-class fares, although the **ALLY** coefficient is also significantly negative in the third column, showing a small 1.9% fare effect. The continuation of Table 5 shows that the **ATI** and **JV** coefficients are significantly different from the **online** coefficient in all three regressions. Another notable change relative to previous results is that the effect of additional coupons is negative for both fare classes.

3.3. Sensitivity tests

Table 6 shows the effects of two sensitivity tests. The first column shows the effect of weighting itineraries by passenger counts. As can be seen, the results are very similar to the baseline estimates in column one of Table 3. The second column shows a regression without city-pair fixed effects. The results are again very similar to the baseline case, indicating that the influence of unobservable factors that affect fares at the city-pair level is not substantial. Note, however, that the coefficients of the population and income variables are much smaller than before, and that the income coefficient reverses sign (to significantly positive).

3.4. Summary

The results of the connecting-market analysis show that JV fares are statistically indistinguishable from online fares except in transpacific case, where online fare effects are stronger. This equivalence is expected given that JV status gives carriers incentives to behave like a single airline in setting fares. Less expected, however, is the finding that connecting fares for carriers with ATI who lack JV status are also similar to online fares, again excluding the transpacific case. The **ATI** and **online** coefficients are statistically indistinguishable in the full-sample economy case and in the weighted results, and though this equivalence does not hold for European economy subsample, it is only because the **ATI** coefficient is somewhat *larger* than the **online** coefficient.

The similarity of ATI and online fares in the connecting case contrasts with the results of earlier research, which tend to show that ATI does not replicate the fare benefits of full cooperation, and this finding may be due to our use of supplementary foreign-carrier fare data. However, the transpacific results, which show the expected shortfall of the ATI fare effect relative to the JV and online effects, are more in line with expectations.

4. Gateway-to-Gateway Data and Variables

4.1. Data and Variables

The data set for the gateway-to-gateway analysis is constructed as follows. As in the connecting analysis, round-trip itineraries between a US city and a foreign city must start and return to the same city. These round trips, which can originate either inside or outside the US, are required to contain just two route segments (and thus ticket coupons), one outbound and one inbound. Single-segment one-way itineraries, which are quite common in GTG markets, are also included in the sample, and fares for round trips are divided by two so that all fares are expressed on a one-way basis. The focus is again on city-pairs, not airport-pairs.

As in the connecting analysis, fares are aggregated up to the carrier-market-year-quarter level, yielding a passenger-weighted average fare. Fares that are below $50 or that are flagged by the fare credibility indicator are dropped, as are bulk fares.[12] The foreign carrier data account for a larger share of the observations in the GTG sample than in the connecting sample. The share of the itineraries from these data ranges between 15 and 19% up to 2003, then ranges between 19% and 24% through the remaining sample years.

As in the connecting analysis, alliance codes are assigned for each itinerary, indicating which (if any) alliance the carrier (or carriers) belongs to, as well as its relevant ATI or JV groups. As explained earlier, these codes are both time specific, reflecting the evolution of alliances, and route specific.

While most round-trip itineraries are online, involving one carrier and no codesharing (indicated, as before, by the dummy variable **online**), some itineraries involve use of different carriers on the outbound and inbound segments. If the two carriers have no alliance relationship, such an itinerary is designated as "interline", with the dummy variable **interline** set at 1. For example, an itinerary where the outbound carrier is American and the inbound carrier is Air France, would have **interline** = 1. The **interline** dummy, however, is set at zero if the itinerary contains two different carriers that have an alliance relationship (for example, if the previous inbound carrier were British Airways instead of Air France). Itineraries that are neither online nor interline are designated by the dummy variable **not_online/interline**. Some of these cases would be itineraries like the one just described, where the inbound and outbound carriers are different but have an alliance relationship, possibly with ATI or a JV. Most of the **not_online/interline** itineraries, however, involve codesharing. For example, the outbound segment could be operated and marketed by American with the inbound segment operated by American but marketed by British Airways. Even though this itinerary has the same operating carrier throughout, the inbound-segment codeshare makes it not online, according to our definition.[13] Note that, just like for online itineraries, the multi-airline itineraries in the **not_online/interline**= 1 category carry the appropriate alliance code in addition to any ATI or JV codes.

The expectation is that interline fares are higher than fares for online itineraries (which serves as the default category) due to lack of a cooperative relationship between the carriers providing the outbound and inbound services. Itineraries with **not_online/interline**= 1 involve cooperation between the carriers and, as a result, their fares are expected to diverge less from the online case than do interline fares.

Although there are some similarities between the GTG and connecting cases, the fundamental differences should be borne in mind. While connecting trips involving two carriers are *necessary* for non-GTG travel in many city-pair markets, two-carrier itineraries are *never necessary* in the GTG case since a single carrier can always be used. But passengers who split the inbound and outbound segments of their GTG trips between nonaligned carriers are expected to pay a penalty for the lack of cooperation, just as in the connecting case.

While the extent of cooperation within a GTG itinerary must be taken into account in understanding fare determination, it is a secondary issue compared to main question on which the GTG analysis is focused. This question is the fare effect of overlapping service by alliance partners on the GTG route. The question is addressed as follows. First, the number of distinct carriers providing nonstop online service on the GTG route is counted, regardless of alliance relationships. This variable, which is based on carriers with at least 5% of the city-pair's passenger traffic, is denoted **totcomps**. It should be noted that connecting competition in the GTG markets is not counted. Since gateway cities tend to be large, connecting service via a third gateway will always be available. With connecting competition present for every GTG market, explicitly controlling for the number of connecting routes seems unnecessary. Even though some connecting routes in GTG markets are circuitous and likely to be little used (e.g., Boston-Atlanta-Paris) while others are more natural (e.g., Los Angeles-Chicago-London), such differences are mainly related to the geographic location of the US endpoint and can be captured by city-pair fixed effects.

Using the **totcomps** variable, the presence of overlapping service by alliance partners is tabulated. The variable **ALLYcomps** is set equal to the number of carrier pairs among those counted in **totcomps** that belong to the same alliance, but where the relationship does not involve ATI or JV status. The variable **ATIcomps** is set equal to the number of carrier pairs among those counted in **totcomps** that have ATI but not JV status. Note that these carriers necessarily are alliance partners, but that this fact is not counted in **ALLYcomps** since the carriers also have ATI. The variable **JVcomps** is set equal to the number of carrier pairs among those counted in **totcomps** that have JV status. These carriers are necessarily alliance partners with ATI, but that fact does not affect that values of **ALLYcomps** and **ATIcomps** since those variables do not count JV partners. As an example, the Los Angeles/Tokyo city-pair market in the first quarter of 2016 had **totcomps**$=6$ and **JVcomps**$=2$, with the JVs being American/Japan Airlines and United/All Nippon. The JVs thus account for four of the six carriers serving the route.

To understand how these variables are used, let the regression equation be written as

$$\mathbf{log\_fare}_{ict} = \alpha+\beta\mathbf{totcomps}_{it}+\gamma\mathbf{ALLYcomps}_{it}+\delta\mathbf{ATIcomps}_{it}+\lambda\mathbf{JVcomps}_{it}+\mathbf{X}_{ict}\theta+\epsilon_{ict}, \tag{3}$$

adapting the approach of Brueckner and Whalen (2000). In (3), ϵ is an error term, $\mathbf{X}$ contains variables such as **interline** and **not_online/interline** along with others to be discussed below, i denotes the city-pair market, c the denotes carrier or carrier pair, and t denotes time. Note that the competition variables are measured at the market level and thus do not have a c

subscript. The coefficient $\beta < 0$ gives the effect on each carrier's fares of adding another competitor to the market holding **ALLYcomps**, **ATIcomps**, and **JVcomps** fixed. The coefficient δ gives the fare effect of increasing **ATIcomps** by 1, holding **totcomps** and the other variables fixed. This change corresponds to the effect of granting ATI to two previously nonaligned carriers serving the route, an effect that would be positive if carriers with ATI do not fully compete. Granting ATI would then reduce the amount of competition provided by the carriers counted in **totcomps**, leading to an increase in fares. If overlapping ATI partners in a GTG market do not compete at all, then granting ATI to the two carriers would be equivalent to removing a competitor from the market. In this case the ATI fare effect would be equal and opposite to the effect of an additional competitor, so that $\delta = -\beta$, or $\beta + \delta = 0$.

The same logic applies to the coefficients γ and λ of **ALLYcomps** and **JVcomps**. The coefficient λ gives the fare effect of granting JV status to two previously nonaligned carriers on a GTG route, an effect that is equivalent to removal of a competitor if $\beta + \lambda = 0$. Similarly, the coefficient γ gives the fare effect of alliance membership for two previously nonaligned carriers in the market. Since a greater degree of collaboration between carriers would be expected to reduce the extent to which they compete on a GTG route, we would expect the JV fare effect would be larger than the ATI effect, which in turn would be larger than the ALLY effect, so that $\lambda > \delta > \gamma \geq 0$ would hold. It is important to realize that the fare effects of **ALLYcomps**, **ATIcomps**, and **JVcomps** are felt by the passengers of each carrier in the market (those of the alliance partners and their competitors).

As in the connecting regressions, we might expect the effects of these various competition measures to change with time. Then the $\beta\,\mathbf{totcomps}_{it}$ term in (3) would be replaced by

$$\beta_{early}\,\mathbf{D}_t\mathbf{totcomps}_{it} \;+\; \beta_{late}\,(1-\mathbf{D}_t)\mathbf{totcomps}_{it}, \tag{4}$$

with β_{early} and β_{late} giving the effects of **totcomps** in the two subperiods and $\mathbf{D}_t$ defined as before. The regressions allow the coefficients of all four competition variables to change with time in this fashion.

It should be noted that extra steps were needed to properly compute the key competition variable **totcomps**. The problem is that, while foreign carriers with ATI or JV status were required to report to the DOT starting in 1997 (and are thus in the ticket sample), other service entirely on foreign carriers is not included in this sample. As a result, data from the T-100 segment survey, which captures foreign carrier service to US endpoints without containing any fare data, is used to supplement the information in the ticket sample, allowing a complete count of competitors on GTG routes. The frequency cutoff for counting as a competitor is 48 departures per quarter. Another point to note is that, following the previous alliance literature, potential endogeneity of **totcomps** and the other competition variables is ignored in the regressions. Some justification for this approach comes from Gayle and Wu (2013), who show that accounting for the endogeneity of carrier entry via a structural model has little effect on estimated competition effects on fares in a subsequent regression.

In addition to **interline** and **not_online/interline**, **X** in (3) contains a number of other variables. The one-way distance of the route is captured by the variable **dist**, which is used in log form. The two point-of-sale dummy variables from the connecting regressions, **EU_pos** and **nonUS/EU_pos**, are again used. One-way itineraries, which tend to be more expensive than round trips on a one-way basis, are capture by the dummy variable **one_way**. First-class tickets are dropped in the regressions, but two dummy variables, **economy** and **business**, are used to indicate the remaining fare classes. The sample also includes a variety of round-trip itineraries with mixed fare classes on the two segments (economy/business, business/first, economy/first), and these itineraries are retained in one specification of the regression, which includes economy, business-class, and mixed-class tickets, with the latter denoted by the dummy variable **mixed**. Two other specifications are restricted solely to economy and business-class itineraries, respectively. The dummy variable **LCC_mkt** captures the effect of low-cost carriers, using a different approach than in the connecting regressions. The variable equals 1 for a particular observation if LCCs are present in the city-pair market. The variable is not turned on, however, for itineraries that themselves include an LCC, since the own-fare effect of LCC status is captured by the carrier variables. All LCCs in the GTG sample are US carriers, and they were listed in section 2.[14]

As in the connecting regressions, the demand variables **mktpop** and **mktinc** (the geometric means of endpoint populations and incomes) also appear in the GTG regressions.[15] The dummy variable **open_skies** is again used, but since the effect of open skies agreements are already captured in part by **totcomps**, an additional fare effect may not emerge. Another regulatory variable that may affect fares captures the existence of a "carve-out" on a route, via the dummy variable **carve_out**. Carve-outs, which are imposed by the DOT, are meant to prevent alliance partners from collaborating in setting GTG fares on routes where they apply, so we might expect a negative effect on fares. However, as argued by Brueckner and Proost (2010), a carve-out may reduce the efficiency of the alliance, leading to higher fares. Table A.5 contains the list of carve-outs and their effective dates (provided by the DOT), which is used to create the **carve_out** variable.

In order to better control for the effects of economies of traffic density, the regressions include the variable **flow_routes**, which counts the number of connecting city-pair markets served by the carrier for which traffic flows across the observation's GTG route. These markets could be "behind-beyond" routes, whose endpoints are non-gateway cities, or they could be routes between gateway and non-gateway cities. With a large value of **flow_routes** associated with high "flow" (or connecting) traffic volume and thus substantial opportunity to exploit economies of density, a negative GTG fare effect might be expected. Another variable, **flow_pax**, counts the number of flow passengers using the GTG route instead of the number of connecting routes that use it. Because of potential endogeneity, this variable is not used in the fare regressions but appears in subsequent analysis.

Finally, the regressions also include year and quarter dummies along with carrier variables. While single-carrier itineraries have a unitary carrier dummy variable to indicate a particular airline, for itineraries with two carriers, the two carrier variables each take the value of 1/2. Some regressions also include city-pair fixed effects, as in the connecting analysis. However, the presence of FEs has bigger effect than in the connecting regressions, mainly by threatening the precision (and thus the statistical significance) of the estimated coefficients. As a result, all the GTG regressions are presented with and without FEs.

4.2. Sample break points and subsample means

Figures 3 and 4 show the evolution of the competition variables over the sample period, which are averaged across city-pairs in each year. As seen in Figure 3, the variable **totcomps** falls from an average of around 2.5 at the beginning of the period to less than 2.0 in 2009, then rises again to above 2.4 at the end of the period. Figure 4 shows that **ALLYcomps** follows the reverse pattern, rising to 0.25 in 2008 and then falling again. The figure thus shows that the number of carrier pairs providing overlapping alliance service averaged between 1/10 and 1/4 over the sample period. The patterns of **ATIcomps** and **JVcomps** are particularly noteworthy in that they show the conversion of ATI partnerships into JVs late in the period. After an initial surge to around 0.12, **ATIcomps** falls gradually and then drops precipitously after 2010. At the same time, **JVcomps** rises dramatically from a low level, with its 2016 value near 0.27 indicating that city-pairs had, on average, around 1/4 carrier pair providing overlapping JV service by the end of the period.

This pattern suggests the year 2010 as a logical break point in a specification that allows competitive effects to differ across the sample period. Thus, the sample is divided into two subperiods, with the early subperiod consisting of the years 1997-2009 and the late subperiod consisting of the years 2010-2016. The coefficients of the competition variables are allowed to differ across these subperiods in a regression on the full sample, as in (2). Once the main results have been presented, additional analysis shows the effect of dropping the break point or choosing a different location for it. Note that this approach contrasts with the one taken in the connecting analysis, where the regressions did not incorporate a break point. The reason is that, while the presence of a break point had little impact in the connecting case, a major impact emerges in the GTG case, as will become clear below.

Table 7 shows summary statistics for all the variables in each of the subperiods (means are again across itineraries and not passenger weighted; see also Table A.8). The average fare (on a one-way basis) is around \$1100, and the average one-way distance is a bit below 4000 miles. Other notable means are the 0.756 value for **online** in 2010-2016 and the 0.0213 value for **interline** (showing its infrequency). Around 40% of itineraries are one-way in both periods. The maximum **totcomps** = 10 value in the 1997-2009 period is attained in the New York/London, Los Angeles/Mexico City, and Los Angeles/Tokyo city-pair markets, but the drop in **totcomps** between the periods yields a smaller maximum value of 8 in 2010-2016. The share of itineraries in markets covered by open-skies agreements rose from 0.345 to 0.562

between the periods, and around 1% of itineraries are on routes subject to carve-outs. The share of itineraries on routes with LCC competition, most of which are to the Caribbean and Latin America, rose from 0.0259 to 0.0778 between the periods. The average GTG itinerary is on a route that carries flow traffic from about 1000 city-pair markets, as indicated by the **flow_routes** means. The average flow passenger count is larger than the count of routes only by about 100, indicating that connecting markets are typically thin.

5. GTG Regression Results

5.1. Main results

Table 8 shows the regression results for a specification that does not include city-pair fixed effects (see also Table A.9 for the time dummy coefficients). As in the connecting analysis, the standard errors for these regressions and all subsequent ones are clustered at the city-pair level, and the regressions are unweighted. The sample for the first column consists of itineraries with economy, business-class or mixed-class tickets. Focusing first on the non-competition variables, the results show higher fares for longer trips and for one-way trips, lower fares for tickets with a European point-of-sale, higher fares for a point-of-sale outside the US and Europe, and higher fares for business and mixed-class tickets (the default is economy). The directional differences show the same pattern as in the connecting results, and the previous explanatory comments apply. Interline tickets are about 11% more expensive than online tickets (the default category), while tickets that are neither online nor interline are about 3% more expensive. The presence of an LCC on a GTG route reduces fares by 10%, while larger and richer markets have higher fares, in contrast to the opposite relationship for connecting markets. Open-skies agreements have no effect on fares (a possibility recognized above), while a carve-out on a route raises fares slightly, contradicting expectations. Again contrary to expectations, a large value for **flow_routes** is associated with higher fares. While economies of density were expected yield a negative **flow_routes** coefficient, a high volume of flow traffic could crowd out O & D traffic on the GTG route, with higher fares caused by the resulting reduction in GTG seats.

Turning to the competition variables, the **totcomps** coefficients show that an extra competitor reduces fares by 4.0% in the 1997-2009 period and by 7.0% in the 2010-2016 period, effects that are in line with the existing literature. Among the **ALLYcomps**, **ATIcomps** and **JVcomps** coefficients, only the 2010-2016 **ATIcomps** and **JVcomps** coefficients are statistically significant. The fare increases by 6.8% when the number of ATI pairs on a route increases by 1, increasing by 4.6% when the number of JV pairs increases by 1. The first column of the continuation of Table 8 carries out Wald tests of the two hypotheses from (1): $\beta + \delta = 0$ and $\beta + \lambda = 0$. With a p values above 0.05 (equal to 0.9498 and 0.0944), neither hypothesis can be rejected, indicating that the effect of removing a competitor ($-\beta$) is the same as the effect of increasing the number of ATI or JV pairs by 1 (δ or λ). The implication is that ATI or JV partners do not compete with one another.

The second and third columns of Table 8 show that the **ATIcomps** and **JVcomps** effects from the first column are a blend of disparate effects that vary across fare classes. The third column of the table, which shows results for the subsample of business-class tickets, shows **totcomps** effects in the two subperiods similar to the those in the first column, but none of the coefficients on the other competition variables is significant. Thus, in contrast to the anticompetitive effect of ATI or JV overlaps shown in the composite regression in the first column, no such effect exists in the case of business-class fares.

As seen in the second column of the table, the composite competition effects are actually driven by economy-class tickets. Both the late-period **ATIcomps** and **JVcomps** coefficients are significant in the second column, and their magnitudes are large, 12.7% and 9.6%, respectively. However, the late-period **totcomps** coefficient from the second column is also large at -8.2%, indicating a substantial economy fare effect from adding a competitor. As in column one, neither of the hypotheses $\beta + \delta = 0$ and $\beta + \lambda = 0$ can be rejected (p values are 0.2045 and 0.2935), indicating that neither ATI nor JV partners compete on GTG routes.

While evidence of an anticompetitive JV overlap effect is expected, the finding of an ATI overlap effect of the same size is somewhat surprising. Given the lower degree of integration under ATI relative to a JV, the partners would be expected to have less capacity to coordinate GTG fares, leading to a smaller overlap effect. Evidently the extent of cooperation allowed under ATI is instead sufficient for the carriers to act as a single airline in setting GTG fares, as do JV partners.

The coefficients on the remaining variables in the economy and business columns of Table 8 are mostly similar to those in the first column. However, LCC presence has a counterintuitive positive effect on business-class fares, and the significance of the **carve_out** coefficient disappears in the second and third columns, indicating the absence of a carve-out fare effect.[16]

Table 9 shows the GTG results when city-pair fixed effects are added to the regressions of Table 8, with the economy subsample representing 1954 individual city-pairs. In the presence of FEs, the coefficients are identified by variation in the variables within, not across, city-pairs. The resulting loss in variance makes it more difficult to identify the effects of interest, but by controlling for time-invariant unobservable factors that may be correlated with the explanatory variables, the use of city-pair FEs can reduce potential bias that would be present in their absence. As seen in the table, the coefficients of the non-competition variables and their significance levels are largely unaffected by inclusion of city-pair FEs. However, the **dist** coefficients become insignificant, a result of routing distances varying only slightly across carriers serving a market. In addition, the coefficients of the population and income variables are altered, given that the FEs remove some of their influence. The **mktpop** coefficients are now negative and significant in the economy and business-class regressions while the **mktinc** coefficients are insignificant in these regressions. The negative **mktpop** effect is consistent with the presence of economies of traffic density, which would lead to lower fares in large markets. Another change is the significantly negative open-skies effect in the business-class regression.

Focusing on the economy results, the coefficients of the two **totcomps** variables are smaller in absolute value than in Table 8, with competition having no significant 1997-2009 effect on economy fares. An extra competitor reduces economy fares in the 2010-2016 period by about 4.6%, in contrast to the previous 8.2% effect. While the **ALLYcomps**, **ATIcomps** and **JV-comps**, coefficients are again mostly insignificant in the business-class regression (except for the early period **ATIcomps** coefficient), all three coefficients are significant in the economy regression for the 2010-2016 subperiod. An additional ATI pair on a GTG route raises the economy fare by 9.6%, while an additional JV pair raises the fare by 4.4%. From the continuation to Table 9, both the $\beta + \delta = 0$ and $\beta + \lambda = 0$ hypotheses cannot be rejected (p values are 0.1624 and 0.8995), again indicating that granting *either* ATI *or* JV to two nonaligned carriers is equivalent to removing a competitor. Therefore, although the point estimates on the competition variables differ somewhat between Tables 9 and 8, as would be expected given the introduction of city-pair FEs, the main conclusions are unaffected. In particular, both ATI and JV partners act like a single carrier in setting GTG fares late in the sample period.

The coefficient of **ALLYcomps** is also significant for the late period in the economy regression of Table 9, but at 2%, the effect of alliance membership by two previously nonaligned carriers is smaller than the ATI and JV effects. The hypothesis $\beta + \gamma = 0$ can indeed be rejected (the p value, which is not shown, is 0.0321), indicating that the effect of two carriers becoming alliance partners is less than the effect of removing a competitor. Thus, it appears that unimmunized alliance partners, who lack the legal ability to coordinate in pricing, may nevertheless not fully compete with one another on GTG routes where they overlap.

5.2. The effect of different break points

Table 10 shows the results of regressions that use other break points for the competitive effects, focusing on economy-class tickets. The first column shows results with no break point at all, where the coefficients of the competition variables are constrained to be the same throughout the sample period. As in the connecting analysis, these coefficients are in the table rows designated by "(_early)." Although the coefficients of the non-competition variables are similar to those in economy regression of Table 8, the single **ATIcomps** coefficient loses significance and the significance level of the single **JVcomps** coefficient falls from the late-period 1% value to 5%, while the coefficient itself becomes smaller, at 3.1%. With the **totcomps** coefficient at 5%, the hypothesis $\beta + \lambda = 0$ cannot be rejected, indicating that granting JV status to two nonaligned carriers is equivalent to removing a competitor.

The GTG regression reported in Calzaretta et al. (2017) also constrains the competition coefficients to be the same throughout their long sample period. But in contrast to the results in the first column of Table 10, the coefficients of their ATI and JV overlap variables are not statistically significant, showing the absence of an anticompetitive effect from overlapping alliance service. Their baseline model, however, includes city-pair FEs, whereas the regression in Table 10 lacks them. When FEs are added to the current regression, the results are as shown in the second column of Table 10. As can be seen, the coefficients of **ALLYcomps**,

ATIcomps and **JVcomps** all become insignificant, mirroring the findings of Calzaretta et al. (2017). But, as was seen in the economy regression of Table 9, which uses FEs and has a break point, anticompetitive overlap effects emerge when a break point is present, even in the presence of FEs. The strong conclusion of Calzaretta et al. (2017) regarding the absence of these effects thus follows from a regression specification that is not sufficiently flexible. In other words, when city-pair FEs are used, the assumption of no break point hides anticompetitive overlap effects that emerge when a break point is allowed.

Instead of suppressing the break point, the third and fourth columns of Table 10 show results with break points placed differently than in the original regressions, with only the FE versions of these regressions reported. In the third column, the early and late periods are 1997-2008 and 2009-2016, while the periods are 1997-2006 and 2007-2016 in the fourth column. In the third column, the coefficients of the competition coefficients are similar to those in the economy column of Table 9, showing that moving the break point back by one year has little effect on the FE results (the same conclusion applies without FEs). The fare effects from ALLY, ATI and JV overlaps in the late period are about 2.9%, 8.8% and 4.1%, respectively. The results in the fourth column of Table 10, where the break point is pushed back by two additional years, are similar to those in the third column, except that the late-period **JVcomps** coefficient is just barely insignificant. This difference is presumably the result of putting the break point too early. Therefore, the conclusion that anticompetitive overlap effects emerge in the latter part of the sample period is quite robust to the exact location of the break point.

5.3. Results for subsamples

Restoring the original break point, Table 11 shows results for various subsamples. The first two columns show regression results for European itineraries, with and without city-pair FEs (EU is used as a shorthand). The focus is on a European subsample, rather than the broader transatlantic sample used in the connecting analysis, because of the importance of these routes. Without FEs (first column), the same pattern of late-period anticompetitive overlaps effects emerges, with a grant of ATI or JV status to two previously nonaligned carriers leading to fare increases of 9.1% and 7.0%, respectively, effects that are close to the 7.5% effect of eliminating a competitor. The continuation of Table 11 shows neither coefficient is significantly different from the **totcomps** coefficient. While the late-period **ALLYcomps** coefficient is insignificant, the early-period coefficient is significantly negative, a counterintuitive finding with no apparent explanation.

Use of city-pair FEs in the Europe regression (second column of Table 11) eliminates the significance of the **JVcomps** coefficient, while making the late-period **ALLYcomps** coefficient significant and positive, indicating a 5.2% fare effect. Therefore, the evidence of an anticompetitive effect from a JV overlap is not as clearcut for Europe as for the full sample, although ATI and ALLY overlaps do emerge.

Other notable changes relative to the full sample are a significantly negative open-skies effect, with fares lower by 4 to 6% on European open-skies routes. In addition, **mktinc** retains its positive effect on fares when FEs are introduced, in contrast to the full-sample results. The significantly positive LCC effect is due to the almost complete absence of US LCCs on European routes during the sample period, with Sun Country being the only such carrier (its presence is associated with high, rather than low, fares). Dropping the LCC variable leaves the remaining results unaffected.

The third and fourth columns of Table 11 show results for the transpacific subsample. As in the case of the connecting regressions, the transpacific estimates differ markedly from those based on the full sample. Fares for interline itineraries and for those that are not online or interline are indistinguishable from online fares (the coefficients of **interline** and **not_online/interline** are insignificant). More importantly, even though the **totcomps** effect is significant and similar to those in previous regressions, the coefficients of each of the **ALLY**, **ATI** and **JV** variables are insignificant in the third column, indicating the complete absence of anticompetitive effects from alliance overlaps on transpacific routes. The reason why such an effect is present elsewhere but absent in the transpacific case is unclear. This finding is mostly preserved in the FE regression (fourth column) although early-period coefficient of **ALLY** becomes significantly positive. Note that the missing coefficients in two regressions indicate the absence of LCCs, carve-outs, and early-period JV overlaps on transpacific routes.

The fifth and sixth columns of Table 11 show the effects of dropping GTG routes with more than four competing carriers, a restriction that Calzaretta et al. (2017) imposed in generating their base sample. In the fifth column (without FEs), the sizes and significance levels of the competition coefficients are the same as in the economy regression of Table 8, and the results in the sixth column are similar to the economy FE results from Table 9. The continuation of Table 11 shows that the **ATI** and **JV** coefficients statistically indistinguishable from the **online** coefficient in both regressions. These conclusions show that our results, and the differences relative to those Calzaretta et al. (2017), are not being driven by routes with the highest levels of competition.[17]

5.4. Weighted results

While passenger-weighting of the main regression had little effect on the results in the connecting analysis, weighting leads to a bigger difference in the GTG case. When the economy regression in column two of Table 8 is weighted, the results are as shown in the first column of Table 12. Notable changes are the reduction in the **totcomps** coefficient and the loss of significance of the late-period **ATIcomps** coefficient. That coefficient, however, is close to being significant and its magnitude is unaffected. A significant JV overlap effect of 7.8% is still present, and it is larger than the late-period **totcomps** effect. In fact, as seen in the continuation of Table 12, the hypothesis $\beta + \lambda = 0$ can be rejected at the 5% level. Thus, the anticompetitive JV overlap effect is greater than the **totcomps** effect, indicating that granting JV status to two carriers is worse than losing a competitor (with the two changes leading to an increase in fares rather than no effect). With the addition of FEs, the late-period **JVcomps** coefficient becomes smaller, and the $\beta + \lambda = 0$ hypothesis can no longer be rejected. The late-period **ATIcomps** coefficient is again close to being significant.

5.5. Summary

The results of the unweighted GTG regressions point to a number of conclusions. First, anticompetitive economy-class fare effects from overlapping ATI and JV service exist in the second part of the sample period. Except for in the European FE regression, statistical tests show that the magnitude of the anticompetitive effect is the same regardless of whether it comes from an ATI or a JV overlap, a surprising conclusion given the greater integration of JVs. The size of the anticompetitive effect implies that granting ATI or JV status to two previouly unaligned carriers is equivalent to removing a competitor from the route, indicating that the partners do not compete. One important implication of the equal-size ATI and JV effects is that, if alliance partners serving a route already have ATI, then granting JV status *has no further anticompetitive effect on GTG fares.*[18]

Weighting of the GTG regressions, which gives a larger role to markets with high passenger volumes, weakens these conclusions somewhat. The anticompetitive fare effect from late-period overlapping JV service is still present, but the effect from overlapping ATI service is no longer statistically significant at conventional levels. However, the ATI effect remains marginally significant and its size is close to that in the unweighted regression. Thus, viewing the unweighted and weighted results as a whole, they strongly suggest the presence of anticompetitive overlap effects for both JV and ATI service.

An additional finding, which appears only in the results with city-pair FEs, is that overlapping service by *unimmunized* alliance partners also yields an anticompetitive fare effect, although a smaller one not equivalent to the effect of losing a competitor. A final conclusion is that carve-outs appear to be ineffective as a policy tool. The **carve_out** coefficient is typically insignificant and thus indistinguishable from zero, indicating that carve-outs do not have the anticipated negative effect on GTG fares.

One puzzle posed by the results concerns the absence of anticompetitive overlap effects in the first part of the sample period. A possible explanation is that the effects of competition were generally weaker in the first part of the period, with the early-period **totcomps** coefficient always smaller than the late-period coefficient. With competitive effects smaller, anticompetitive effects may have been smaller too, and harder to measure. Other explanations, however, may exist.

5.6. Flow regressions

In a exercise that blends consideration of both connecting and GTG routes, this section shows regressions that an relate an airline's flow traffic on a GTG route (as well as its number of flow routes) to its ATI or JV status. It is well known that by, stimulating connecting travel to foreign destinations, alliances have greatly increased the volume of flow traffic on their GTG routes, and this exercise can provide further confirmation of this phenomenon.[19]

To carry out the regressions, we tabulated for each GTG-route/carrier combination the values of **flow_pax** (the number of connecting passengers flowing across the carrier's GTG route) and **flow_routes** (the number of city pairs connected by the carrier across the route). The first regression, which is run at the carrier-route-year-quarter level, relates **flow_pax** to dummy variables indicating whether the carrier operates a JV or has ATI on the route (denoted **JV_route** and **ATI_route**). If carrier-level flow traffic on GTG routes with JV or ATI status is higher than on routes without such status, the coefficients of these variables should be positive.[20]

Additional variables are **open_skies**, the population and income measures, and **totcomps**. By encouraging service on a GTG route, an open-skies agreement is expected to raise connecting traffic and thus **flow_pax**. When the endpoints of a GTG route are large or rich, O & D traffic in the GTG market is high, which spurs economies of traffic density, reducing the cost of connecting trips and thus increasing flow traffic on the route. Conversely, by reducing each carrier's share of O & D traffic on a GTG route, a high value of **totcomps** impairs realization of economies of traffic density, thus potentially reducing **flow_pax**. The second regression relates **flow_routes** to this same collection of explanatory variables, using the same logic. The regressions also include year and quarter dummies, whose coefficients are not reported. Since use of carrier variables is not appropriate in this setting, they do not appear. The regressions are run with and without city-pair FEs.

Table 13 shows the results, with the **flow_pax** regressions presented in the first three columns and the **flow_routes** regressions shown in the last three columns. As expected, **flow_pax** is high on JV and ATI routes, with both the **ATI_route** and **JV_route** coefficients positive and significant. An open-skies route also has higher flow traffic, as do routes with large or high-income endpoints. The effect of **totcomps**, however, is positive instead of negative.

With city-pair fixed effects, as seen in the table's second column, the coefficient of **ATI_route** remains significant while the **JV_route** coefficient loses significance, as does the coefficient of **open_skies** (whose effect is captured by the FEs). While the income coefficient retains its significance, the population coefficient becomes insignificant. Interestingly, the effect of **totcomps** reverses from positive to the expected negative direction. The third regression replaces the JV and ATI variables with a single variable **JV_or_ATI_route**, which indicates either an ATI or JV route for the carrier. The coefficient of this variable is significantly positive, and the effects of the other variables match those in the second column, again showing that alliances stimulate flow traffic on the routes between their gateway cities.

Because the **flow_pax** and **flow_routes** variables are closely related, the results of the **flow_routes** regressions, shown in the last three columns of Table 13, mirror the previous findings. The results show that ATI or JV status on a GTG route encourages a carrier to connect the endpoints of a large number of city-pairs across that route. Overall, the results of Table 13 show how a carrier's ATI or JV status stimulates network connections that make use of a GTG route.

6. Simulating the Effect of ATI/JV Removal

The empirical results so far have shown that airline cooperation via ATI or JV status reduces fares for connecting passengers while increasing them for GTG passengers. Therefore, if a current ATI or JV agreement were removed, connecting passengers would pay higher fares and GTG passengers would pay lower fares. An important question concerns the net effect on passengers overall from such an action. In other words, would removal of an ATI or JV agreement raise or lower aggregate fare outlays for passengers as whole? The answer obviously depends on magnitudes of the GTG and connecting fare changes and the numbers of affected passengers.

The purpose of this section is to address this question through some illustrative calculations. The calculations are done separately for two GTG routes served by different JV partners, focusing on the GTG passengers on the route and on the connecting passengers flowing across the route. The first GTG route, denoted Route A, is a route with two large endpoints and substantial GTG traffic, some of which is carried by airlines other than the JV partners. For the second GTG route, denoted Route B, one endpoint is large, while the other is medium-sized. Route B carries less GTG traffic than route A (all of it using the two JV partners) but substantially more connecting traffic.

The exercise consists of removing the JV (and the associated alliance membership and

ATI) for the route in question, reducing the carriers to nonaligned status, and then computing the change in aggregate fare outlays for GTG and connecting passengers, focusing on economy-class passengers (round-trip plus one-way). This action is unrealistic since removal of either of the JVs would affect additional routes beyond the one considered. However, the exercise exposes the gains and losses for the two groups of passengers, and it could be generalized to include additional routes.

In addition to not identifying the two GTG routes, the fare levels and traffic volumes underlying the calculations are not provided to maintain data confidentiality. Instead, just the overall effects on fare outlays are presented.

The first row of Table 14 shows changes in aggregate fare outlays for GTG economy passengers on the two routes for the third quarter of 2015. To compute the GTG fare effects from removal of the JVs, the coefficient estimates from the second column of Table 9, which pertain to the full sample rather than the transatlantic subsample, are used.[21] Since the **JVcomps** and **ATIcomps** coefficients in this column are statistically indistinguishable but nevertheless differ notably in their magnitudes, the fare effect is computed using an average of the **JV-comps** and **ATIcomps** coefficient values, which equals 0.070 (indicating a 7% fare increase from overlapping JV or ATI service). Using this value, the new fare following removal of the JV would equal the JV fare times $1/1.07 = 0.935$, and the new aggregate fare outlay would equal the current one times this factor (for a reduction of 6.5%). Subtracting the current outlay from the smaller new outlay then yields the reduction in the aggregate fare outlay shown in the first row of the table. The numbers show that, with removal of the JV, the aggregate fare outlay for Route A GTG passengers would be reduced by $2.06 million, while outlay for Route B GTG passengers would be reduced by $469,000, with these differences mainly reflecting the sizes of the GTG markets. Note that on Route A, these reductions pertain to the GTG passengers served by the other airlines serving the route as well as those using the JV.[22]

The second row of Table 14 shows changes in aggregate fare outlays for JV connecting passengers flowing across the two GTG routes. To compute the change in connecting fare outlays for JV passengers, the average of the **ATI** and **JV** coefficient estimates from column 2 of Table 3 is used, recalling that the coefficients are statistically indistinguishable. The averaged value of -0.072 indicates that JV fares are 7.2% below interline fares, or that they equal 92.8% of interline fares. Therefore, with removal of the JV, the new fare is equal is to 1/0.928 times the current JV fare (for an increase of 7.8%), and new aggregate fare outlay is equal to the current one times this factor.[23] Subtracting the current outlay from this new larger value then yields the increase in the aggregate the fare outlay for current JV passengers, which is shown in the second row of Table 14. The numbers show that, with removal of the JV, the aggregate fare outlay for connecting passengers on Route A would rise by \$3.10 million, while the outlay for connecting passengers on Route B would rise by \$10.81 million. The larger magnitude of the second number mainly reflects the larger connecting JV traffic volume on Route B.

Since, for both routes, these fare increases are larger than the aggregate fare reductions for GTG passengers, passengers as a whole lose from removal of the JV, facing higher fare outlays. As seen in the last row of Table 14, the Route A and Route B net increases are \$1.04 million and \$10.34 million. In other words, on both routes, the losses for current JV connecting passengers, who no longer benefit from lower fares after removal of the JV, more than offset the gains for GTG passengers (those traveling on JV partners as well as on other carriers), who benefit from lower fares via increased competition. Therefore, removal of the JV is undesirable.

The changes in consumer welfare are equal to the negative of the net changes in fare outlays in Table 14, $-\$1.04$ million for Route A and $-\$10.34$ million for Route B. However, since consumers would respond to the fare changes from JV removal, GTG traffic would rise and connecting traffic would fall. As a result, the change in fare outlays in Table 14 overstate the negative effect on consumer welfare, as captured by the change in consumer surplus. Once the calculations are adjusted appropriately, assuming a price elasticity of demand of -1.5, the change in consumer surplus on Route A is $-\$0.76$ million, and the change in consumer surplus on Route B is $-\$9.68$ million.

These consumer-surplus results are likely to generalize beyond the two GTG routes considered. They are almost certain to hold for routes with small GTG gateway markets, where the number of GTG passengers is probably small compared to the number of connecting passengers on the route, making the GTG gain small relative to the loss for connecting passengers when the JV is removed. Moreover, since connecting traffic is likely to exceed GTG traffic even on routes with large endpoints such as Route A, this relationship is still likely to hold, ensuring a consumer surplus loss from removal of a JV. Extension of the simulation exercise to a larger number of routes, a possible subject for future work, could confirm this conjecture.

7. Conclusion

The evidence in this paper shows two sides of the fare effects of international airline alliances. Cooperation between alliance partners reduces the fares for connecting interline trips relative to the fares charged by nonaligned carriers, with carriers that enjoy ATI or JV status both charging fares that are indistinguishable from online fares. But cooperation in fare setting on gateway-to-gateway routes where alliance partners overlap leads to higher economy fares, with a grant of ATI or JV status to previously nonaligned carriers equivalent to removing a competitor from the route. The results thus show that ATI or JV partners do not compete with one another in setting economy fares on routes where they overlap. While this conclusion is expected for JV partners, its emergence in the ATI case as well is noteworthy.

With alliances thus having a downside as well as an upside when it comes to pricing, what stance should regulators take in acting on requests for ATI or JV status? The simulation results in the paper show that the upside of alliances dominates the downside, with removal of JVs on two representative GTG routes leading to decreases in consumer welfare for economy passengers. The calculations show that the harm to JV connecting passengers, who lose from higher fares when the JV is removed, more than offset the gains to GTG passengers, who benefit from lower fares due an increase in GTG competition.

Even though the downside of alliances is dominated by the upside, the simulations show that the downside is larger for alliances whose GTG markets are "thick," having substantial traffic (as in the simulated Route A case). Regulators have therefore been properly concerned about granting ATI or JV status for such alliances, as seen in the repeated failures of oneworld partners American and British Airways to gain such approval.

However, if a grant of ATI or JV status is accompanied by entry of new carriers on the GTG route, then the anticompetitive alliance effect can be offset, eliminating the downside for GTG passengers. The New York-London GTG route experienced exactly this combination of events, with the grant of immunity and JV status to American and British Airways roughly coinciding with entry of new carriers on the route in response to the US-EU open-skies agreement. US regulators had been wary of immunity for AA and BA up until that time, reflecting an implicit awareness of its possible downside on a heavily traveled GTG route with no potential for entry of new competitors. The results of the paper suggest that, even though alliances are on balance beneficial, such hesitancy is appropriate and should guide similar future decisions. Although a policy of requiring slot divestitures at capacity-constrained gateway airports can help foster beneficial entry of additional carriers when granting ATI or JV status, helping to justify such a decision, the paper's findings suggest that carve-outs are not a useful tool for restraining GTG fare increases.

Another important implication of our results is that, once ATI has been granted, a further grant of JV status to the alliance partners has only small fare effects. JV status will lead to no further reduction in connecting fares, and it will lead to no further increase in GTG fares. With JV status potentially conferring other passenger benefits, including greater scheduling convenience as departures are further coordinated, granting JV status to already immunized alliance partners would appear to be beneficial.

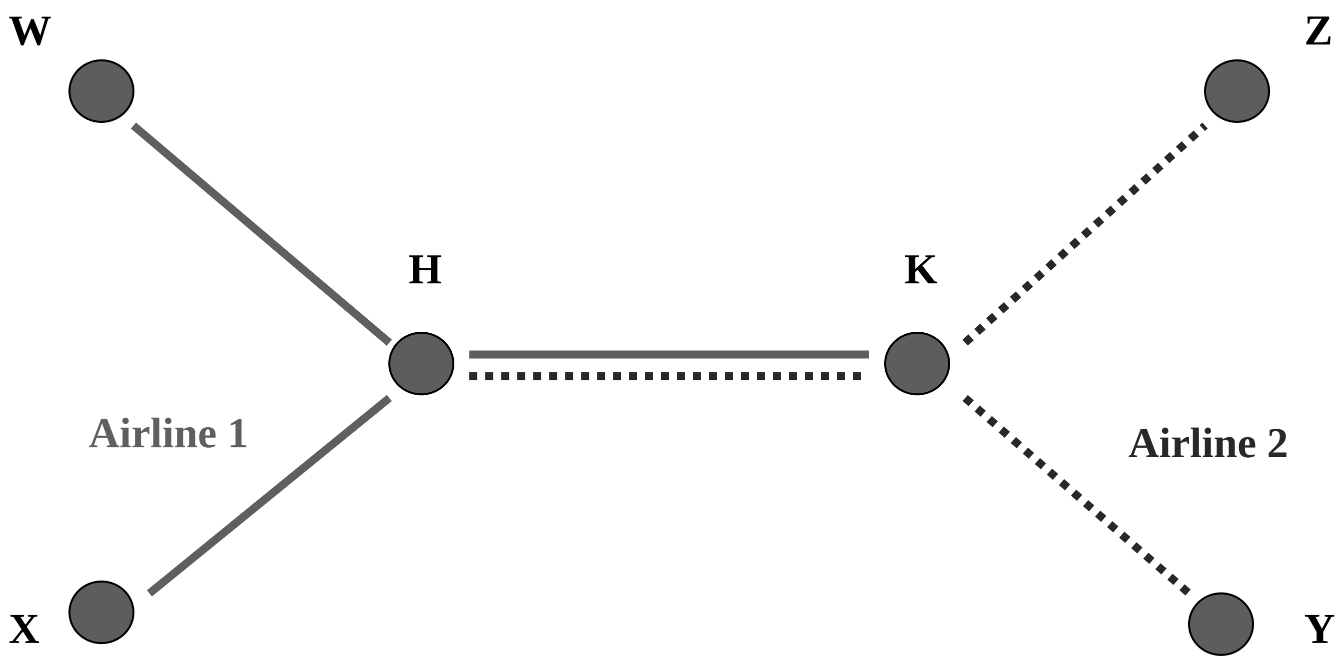

Figure 1: Airline alliance

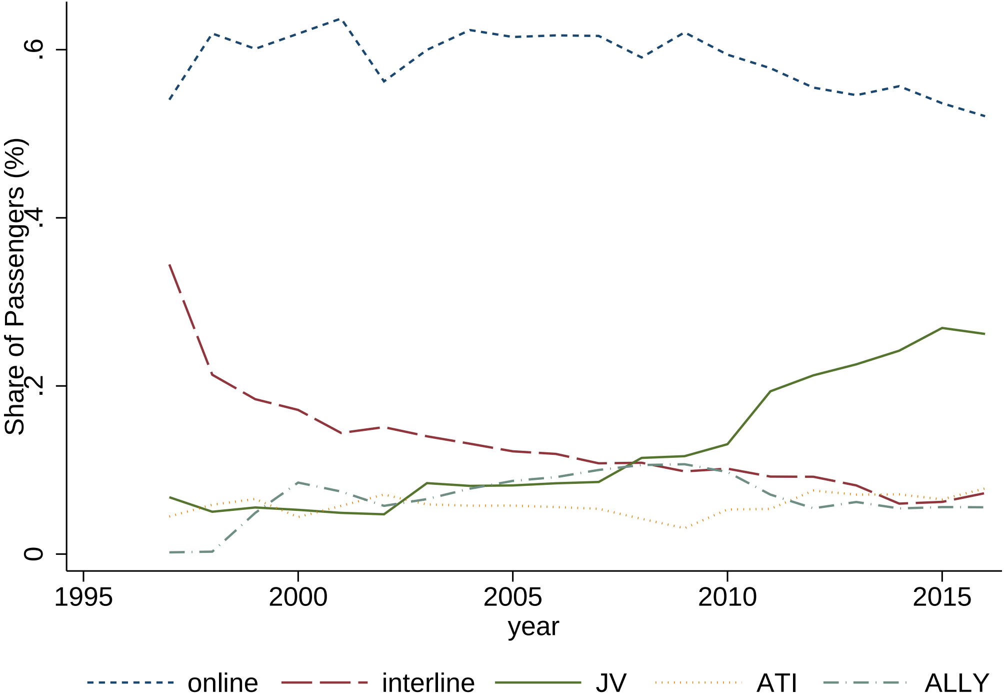

Figure 2: Patterns of cooperation in connecting markets

Figure 3: totcomps_avg

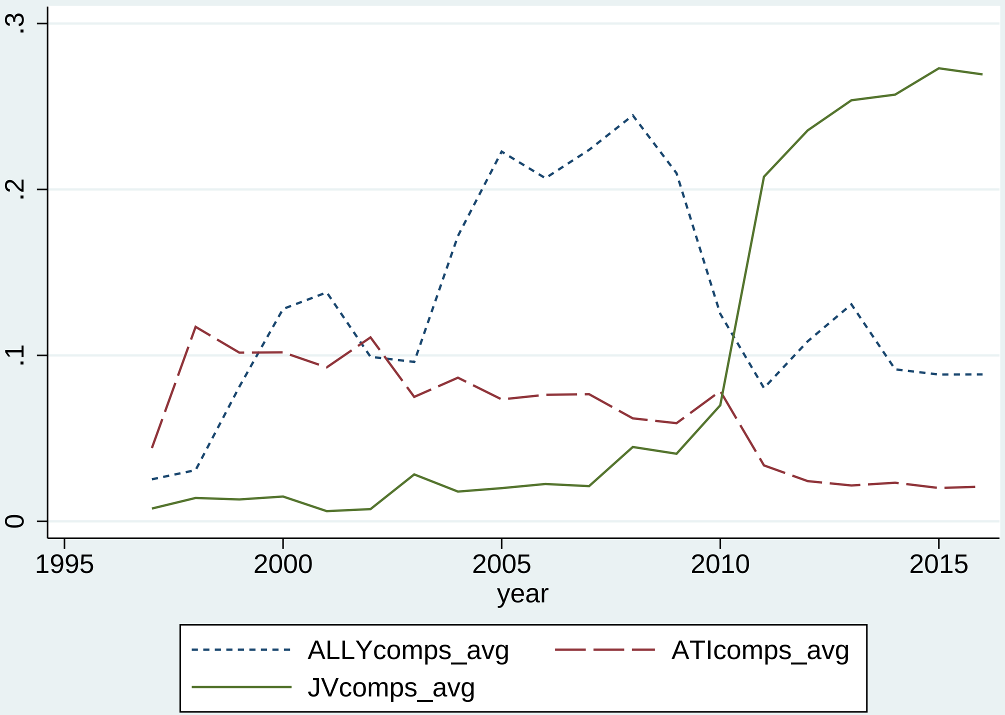

Figure 4: Alliance competition variables

Table 1: Connecting-Sample Summary Statistics

VARIABLES	N	mean	sd	min	max
fare	4,287,269	1,704	1,551	200	81,920
passengers	4,287,269	1.667	2.440	1	372
dist	4,287,269	6,441	2,172	808	17,476
EU_pos	4,287,269	0.163	0.369	0	1
nonUS/EU_pos	4,287,269	0.218	0.413	0	1
business	4,287,269	0.0749	0.263	0	1
online	4,287,269	0.458	0.498	0	1
interline	4,287,269	0.184	0.388	0	1
ALLY	4,287,269	0.0927	0.290	0	1
ATI	4,287,269	0.0779	0.268	0	1
JV	4,287,269	0.187	0.390	0	1
coupons	4,287,269	5.269	1.133	3	8
comps_connect	4,287,269	3.392	1.647	1	12
LCC_connect	4,287,269	0.0195	0.138	0	1
log_mktpop	4,248,111	15.76	0.963	10.58	18.93
log_mktinc	4,241,062	6.696	0.629	4.061	8.184
open_skies	4,287,269	0.618	0.486	0	1

Table 2: Connecting Results with Break Points

VARIABLES	(1) No break	(2) 97-09 10-16	(3) 97-08 09-16	(4) 97-06 07-16
log_dist	0.125**	0.126**	0.126**	0.125**
	(13.13)	(13.32)	(13.26)	(13.13)
EU_pos	-0.0557**	-0.0557**	-0.0557**	-0.0558**
	(-23.05)	(-23.03)	(-23.05)	(-23.08)
nonUS/EU_pos	0.0689**	0.0692**	0.0691**	0.0689**
	(24.52)	(24.73)	(24.70)	(24.62)
business	1.303**	1.303**	1.303**	1.303**
	(364.3)	(363.7)	(363.8)	(363.8)
online	-0.0737**	-0.0740**	-0.0737**	-0.0734**
	(-38.31)	(-37.96)	(-37.79)	(-37.87)
ALLY	-0.00730*	-0.00944**	-0.00882**	-0.00736*
	(-2.122)	(-2.868)	(-2.657)	(-2.183)
ATI(_early)	-0.0644**	-0.0398**	-0.0441**	-0.0569**
	(-24.28)	(-13.14)	(-14.31)	(-18.34)
ATI_late	—	-0.0991**	-0.0896**	-0.0701**
		(-26.60)	(-24.67)	(-20.18)
JV(_early)	-0.0721**	-0.0667**	-0.0726**	-0.0847**
	(-23.45)	(-18.97)	(-20.13)	(-21.12)
JV_late	—	-0.0758**	-0.0725**	-0.0693**
		(-22.71)	(-21.79)	(-21.93)
coupons	0.00354**	0.00349**	0.00353**	0.00359**
	(4.805)	(4.783)	(4.830)	(4.895)
comps_connect	-0.00264**	-0.00256**	-0.00258**	-0.00262**
	(-5.052)	(-5.016)	(-5.033)	(-5.051)
LCC_connect	-0.0533**	-0.0529**	-0.0524**	-0.0523**
	(-9.738)	(-9.584)	(-9.499)	(-9.528)
log_mktpop	-0.764**	-0.761**	-0.762**	-0.764**
	(-28.48)	(-28.36)	(-28.39)	(-28.44)
log_mktinc	-0.476**	-0.485**	-0.480**	-0.473**
	(-31.92)	(-32.17)	(-31.81)	(-31.27)
open_skies	-0.0674**	-0.0690**	-0.0687**	-0.0675**
	(-19.58)	(-20.01)	(-19.89)	(-19.47)
Constant	20.93**	20.93**	20.92**	20.90**
	(46.36)	(46.34)	(46.30)	(46.26)
Observations	4,241,062	4,241,062	4,241,062	4,241,062
Adjusted R-squared	0.571	0.571	0.571	0.571

Clustered t-statistics in parentheses
** p<0.01, * p<0.05
Sample includes economy and business-class itineraries
Regressions contain city-pair fixed effects

Table 3: Connecting Results by Fare Class

VARIABLES	Economy+Business	Economy	Business
log_dist	0.125**	0.117**	0.102**
	(13.13)	(11.54)	(3.988)
EU_pos	-0.0557**	-0.0516**	-0.115**
	(-23.05)	(-22.25)	(-12.43)
nonUS/EU_pos	0.0689**	0.0841**	-0.0853**
	(24.52)	(28.68)	(-12.43)
business	1.303**	—	—
	(364.3)		
online	-0.0737**	-0.0704**	-0.125**
	(-38.31)	(-35.52)	(-24.69)
ALLY	-0.00730*	-0.00921**	0.0266**
	(-2.122)	(-2.679)	(4.066)
ATI	-0.0644**	-0.0686**	-0.0195*
	(-24.28)	(-24.86)	(-2.551)
JV	-0.0721**	-0.0748**	-0.0652**
	(-23.45)	(-23.28)	(-10.05)
coupons	0.00354**	0.00634**	-0.0232**
	(4.805)	(8.363)	(-14.43)
comps_connect	-0.00264**	-0.00274**	-0.00136
	(-5.052)	(-5.142)	(-0.839)
LCC_connect	-0.0533**	-0.0594**	0.0425*
	(-9.738)	(-10.76)	(2.227)
log_mktpop	-0.764**	-0.858**	0.154*
	(-28.48)	(-30.09)	(2.058)
log_mktinc	-0.476**	-0.517**	0.117**
	(-31.92)	(-31.59)	(3.698)
open_skies	-0.0674**	-0.0593**	-0.150**
	(-19.58)	(-16.37)	(-11.66)
Constant	20.93**	22.72**	4.001**
	(46.36)	(47.64)	(3.210)
Observations	4,241,062	3,923,022	318,040
Adjusted R-squared	0.571	0.385	0.383

Robust t-statistics in parentheses

** $p<0.01$, * $p<0.05$

Regressions contain city-pair fixed effects

Table 3 continued

TESTS	Economy+Business	Economy	Business
ATI = online ($\nu = \tau$)	$p = 0.0005$	$p = 0.5092$	$p = 0.0000$
JV = online ($\mu = \tau$)	$p = 0.4971$	$p = 0.0687$	$p = 0.0000$

Table 4: Connecting Transatlantic Results

VARIABLES	Business+Economy	Economy	Business
log_dist	0.00391	-0.000289	0.117**
	(0.337)	(-0.0262)	(2.943)
EU_pos	-0.0537**	-0.0495**	-0.127**
	(-22.70)	(-21.91)	(-13.92)
nonUS/EU_pos	-0.0322**	-0.0129**	-0.292**
	(-7.301)	(-2.819)	(-23.46)
business	1.327**	—	—
	(260.1)		
online	-0.0948**	-0.0906**	-0.144**
	(-42.37)	(-41.38)	(-15.65)
ALLY	-0.0442**	-0.0510**	0.0127
	(-16.65)	(-19.17)	(1.264)
ATI	-0.102**	-0.106**	-0.0525**
	(-37.37)	(-39.05)	(-5.206)
JV	-0.0913**	-0.0936**	-0.0624**
	(-38.00)	(-38.85)	(-7.012)
coupons	0.00498**	0.00772**	-0.0345**
	(5.425)	(8.499)	(-11.13)
comps_connect	-0.00340**	-0.00422**	0.00133
	(-6.648)	(-8.023)	(0.662)
LCC_connect	-0.0924**	-0.0968**	-0.0349
	(-10.88)	(-11.23)	(-0.882)
log_mktpop	-0.837**	-0.928**	0.111
	(-27.02)	(-29.57)	(1.455)
log_mktinc	-0.409**	-0.446**	-0.152*
	(-20.89)	(-21.56)	(-1.989)
open_skies	-0.0379**	-0.0260**	-0.227**
	(-10.21)	(-7.646)	(-14.62)
Constant	22.38**	24.03**	6.778**
	(42.90)	(45.17)	(4.669)
Observations	2,208,735	2,065,301	143,434
Adjusted R-squared	0.512	0.334	0.200

Robust t-statistics in parentheses
** p<0.01, * p<0.05
Regressions contain city-pair fixed effects

Table 4 continued

TESTS	Economy+Business	Economy	Business
ATI = online ($\nu = \tau$)	$p = 0.0049$	$p = 0.0000$	$p = 0.0000$
JV = online ($\mu = \tau$)	$p = 0.0988$	$p = 0.1498$	$p = 0.0000$

Table 5: Connecting Transpacific Results

VARIABLES	Business+Economy	Economy	Business
log_dist	0.349**	0.368**	0.269**
	(16.85)	(16.98)	(6.640)
nonUS/EU_pos	0.105**	0.125**	-0.0622**
	(27.84)	(32.91)	(-6.964)
business	1.296**	—	—
	(225.7)		
online	-0.0933**	-0.0978**	-0.138**
	(-28.61)	(-27.34)	(-23.29)
ALLY	-0.00898*	-0.00487	-0.0190*
	(-2.524)	(-1.360)	(-2.385)
ATI	0.0222**	0.0269**	-0.0285
	(3.482)	(3.976)	(-1.958)
JV	-0.0751**	-0.0835**	-0.0861**
	(-12.54)	(-12.93)	(-7.433)
coupons	-0.00652**	-0.00535**	-0.0210**
	(-6.597)	(-5.222)	(-9.418)
comps_connect	-0.00245**	-0.00234**	-0.000414
	(-3.077)	(-2.810)	(-0.264)
LCC_connect	-0.0737**	-0.0729**	-0.0623*
	(-7.250)	(-6.977)	(-1.977)
log_mktpop	-0.493**	-0.571**	0.126
	(-7.926)	(-9.122)	(1.678)
log_mktinc	-0.240**	-0.231**	-0.104**
	(-10.38)	(-9.364)	(-2.864)
open_skies	-0.0503**	-0.0401**	-0.0884**
	(-7.585)	(-5.998)	(-6.709)
Constant	13.60**	14.72**	4.100**
	(13.29)	(14.29)	(3.161)
Observations	1,276,667	1,153,528	123,139
Adjusted R-squared	0.533	0.183	0.353

Robust t-statistics in parentheses
** p<0.01, * p<0.05
Regressions contain city-pair fixed effects

Table 5 continued

TESTS	Economy+Business	Economy	Business
ATI = online ($\nu = \tau$)	$p = 0.0000$	$p = 0.0000$	$p = 0.0000$
JV = online ($\mu = \tau$)	$p = 0.0001$	$p = 0.0031$	$p = 0.0000$

Table 6: Weighted, no FE Results

VARIABLES	Weighted	No FE
log_dist	0.0779**	0.484**
	(6.039)	(139.6)
EU_pos	-0.0562**	-0.0984**
	(-16.90)	(-34.09)
nonUSEU_pos	0.0799**	0.114**
	(21.29)	(40.58)
business	1.295**	1.331**
	(252.2)	(384.4)
online	-0.0685**	-0.0835**
	(-24.46)	(-38.64)
ALLY	0.00119	-0.0246**
	(0.221)	(-7.314)
ATI	-0.0647**	-0.0749**
	(-15.80)	(-27.91)
JV	-0.0757**	-0.0715**
	(-14.12)	(-23.05)
coupons	-0.00122	-0.00736**
	(-1.203)	(-9.718)
comps_connect	-0.00324**	-0.0150**
	(-5.185)	(-22.631)
LCC_connect	-0.0501**	-0.0432**
	(-7.669)	(-8.039)
log_mktpop	-0.759**	-0.0169**
	(-21.29)	(-12.24)
log_mktinc	-0.465**	0.0289**
	(-22.17)	(12.29)
openskies	-0.0531**	-0.0686**
	(-10.57)	(-27.43)
Constant	21.24**	2.962**
	(36.46)	(83.94)
Observations	4,241,062	4,287,269
Adjusted R-squared	0.610	0.567

Robust t-statistics in parentheses
** p<0.01, * p<0.05

Table 6 continued

TESTS	Weighted	No FE
ATI = online ($\nu = \tau$)	$p = 0.3516$	$p = 0.0019$
JV = online ($\mu = \tau$)	$p = 0.0695$	$p = 0.0000$

Table 7: GTG Summary Statistics

	1997-2009					2010-2016				
VARIABLES	N	mean	sd	min	max	N	mean	sd	min	max
fare	274,067	1,082	1,019	25.50	39,047	210,597	1,110	1,005	25.50	8,553
passengers	274,067	45.96	151.2	1	6,032	210,597	50.62	165.8	1	5,899
dist	274,067	3,799	1,797	127	10,201	210,597	3,947	1,801	119	10,210
EU_pos	274,067	0.226	0.418	0	1	210,597	0.242	0.429	0	1
nonUS/EU_pos	274,067	0.258	0.437	0	1	210,597	0.245	0.430	0	1
one_way	274,067	0.401	0.490	0	1	210,597	0.370	0.483	0	1
economy	274,067	0.539	0.498	0	1	210,597	0.508	0.500	0	1
business	274,067	0.301	0.459	0	1	210,597	0.221	0.415	0	1
online	274,067	0.802	0.398	0	1	210,597	0.746	0.435	0	1
interline	274,067	0.0462	0.210	0	1	210,597	0.0102	0.101	0	1
not_online/interline	274,067	0.152	0.359	0	1	210,597	0.244	0.429	0	1
totcomps	274,067	2.344	1.527	1	10	210,597	2.358	1.520	1	8
ALLYcomps	274,067	0.202	0.564	0	5	210,597	0.126	0.424	0	5
ATIcomps	274,067	0.0594	0.236	0	1	210,597	0.0378	0.194	0	2
JVcomps	274,067	0.0334	0.182	0	3	210,597	0.266	0.514	0	2
LCC_mkt	274,067	0.0237	0.152	0	1	210,597	0.0615	0.240	0	1
log_mktpop	274,067	12.18	11.90	8.91	13.64	210,597	12.28	11.97	8.62	13.68
log_mktinc	274,067	3.40	2.60	1.43	4.25	210,597	3.60	2.71	1.27	4.35
open_skies	274,067	0.486	0.500	0	1	210,597	0.732	0.443	0	1
carve_out	274,067	0.0180	0.133	0	1	210,597	0.00353	0.0593	0	1
flow_pax	274,067	1,247	1,232	0	12,803	210,597	1,442	1,412	0	14,114
flow_routes	274,067	1,089	1,088	0	11,653	210,597	1,310	1,293	0	12,758

Table 8: GTG Results w/o City-pair Fixed Effects

VARIABLES	all but first	economy	business
log_dist	0.561**	0.472**	0.777**
	(29.61)	(30.45)	(31.74)
EU_pos	-0.0521**	-0.0591**	-0.0741**
	(-5.312)	(-7.383)	(-5.241)
nonUS/EU_pos	0.0432**	0.0828**	-0.0299**
	(6.794)	(10.97)	(-3.328)
one_way	0.281**	0.373**	0.0862**
	(42.41)	(48.53)	(7.435)
business	1.063**	—	—
	(67.21)		
mixed	0.739**	—	—
	(36.98)		
interline	0.112**	0.134**	0.0665**
	(6.981)	(7.507)	(2.782)
not_online/interline	0.0274**	0.0143	0.116**
	(3.211)	(1.798)	(7.796)
totcomps_97_09	-0.0398**	-0.0375**	-0.0427**
	(-5.250)	(-5.547)	(-5.339)
totcomps_10_16	-0.0705**	-0.0821**	-0.0351**
	(-8.704)	(-11.42)	(-2.590)
ALLYcomps_97_09	0.0178	0.0127	0.0110
	(1.152)	(0.790)	(0.792)
ALLYcomps_10_16	0.0191	0.0250	0.00131
	(1.350)	(1.544)	(0.0625)
ATIcomps_97_09	0.00710	-0.00370	0.0138
	(0.271)	(-0.142)	(0.437)
ATIcomps_10_16	0.0684*	0.127**	-0.0378
	(2.000)	(3.457)	(-0.801)
JVcomps_97_09	0.00980	0.00158	-0.00786
	(0.415)	(0.0721)	(-0.174)
JVcomps_10_16	0.0462*	0.0962**	-0.0325
	(2.544)	(5.819)	(-1.088)
LCC_mkt	-0.0994**	-0.155**	0.112*
	(-3.397)	(-7.158)	(2.312)
log_mktpop	0.0639**	0.0346**	0.118**
	(4.637)	(2.865)	(7.196)
log_mktinc	0.143**	0.0672**	0.235**
	(9.151)	(4.940)	(9.998)
open_skies	-0.0107	-0.0152	0.0395
	(-0.800)	(-1.364)	(1.824)
carve_out	0.0415*	0.0118	0.0628
	(1.986)	(0.438)	(1.584)
flow_routes	4.72e-05**	4.63e-05**	4.98e-05**
	(6.771)	(6.743)	(6.888)
Observations	437,819	254,656	129,143
R^2	0.599	0.550	0.471

Robust t-statistics in parentheses

** p<0.01, * p<0.05

Table 8 continued

TEST	all but first	economy	business
totcomps_10_16 + ATIcomps_10_16 = 0 ($\beta + \delta = 0$)	$p = 0.9498$	$p = 0.2045$	$p = 0.1012$
totcomps_10_16 + JVcomps_10_16 = 0 ($\beta + \lambda = 0$)	$p = 0.0944$	$p = 0.2935$	$p = 0.0048$

Table 9: GTG Results with City-pair Fixed Effects

VARIABLES	all but first	economy	business
log_dist	-0.433	-2.235	0.511
	(-0.295)	(-1.460)	(0.237)
EU_pos	-0.0515**	-0.0312**	-0.109**
	(-5.452)	(-4.284)	(-8.365)
nonUS/EU_pos	0.0383**	0.0569**	-0.00340
	(6.856)	(9.686)	(-0.445)
one_way	0.282**	0.378**	0.0842**
	(42.10)	(48.62)	(7.186)
business	1.059**	—	—
	(66.44)		
mixed	0.734**	—	—
	(37.13)		
interline	0.139**	0.161**	0.0784**
	(10.80)	(9.858)	(3.511)
not_online/interline	0.0348**	0.0211**	0.119**
	(4.099)	(2.632)	(7.984)
totcomps_97_09	-0.0243**	-0.0105	-0.0433**
	(-4.351)	(-1.576)	(-5.173)
totcomps_10_16	-0.0450**	-0.0463**	-0.0368*
	(-5.925)	(-5.188)	(-2.563)
ALLYcomps_97_09	0.0153	0.00695	0.0126
	(1.594)	(0.673)	(1.123)
ALLYcomps_10_16	0.0192*	0.0232*	-0.00195
	(2.119)	(2.028)	(-0.124)
ATIcomps_97_09	0.0235	-0.00930	0.0755**
	(1.008)	(-0.329)	(3.074)
ATIcomps_10_16	0.0628*	0.0965*	0.00372
	(1.967)	(2.531)	(0.0946)
JVcomps_97_09	0.0184	0.0107	0.0447
	(0.792)	(0.487)	(0.887)
JVcomps_10_16	-0.0114	0.0440*	-0.0353
	(-0.677)	(2.140)	(-1.201)
LCC_mkt	-0.0601**	-0.138**	0.0880*
	(-2.598)	(-5.651)	(2.155)
log_mktpop	-0.275**	-0.311**	-0.111
	(-2.901)	(-3.642)	(-0.536)
log_mktinc	0.314**	0.103	0.582**
	(3.934)	(1.233)	(3.989)
open_skies	-0.00801	-0.00336	0.0122
	(-0.679)	(-0.274)	(0.600)
carve_out	0.0270	-0.00114	0.0769*
	(1.495)	(-0.0457)	(2.279)
flow_routes	2.77e-05**	2.71e-05**	2.96e-05**
	(5.780)	(4.601)	(6.182)
Observations	437,819	254,656	129,143
R^2	0.624	0.598	0.529

Robust t-statistics in parentheses

** p<0.01, * p<0.05

Table 9 continued

TEST	all but first	economy	business
totcomps_10_16 + ATIcomps_10_16 = 0 ($\beta + \delta = 0$)	$p = 0.5588$	$p = 0.1624$	$p = 0.3968$
totcomps_10_16 + JVcomps_10_16 = 0 ($\beta + \lambda = 0$)	$p = 0.0001$	$p = 0.8995$	$p = 0.0060$

Table 10: GTG Results with Other Break Points[†]

VARIABLES	no break	no break/FE	97-08 09-16/FE	97-06 07-16/FE
log_dist	0.473**	-2.316	-2.223	-2.080
	(30.20)	(-1.512)	(-1.461)	(-1.379)
EU_pos	-0.0603**	-0.0316**	-0.0312**	-0.0311**
	(-7.309)	(-4.321)	(-4.270)	(-4.265)
nonUS/EU_pos	0.0832**	0.0568**	0.0569**	0.0568**
	(10.75)	(9.616)	(9.692)	(9.701)
one_way	0.373**	0.378**	0.378**	0.378**
	(48.49)	(48.51)	(48.56)	(48.45)
interline	0.142**	0.167**	0.161**	0.162**
	(7.737)	(10.02)	(9.879)	(9.885)
not_online/interline	0.0145	0.0213**	0.0211**	0.0213**
	(1.822)	(2.662)	(2.654)	(2.690)
totcomps(_early)	-0.0500**	-0.0175*	-0.00960	-0.00378
	(-7.387)	(-2.541)	(-1.438)	(-0.558)
totcomps_late	—	—	-0.0462**	-0.0436**
			(-5.164)	(-5.182)
ALLYcomps(_early)	0.0163	0.00947	0.00736	0.00732
	(1.054)	(0.985)	(0.666)	(0.601)
ALLYcomps_late	—	—	0.0291**	0.0304**
			(2.630)	(2.792)
ATIcomps(_early)	0.0356	0.0131	-0.0141	-0.0302
	(1.479)	(0.557)	(-0.465)	(-0.983)
ATIcomps_late	—	—	0.0884*	0.0805*
			(2.210)	(2.392)
JVcomps(_early)	0.0313*	-0.00978	-0.000270	-0.0310
	(2.027)	(-0.623)	(-0.0109)	(-1.154)
JVcomps_late	—	—	0.0408*	0.0366
			(2.042)	(1.932)
LCC_mkt	-0.177**	-0.165**	-0.135**	-0.129**
	(-8.271)	(-7.050)	(-5.550)	(-5.651)
log_mktpop	0.0336**	-0.275**	-0.318**	-0.336**
	(2.746)	(-2.936)	(-3.747)	(-3.957)
log_mktinc	0.0708**	0.0990	0.0975	0.0999
	(5.095)	(1.188)	(1.176)	(1.199)
open_skies	-0.0196	-0.0113	-0.00203	0.00220
	(-1.725)	(-0.845)	(-0.166)	(0.175)
carve_out	-0.00618	-0.0130	0.000280	0.00398
	(-0.218)	(-0.510)	(0.0111)	(0.155)
flow_routes	4.67e-05**	2.69e-05**	2.69e-05**	2.67e-05**
	(6.628)	(4.215)	(4.561)	(4.528)
Observations	254,656	254,656	254,656	254,656
R^2	0.549	0.598	0.598	0.599

Clustered t-statistics in parentheses

** p<0.01, * p<0.05

[†]Results are for economy fares

Table 11: GTG Results for Subsamples

VARIABLES	EU	EU/FE	Trans-Pac.	T-Pac./FE	totcomps$\leq$ 4	totcomps$\leq$ 4/FE
log_dist	0.311**	-1.373	0.383**	7.785	0.463**	-3.733*
	(8.184)	(-0.390)	(6.506)	(1.594)	(33.00)	(-2.196)
EU_pos	-0.0305**	-0.0317**	—	—	-0.0576**	-0.0294**
	(-4.177)	(-4.333)			(-7.148)	(-3.984)
nonUS/EU_pos	—	—	0.138**	0.140**	0.0786**	0.0537**
			(10.902)	(11.173)	(11.10)	(9.571)
one_way	0.401**	0.402**	0.358**	0.359**	0.366**	0.371**
	(30.98)	(30.84)	(16.11)	(16.07)	(53.90)	(54.05)
interline	0.269**	0.264**	0.0670	0.0569	0.147**	0.174**
	(11.52)	(11.87)	(1.347)	(1.287)	(8.526)	(10.80)
not_online/interline	0.0163	0.0110	0.0169	0.0100	0.0199**	0.0267**
	(1.472)	(0.996)	(0.665)	(0.388)	(2.646)	(3.496)
totcomps_97_09	-0.0264**	-0.0180**	-0.0610**	-0.0304**	-0.0526**	-0.0169*
	(-4.357)	(-2.669)	(-4.558)	(-3.729)	(-6.748)	(-2.288)
totcomps_10_16	-0.0746**	-0.0597**	-0.0657**	-0.0334*	-0.0923**	-0.0575**
	(-7.506)	(-4.771)	(-3.955)	(-2.232)	(-11.56)	(-6.679)
ALLYcomps_97_09	-0.0472**	-0.0274*	0.0374	0.0347**	0.00454	0.00617
	(-3.342)	(-2.391)	(1.459)	(2.761)	(0.254)	(0.442)
ALLYcomps_10_16	0.0185	0.0519*	0.0166	0.0220	0.0126	0.0158
	(0.736)	(2.222)	(0.811)	(1.176)	(0.681)	(0.920)
ATIcomps_97_09	0.0574	0.0298	0.0348	-0.0421	0.0155	-0.00372
	(1.853)	(0.874)	(1.734)	(-1.232)	(0.568)	(-0.124)
ATIcomps_10_16	0.0911**	0.104**	0.0283	-0.00738	0.125**	0.0792*
	(3.016)	(2.901)	(0.931)	(-0.273)	(2.831)	(2.029)
JVcomps_97_09	0.0253	0.00658	—	—	0.0205	0.0287
	(1.315)	(0.319)			(0.869)	(1.167)
JVcomps_10_16	0.0703**	0.0406	0.0162	0.00190	0.0894**	0.0533*
	(3.323)	(1.558)	(0.528)	(0.0629)	(4.942)	(2.101)
LCC_mkt	0.194**	0.0747**	—	—	-0.153**	-0.129**
	(14.24)	(2.728)			(-7.285)	(-5.366)
log_mktpop	0.0377**	0.315	0.159**	0.223	0.0375**	-0.345**
	(3.083)	(1.336)	(6.579)	(0.658)	(3.306)	(-4.041)
log_mktinc	0.168**	0.550**	0.127**	0.249	0.0648**	0.110
	(4.275)	(2.772)	(7.549)	(1.352)	(4.769)	(1.335)
open_skies	-0.0600**	-0.0370*	-0.00809	0.0316	-0.0128	-0.00557
	(-3.720)	(-2.160)	(-0.304)	(1.105)	(-1.117)	(-0.434)
carve_out	-0.00739	-0.0316	—	—	0.000192	-0.00448
	(-0.349)	(-1.705)			(0.00686)	(-0.188)
flow_routes	2.35e-05**	1.27e-05**	4.30e-05**	1.53e-05	5.10e-05**	3.46e-05**
	(5.019)	(3.534)	(4.709)	(0.975)	(6.750)	(5.789)
Observations	110,792	110,792	32,546	32,546	234,529	234,529
R^2	0.305	0.333	0.329	0.373	0.563	0.613

Clustered t-statistics in parentheses

** p<0.01, * p<0.05

Table 11 continued

TEST	EU	EU/FE	Trans-Pac.	T-Pac./FE	totcomps≤ 4	totcomps≤ 4/FE
totcomps_10_16 + ATIcomps_10_16 = 0 ($\beta + \delta = 0$)	$p = 0.5499$	$p = 0.1614$	—	—	0.4533	0.5755
totcomps_10_16 + JVcomps_10_16 = 0 ($\beta + \lambda = 0$)	$p = 0.7978$	$p = 0.3521$	—	—	0.8493	0.8629

Table 12: GTG Weighted Results

VARIABLES	economy	economy/FE
log_dist	0.523**	-1.765
	(25.70)	(-0.977)
EU_pos	-0.135**	-0.0712**
	(-8.551)	(-5.428)
nonUS/EU_pos	0.127**	0.0396**
	(5.875)	(4.367)
one_way	0.257**	0.286**
	(12.09)	(15.41)
interline	0.0442	0.0964**
	(1.761)	(3.296)
not_online/interline	-0.0755**	-0.0532**
	(-4.243)	(-2.817)
totcomps_97_09	-0.0269**	-0.0296**
	(-4.237)	(-2.654)
totcomps_10_16	-0.0361*	-0.0387**
	(-2.252)	(-2.979)
ALLYcomps_97_09	0.0138	0.0189*
	(1.032)	(2.121)
ALLYcomps_10_16	0.0242	-0.0166
	(1.119)	(-1.108)
ATIcomps_97_09	0.0285	0.00911
	(0.913)	(0.325)
ATIcomps_10_16	0.130	0.126
	(1.701)	(1.803)
JVcomps_97_09	-0.0294	0.0175
	(-0.745)	(0.715)
JVcomps_10_16	0.0776**	0.0545**
	(3.012)	(2.833)
LCC_mkt	-0.189**	-0.143**
	(-5.627)	(-5.831)
log_mktpop	-0.0507**	-0.241
	(-3.031)	(-1.907)
log_mktinc	0.0749**	-0.182
	(3.601)	(-1.434)
open_skies	0.000135	0.0564*
	(0.00775)	(2.421)
carve_out_car	0.0239	0.0217
	(0.655)	(0.699)
flow_routes	3.02e-05**	2.18e-05**
	(4.212)	(3.536)
Observations	254,656	254,656
R^2	0.780	0.827

Robust t-statistics in parentheses

** p<0.01, * p<0.05

Table 12 continued

TEST	economy	economy/FE
totcomps_10_16 + ATIcomps_10_16 = 0 ($\beta + \delta = 0$)	$p = 0.2179$	$p = 0.1787$
totcomps_10_16 + JVcomps_10_16 = 0 ($\beta + \lambda = 0$)	$p = 0.0465$	$p = 0.4244$

Table 13: Alliance Effects on Flow Traffic

VARIABLES	flow_pax	flow_pax/FE	flow_pax/FE	flow_routes	flow_routes/FE	flow_routes/FE
JV_route	211.6*	104.4	—	251.5**	114.0	—
	(2.530)	(1.567)		(3.246)	(1.870)	
ATI_route	317.4**	229.1**	—	284.3**	202.2**	—
	(6.388)	(5.164)		(6.604)	(5.317)	
JV_or_ATI_route	—	—	242.0**	—	—	216.2**
			(5.299)			(5.494)
open_skies	124.9*	14.97	31.43	130.1**	24.02	42.01
	(2.240)	(0.239)	(0.507)	(2.798)	(0.429)	(0.762)
log_mktpop	120.1*	578.8	420.4	109.6*	519.3	346.1
	(2.461)	(1.584)	(1.169)	(2.569)	(1.720)	(1.140)
log_mktinc	369.4**	1,280**	1,169**	342.6**	919.5**	798.8**
	(7.496)	(4.561)	(4.210)	(7.916)	(4.008)	(3.522)
totcomps	111.2**	-143.8**	-142.0**	92.11**	-125.0**	-123.1**
	(3.570)	(-5.675)	(-5.618)	(3.185)	(-5.761)	(-5.682)
Constant	-2,340**	-9,815*	-7,648	-2,219**	-8,218*	-5,850
	(-4.053)	(-2.346)	(-1.871)	(-4.418)	(-2.339)	(-1.665)
Observations	47,958	47,958	47,958	47,958	47,958	47,958
R^2	0.156	0.640	0.639	0.175	0.655	0.654

Clustered t-statistics in parentheses

** $p<0.01$, * $p<0.05$

Table 14: Simulation Results, 2015 Q3

	Route A	*Route B*
Change in GTG fare outlay with JV/ATI removal	−\$2,057,646	−\$468,799
Change in connecting fare outlay with JV/ATI removal	+\$3,096,354	+\$10,806,215
Net change in outlay	+\$1,038,708	+\$10,337,416

References

Bilotkach, V., Hüschelrath, K., 2013. Airline alliances, antitrust immunity, and market foreclosure. *Review of Economics and Statistics* 95, 1368-1385.

Brueckner, J.K., Whalen, W.T., 2000. The price effects of international airline alliances. *Journal of Law and Economics* 43, 503-545.

Brueckner, J.K., 2001. The economics of international codesharing: An analysis of airline alliances. *International Journal of Industrial Organization* 19, 1475-1498.

Brueckner, J.K., 2003. International airfares in the age of alliances: The effects of codesharing and antitrust immunity. *Review of Economics and Statistics* 85, 105-118.

Brueckner, J.K., Proost, S., 2010. Carve-outs under airline antitrust immunity. *International Journal of Industrial Organization* 28, 657-668.

Brueckner, J.K., Lee, D., Singer, E., 2011. Alliances, codesharing, antitrust immunity and international airfares: Do previous patterns persist? *Journal of Competition Law and Economics* 7, 573-602.

Brueckner, J.K., Lee, D., Singer, E., 2014. City-pairs versus airport-pairs: A market definition methodology for the airline industry. *Review of Industrial Organization* 44, 1-25.

Brueckner, J.K., Lee, D., Singer, E., 2016. Ex post analysis of Air New Zealand revenue-sharing joint venture agreements. Unpublished paper, Compass Lexecon.

Calzaretta, R.J., Eilat, Y., Israel, M.A., 2017. Airline cooperation and international travel: Fare and output effects. *Journal of Competition Law and Economics* 13, 501-548.

Gayle, P., Wu, C.-Y., 2013. A re-examination of incumbents' response to the threat of entry: Evidence from the airline industry. *Economics of Transportation* 2, 119-130.

Gayle, P., Brown, D., 2014. Airline strategic alliances in overlapping markets: Should policymakers be concerned? *Economics of Transportation* 3, 243-256.

Gillespie, W., Richard, O.M., 2012. Antitrust immunity and international airline alliances. *Antitrust Law Journal* 78, 443-455.

Park, J.-H., 1997. The effect of airline alliances on markets and economic welfare. *Transportation Research E* 33, 181195.

Park, J.-H., Zhang, A., 1998. Airline alliances and partner firms output. *Transportation Research Part E* 34, 245-55.

Park, J.-H., Zhang, A. , 2000. An empirical analysis of global airline alliances: Cases in the north Atlantic markets. *Review of Industrial Organization* 16: 367-84.

U.S. General Accounting Office, 1995. Airline alliances produce benefits, but effect on competition is uncertain. Unpublished paper.

Whalen, W.T., 2007. A panel data analysis of code sharing, antitrust immunity and open skies treaties in international aviation markets. *Review of Industrial Organization* 30, 39-61.

Wan, X., Zou, L., Dresner, M., 2009. Assessing the price effects of airline alliances on parallel routes. *Transportation Research Part E* 45, 627-641.

Willig, R., Israel, M., Keating, B., 2010. Competitive effects of airline antitrust immunity. Unpublished paper, Compass Lexecon.

Footnotes

[1]In an earlier paper, Park (1997) presented a less complete theoretical analysis of alliances.

[2]Also lacking access to DB1B fare data, Bilotkach and Hüschelrath (2013) offer a cautionary study on the effects of alliances by exploring the possibility of "foreclosure" by alliances of non-alliance service to their hub airports. The logic is that the growth of alliances reduces or eliminates interline service between a nonaligned carrier and an alliance member, as that carrier increasingly relies on its partner(s) in providing interline service. Using a panel of U.S.-transatlantic segment-level passenger data from the 1992-2008 period, the results confirm this expectation, with nonaligned traffic between alliance hubs and other non-hub endpoints falling as alliances are formed, indicating (according to the authors) market foreclosure.

[3]In another older study using a structural approach, Park and Zhang (2000) estimate demand and supply curves for travel on GTG routes served by alliances, relying on posted fares rather than transaction data and using O & D plus flow traffic as an approximation for GTG O & D traffic. They then compute fare and traffic effects of alliances from the estimated structural coefficients, finding an increase in traffic and a reduction in GTG fares. Park and Zhang (1988) carry out a similar exercise.

[4]For example, if a non-reporting carrier such as Air Europa serves Boston-Madrid nonstop with connections beyond MAD in Europe, then all BOS to Europe itineraries are excluded from the sample because connecting competition cannot be measured.

[5]The approach reflected in these variable definitions differs from that of Brueckner et al. (2011). They instead define the cooperation variables in cumulative fashion, with the ATI variable indicating the incremental fare effect of immunity beyond the effect of an existing alliance relationship (as captured by their alliance variable). Thus, the sum of their alliance and ATI coefficients gives the fare reduction associated with an immunized alliance relationship, whereas the fare effect under the current approach is simply given by the **ATI** coefficients. While they also included codesharing as an additional incremental cooperation variable, codesharing is not considered here.

[6]Following Brueckner et al. (2011), country rather than city populations are used to represent the sizes of foreign endpoints. Because the endpoint cities of connecting routes are often relatively small, their yearly populations are frequently unavailable.

[7]The maximum fare of $81,920 in Table 1 was not flagged by the DB1B fare credibility indicator and thus remained in the sample. Given the large number of observations, a few

fares this large have no effect on the results.

[8]Using the example from footnote 4, connecting trips from Boston solely on Air Europa, a non-reporting carrier, are not present in the data.

[9]Note that the "ATI(_early)" label in the table refers to the single **ATI** coefficient when there is no break point and to the early-period **ATI** coefficients when there is a break point, and similarly for the **JV** competition variable.

[10]The study of Brueckner (2003) estimated a regression similar to the first one in Table 3, using data from the third quarter of 1999, and it found much larger cooperation effects, with an immunized itinerary that involves codesharing priced more than 25% below an itinerary where cooperation is absent. When a regression like Brueckner's is run on Q3 1999 data from the current sample, it also yields large cooperation effects, with an **ATI** coefficient of -0.15 (the **ATI** category includes JV's to match the earlier study). In addition, the coefficient of a separate codesharing variable is -0.06. The fact that results like those of Brueckner (2003) are generated in a regression using this single quarter of data means that the overall difference between his 2003 results and those in Table 3 is due to the current use of a multi-year sample instead of focusing on a single quarter early in the period.

[11]As explained above, many connecting markets where competition cannot be counted are dropped from the sample. If the **comps_connect** variable is removed, however, these markets can be added back to the sample, more than doubling its size. When this change is made, the **online** coefficient in the column-one regression of Table 2 becomes -0.0962, while the **ATI** and **JV** coefficients become -0.0555 and -0.0620, respectively. Along with the **ATI** coefficient, equality of the **JV** and **online** coefficients now can be rejected, in contrast to the previous conclusion that the latter two coefficients were statistically indistinguishable. However, the removal of the **comps_connect** variable, which belongs in the regression on theoretical grounds, is likely to bias the remaining coefficients, reducing the credibility of these results.

[12]Relative to connecting trips, a smaller minimum GTG fare ($50 vs. $200) makes sense given the potentially short distances of some GTG trips.

[13]In another example, the outbound segment could be operated and marketed by American with the inbound segment operated by British Airways but marketed by American. The different operating carriers make this example not online, but it additional involves codesharing.

[14]Icelandic Airlines, which is in the ticket sample and serves only Reykjavik, is not treated as a low-cost carrier, which means that **LCC_mkt** equals 0 instead of 1 for trips to or from

Reykjavik (REK) not involving Icelandic.

[15]Since gateway cities tend to be larger than those in the connecting sample, making their populations more readily available, city rather than country populations are used to measure the sizes of foreign endpoints. Since missing population data nevertheless is a limitation along with missing income data, not all GTG itineraries could be included in the sample.

[16]It could be argued that the positive carve-out effect in the first column of Table 8 reflects reverse causation, where carve-outs are imposed in markets with high fares. However, the insignificance of the **carve_out** coefficient in the economy and business-class regressions casts doubt on this interpretation. The possibility of reverse causation is further diminished by coefficient's insignificance in the regressions with city-pair FEs (Table 9 below), which control for unobserved market characteristics that might prompt imposition of carve-outs.

[17]Removal of GTG routes to Canada, Mexico and the Caribbean from the sample has little effect on the results. The late period **ATIcomps** and **JVcomps** effects in the economy regression (column two of Table 8) change to 13.2% and 7.4%, respectively, and the tests in the continuation of Table 8 are unaffected. Similar changes occur in the FE regression.

[18]Note that adding a JV or ATI partner to a route previously served by the other partner would have no fare effect.

[19]See US General Accounting Office (1995), for example, along with Park and Zhang (1998, 2000).

[20]The regressions are run on the set of 1457 city-pair markets that have service throughout the sample period. In addition, the relatively few observations with zero values of **flow_pax** and **flow_routes** are included in the regresssions, but the results are similar when these observations are deleted.

[21]Recall that the **JVcomps** coefficient for EU/FE regression (column 2 of Table 10) is insignificant, making its use in the simulation unadvisable. Alternately, the EU regression without FEs (column 1 of Table 11) could be used instead of the Table 9 regression, in which case the average of the **ATIcomps** and **JVcomps** coefficients would equal 0.08, a slightly larger than the 0.07 value used in Table 14.

[22]GTG fare changes are not counted for JV passengers who split carriers on the inbound and outbound segments. With removal of the JV, these passengers would become interline passengers, paying a slight fare premium.

[23]Note that codeshare connecting trips with JV partners become interline trips with removal of the JV, given that the carriers become nonaligned (recall the discussion in section 2). Their fares thus rise by this factor along with those of other JV trips.

Online Appendix

Table A.1: ATI and JV Groups

ATI GROUPS

alliance	main airlines
American/Brussels	AA/SN
American/Canadian	AA/CP
American/Swiss/Sabena	AA/SR/SN
Atlantic Excellence	DL/OS/SN/SR
CO/COPA	CO/CM
CO/COPA/UA	CO/CM/UA
DL/VA (Virgin Blue)	DL/VA
DL/VS (Virgin Atlantic)	DL/VS
Oneworld	AA/US/AY/BA/IB/RJ
Oneworld	AA/AY
Oneworld	AA/US/QF
Oneworld	AA/US/JL
Oneworld	AA/US/LA/LP
SkyTeam	DL/NW/AF/AZ/KL/OK
SkyTeam	NW/KL
SkyTeam	CO/CM/NW
SkyTeam	DL/KE/NW
Star	UA/CO/AC/BD/LH/LO/LX/OS /SN/SK/TP/VO
Star	UA/CO/NH/NQ
Star	UA/CM
Star	UA/CO/OZ
Star	UA/CO/NZ
Star	UA/CO/AC
United/Lufthansa	UA/LH
Wings	NW/KL

JV GROUPS

alliance	main airlines
DL/VA (Virgin Blue)	DL/VA
DL/VS (Virgin Atlantic)	DL/VS
Oneworld	AA/US/AY/BA/IB
Oneworld	AA/US/JL
SkyTeam	DL/NW/AF/AZ/KL
SkyTeam	NW/KL
Star	UA/CO/AC/BD/LH/LX/OS/ SN/VO
Star	UA/CO/AC
Star	UA/CO/NH/NQ
Wings	NW/KL

Airline codes	
AA-American	LP-LAN Peru
AC-Air Canada	LX-Swiss International
AF-Air France	NH-All Nippon
AY-Finnair	NQ-Air Japan
AZ-Alitalia	NW-Northwest
BA-British Airways	OS-Austrian
BD-British Midland	OZ-Asiana
CM-COPA	QF-Qantas
CO-Continental	RJ-Royal Jordanian
CP-Canadian Pacific	SK-SAS
DL-Delta	SR-Swissaiir
JL-Japan Airlines	SN-Brussels Airlines
IB-Iberia	TP-TAP
KE-Korean	UA-United
KL-KLM	US-US Airways
LA-LAN Chile	VA-Virgin Australia
LH-Lufthansa	VO-VLM Airlines
LO-Lot	VS-Virgin Atlantic

Table A.2: Alliance Membership Dates for Individual Airlines

alliance	airline	start	end
American/Brussels	Brussels Airlines	Jun 04	Dec 09
American/Brussels	American Airlines	Jun 04	Dec 09
American/Canadian	Canadian Pacific Air Lines	Sep 96	Jun 00
American/Canadian	American Airlines	Sep 96	Jun 00
American/Swiss/Sabena	Sabena Belgian World Air	Jun 00	Dec 01
American/Swiss/Sabena	American Airlines	Jun 00	Mar 04
American/Swiss/Sabena	Swissair	Jun 00	Mar 02
American/Swiss/Sabena	Swiss International Air Lines	Jun 02	Mar 04
Atlantic Excellence	Sabena Belgian World Air	Jun 96	Mar 00
Atlantic Excellence	Delta Airlines	Jun 96	Mar 00
Atlantic Excellence	Swissair	Jun 96	Mar 00
Atlantic Excellence	Austrian Airlines	Jun 96	Mar 00
CO/COPA	Continental Airlines	Jun 01	Jun 07
CO/COPA	COPA	Jun 01	Jun 07
CO/COPA/UA	Continental Airlines	Dec 09	Mar 12
CO/COPA/UA	COPA	Dec 09	Mar 12
CO/COPA/UA	United Airlines	Dec 10	Mar 12
DL/VA (Virgin Blue)	Delta Airlines	Jun 11	--
DL/VA (Virgin Blue)	Virgin Australia International Airlines	Jun 11	--
DL/VS (Virgin Atlantic)	Virgin Atlantic	Sep 13	--
DL/VS (Virgin Atlantic)	Delta Airlines	Sep 13	--
Oneworld	Canadian Pacific Air Lines	Mar 99	Jun 00
Oneworld	British Airways	Mar 99	--
Oneworld	Qantas Airways	Mar 99	--
Oneworld	American Airlines	Mar 99	--
Oneworld	Cathay Pacific Airways	Mar 99	--
Oneworld	Finnair	Sep 99	--
Oneworld	Iberia	Sep 99	--
Oneworld	LAN Chile	Jun 00	--
Oneworld	Aer Lingus	Jun 00	Mar 07
Oneworld	LATAM Airlines Peru	Jun 00	--
Oneworld	Japan Asia Airways	Jun 07	--
Oneworld	Japan Transocean Air	Jun 07	--
Oneworld	Japan Air Commuter	Jun 07	--
Oneworld	Japan Airlines	Jun 07	--
Oneworld	Royal Jordanian	Jun 07	--
Oneworld	Beijing Capital Airlines	Jun 07	--
Oneworld	Malev Hungarian Airlines	Jun 07	Mar 12
Oneworld	Royal Wings	Jun 07	--
Oneworld	LATAM Airlines Ecuador	Jun 07	--
Oneworld	LATAM Airlines Argentina	Jun 07	--
Oneworld	Cathay Dragon	Dec 07	--
Oneworld	Mexicana	Dec 09	Sep 10
Oneworld	Siberia Airlines	Dec 10	--

Oneworld	Air Berlin	Mar 12	--
Oneworld	Malaysia Airlines	Mar 13	--
Oneworld	LATAM Airlines Colombia	Oct 13	--
Oneworld	Qatar Airways	Dec 13	--
Oneworld	LATAM Airlines Brasil	Mar 14	--
Oneworld	SriLankan Airlines	Jun 14	--
Oneworld	US Airways	Jun 14	Jun 15
SkyTeam	Air France	Jun 00	--
SkyTeam	Aeromexico	Jun 00	--
SkyTeam	Korean Airlines	Jun 00	--
SkyTeam	Delta Airlines	Jun 00	--
SkyTeam	Czech Airlines	Mar 01	--
SkyTeam	Alitalia	Sep 01	--
SkyTeam	Continental Airlines	Sep 04	Sep 09
SkyTeam	Northwest Airlines	Dec 04	Dec 12
SkyTeam	KLM	Dec 04	--
SkyTeam	Aeroflot	Jun 06	--
SkyTeam	Kenya Airways	Sep 07	--
SkyTeam	COPA	Sep 07	Sep 09
SkyTeam	Air Europa Lineas Aereas	Sep 07	--
SkyTeam	China Soutern Airlines	Dec 07	--
SkyTeam	Vietnam Airlines	Jun 10	--
SkyTeam	TAROM	Jun 10	--
SkyTeam	Shanghai Airlines	Jun 11	--
SkyTeam	China Eastern Airlines	Jun 11	--
SkyTeam	China Airlines	Sep 11	--
SkyTeam	Saudi Arabian Airlines	Jun 12	--
SkyTeam	Middle Eastern Airlines	Jun 12	--
SkyTeam	Aerolineas Argentinas	Sep 12	--
SkyTeam	Xiamen Airlines	Dec 12	--
SkyTeam	Garuda Indonesia	Mar 14	--
Star	Air Canada	Jun 97	--
Star	Lufthansa	Jun 97	--
Star	SAS	Jun 97	--
Star	Thai Airways	Jun 97	--
Star	United Airlines	Jun 97	--
Star	Rotana Jet Aviation	Dec 97	Mar 07
Star	Ansett Airlines	Mar 99	Sep 01
Star	Air India Limited	Mar 99	--
Star	All Nippon Airways	Dec 99	--
Star	Conviasa	Mar 00	Mar 15
Star	Austrian Airlines	Mar 00	--
Star	Lauda Air	Mar 00	Sep 12
Star	Singapore Airlines	Jun 00	--
Star	Cambodia Bayon Airlines	Sep 00	Jun 12
Star	Mexicana	Sep 00	Mar 04
Star	Air Japan	Dec 01	--

Star	Asiana	Mar 03	--
Star	Linea Aerea del Caribe	Jun 03	Mar 12
Star	LOT Polish Airlines	Dec 03	--
Star	US Airways	Jun 04	Mar 14
Star	Croatia Airlines	Dec 04	--
Star	Blue1	Dec 04	--
Star	Adria Airways	Dec 04	--
Star	TAP Portugal	Mar 05	--
Star	South African Airways	Jun 06	--
Star	Swiss International Air Lines	Jun 06	--
Star	Shanghai Airlines	Dec 07	Sep 10
Star	Air China	Dec 07	--
Star	Turkish Airlines	Jun 08	--
Star	Egyptair	Sep 08	--
Star	Continental Airlines	Dec 09	Mar 12
Star	Brussels Airlines	Dec 09	--
Star	Aegean Airlines	Jun 10	--
Star	LATAM Airlines Brasil	Jun 10	Dec 13
Star	Ethiopian Airlines	Dec 11	--
Star	Aero Republica	Jun 12	--
Star	Avianca	Jun 12	--
Star	LACSA	Jun 12	--
Star	TACA	Jun 12	Mar 13
Star	COPA	Jun 12	--
Star	Shenzen Airlines	Dec 12	--
Star	EVA Airways	Jun 13	--
Star	Air India	Jun 14	--
Star	Oceanair Linhas Aereas	Sep 15	--
United/Lufthansa	Lufthansa	Jun 96	Mar 97
United/Lufthansa	United Airlines	Jun 96	Mar 97
Wings	Northwest Airlines	Mar 93	Sep 04
Wings	KLM	Mar 93	Sep 04

Table A.3: ATI Dates for Airlines/Alliances

alliance	airline	ATI start	ATI end
American/Brussels	Brussels Airlines	Jun 04	Dec 09
American/Brussels	American Airlines	Jun 04	Dec 09
American/Canadian	Canadian Pacific Air Lines	Sep 96	Jun 00
American/Canadian	American Airlines	Sep 96	Jun 00
American/Swiss/Sabena	Sabena Belgian World Air	Jun 00	Dec 01
American/Swiss/Sabena	American Airlines	Jun 00	Mar 04
American/Swiss/Sabena	Swissair	Jun 00	Mar 02
American/Swiss/Sabena	Swiss International Airlines	Jun 02	Mar 04
Atlantic Excellence	Sabena Belgian World Air	Jun 96	Mar 00
Atlantic Excellence	Delta Airlines	Jun 96	Mar 00
Atlantic Excellence	Swissair	Jun 96	Mar 00
Atlantic Excellence	Austrian Airlines	Jun 96	Mar 00
CO/COPA	Continental Airlines	Jun 01	Jun 07
CO/COPA	COPA	Jun 01	Jun 07
CO/COPA/UA	Continental Airlines	Dec 09	Mar 12
CO/COPA/UA	COPA	Dec 09	Mar 12
CO/COPA/UA	United Airlines	Dec 10	Mar 12
DL/VA (Virgin Blue)	Delta Airlines	Jun 11	--
DL/VA (Virgin Blue)	Virgin Australia International Airlines	Jun 11	--
DL/VS (Virgin Atlantic)	Virgin Atlantic	Sep 13	--
DL/VS (Virgin Atlantic)	Delta Airlines	Sep 13	--
Oneworld	Lan Chile	Jun 00	--
Oneworld	American Airlines	Jun 00	--
Oneworld	Finnair	Sep 02	Jun 10
Oneworld	American Airlines	Sep 02	Jun 10
Oneworld	LATAM Airlines Peru	Dec 05	--
Oneworld	Finnair	Sep 10	--
Oneworld	British Airways	Sep 10	--
Oneworld	Iberia	Sep 10	--
Oneworld	Royal Jordanian	Sep 10	--
Oneworld	American Airlines	Sep 10	--
Oneworld	Japan Asia Airways	Dec 10	--
Oneworld	Japan Transocean Air	Dec 10	--
Oneworld	Japan Air Commuter	Dec 10	--
Oneworld	Japan Airlines	Dec 10	--
Oneworld	American Airlines	Dec 10	--
Oneworld	Beijing Capital Airlines	Dec 10	--
Oneworld	Royal Wings	Dec 10	--
Oneworld	Qantas	Dec 11	--
Oneworld	American Airlines	Dec 11	--
Oneworld	US Airways	Jun 14	Jun 15
Oneworld	US Airways	Jun 14	Jun 15
Oneworld	US Airways	Jun 14	Jun 15
Oneworld	US Airways	Jun 14	Jun 15

SkyTeam	Air France	Mar 02	--
SkyTeam	Alitalia	Mar 02	--
SkyTeam	Delta Airlines	Mar 02	--
SkyTeam	Czech Airlines	Mar 02	--
SkyTeam	Korean Airlines	Jun 02	--
SkyTeam	Delta Airlines	Jun 02	--
SkyTeam	Northwest Airlines	Dec 04	Mar 08
SkyTeam	KLM	Dec 04	Mar 08
SkyTeam	Continental Airlines	Sep 07	Sep 09
SkyTeam	COPA	Sep 07	Sep 09
SkyTeam	Northwest Airlines	Jun 08	Dec 12
SkyTeam	KLM	Jun 08	--
SkyTeam	Northwest Airlines	Dec 08	Dec 12
SkyTeam	Northwest Airlines	Dec 08	Sep 09
Star	Lufthansa	Jun 97	--
Star	SAS	Jun 97	--
Star	United Airlines	Jun 97	--
Star	Air Canada	Dec 97	--
Star	United Airlines	Dec 97	--
Star	Conviasa	Mar 01	Mar 15
Star	Austrian Airlines	Mar 01	--
Star	Air New Zealand	Jun 01	--
Star	United Airlines	Jun 01	--
Star	Asiana	Jun 03	--
Star	Air Canada	Mar 07	--
Star	LOT Polish Airlines	Mar 07	--
Star	TAP Portugal	Mar 07	--
Star	Swiss International Airlines	Mar 07	--
Star	Cambodia Bayon Airlines	Mar 08	Jun 12
Star	Continental Airlines	Dec 09	Mar 12
Star	Continental Airlines	Dec 10	Mar 12
Star	Continental Airlines	Dec 10	Mar 12
Star	Continental Airlines	Dec 10	Mar 12
Star	Continental Airlines	Dec 10	Mar 12
Star	All Nippon Airways	Dec 10	--
Star	United Airlines	Dec 10	--
Star	Air Japan	Dec 10	--
Star	Brussels Airlines	Dec 11	--
Star	COPA	Jun 12	--
Star	United Airlines	Jun 12	--
Star	United Airlines	Jun 12	--
United/Lufthansa	Lufthansa	Jun 96	Mar 97
United/Lufthansa	United Airlines	Jun 96	Mar 97
Wings	Northwest Airlines	Mar 93	Sep 04
Wings	KLM	Mar 93	Sep 04

Table A.4: JV Dates for Airlines/Alliances

alliance	airline	JV start	JV end
DL/VA (Virgin Blue)	Delta Airlines	Jun 11	--
DL/VA (Virgin Blue)	Virgin Australia International Airlines	Jun 11	--
DL/VS (Virgin Atlantic)	Virgin Atlantic	Sep 13	--
DL/VS (Virgin Atlantic)	Delta Airlines	Sep 13	--
Oneworld	Finnair	Dec 10	--
Oneworld	British Airways	Dec 10	--
Oneworld	Iberia	Dec 10	--
Oneworld	American Airlines	Dec 10	--
Oneworld	Japan Asia Airways	Mar 11	--
Oneworld	Japan Transocean Air	Mar 11	--
Oneworld	Japan Air Commuter	Mar 11	--
Oneworld	Japan Airlines	Mar 11	--
Oneworld	American Airlines	Mar 11	--
Oneworld	Beijing Capital Airlines	Mar 11	--
Oneworld	Royal Wings	Mar 11	--
Oneworld	US Airways	Jun 14	Jun 15
Oneworld	US Airways	Jun 14	Jun 15
SkyTeam	Northwest Airlines	Dec 04	Mar 08
SkyTeam	KLM	Dec 04	Mar 08
SkyTeam	Northwest Airlines	Jun 08	Dec 12
SkyTeam	Air France	Jun 08	--
SkyTeam	Alitalia	Jun 08	--
SkyTeam	KLM	Jun 08	--
SkyTeam	Delta Airlines	Jun 08	--
Star	Lufthansa	Mar 03	--
Star	United Airlines	Mar 03	--
Star	Air Canada	Dec 09	--
Star	Continental Airlines	Dec 09	Mar 12
Star	Cambodia Bayon Airlines	Sep 10	Jun 12
Star	Air Canada	Mar 11	--
Star	Continental Airlines	Mar 11	Mar 12
Star	United Airlines	Mar 11	--
Star	Continental Airlines	Jun 11	Mar 12
Star	All Nippon Airways	Jun 11	--
Star	United Airlines	Jun 11	--
Star	Air Japan	Jun 11	--
Star	Conviasa	Sep 11	Mar 15
Star	Austrian Airlines	Sep 11	--
Star	Swiss International Air Lines	Sep 11	--
Star	Brussels Airlines	Dec 11	--
Wings	Northwest Airlines	Mar 93	Sep 04
Wings	KLM	Mar 93	Sep 04

Table A.5: Alliance Carve-Outs

Alliance	City-pair carve out	Scope	Dates	Active?
AA/ CAI	New York – Toronto		7/96 - 6/00	No
AA/ Lan/ Lan Peru	Miami-Santiago Miami- Lima	U.S. POS, time-sensitive traffic only	9/99 - 10/05 -	Yes
AA/ Swiss/ Sabena	Chicago-Zurich Chicago-Brussels	U.S. POS, time-sensitive traffic only	5/00 - 11/01 (Zurich) 5/00 - 3/02 (Brussels)	No
DL/ Austrian/ Swiss/ Sabena	Atlanta-Zurich Atlanta-Brussels Cincinnati-Zurich New York-Brussels New York-Vienna New York-Geneva New York-Zurich	U.S. POS, time-sensitive traffic only	6/96 – 8/00	No
DL/ Air France/ Alitalia/ Czech	Atlanta-Paris* Cincinnati-Paris*	U.S. POS, time-sensitive traffic only	1/02 – 4/09	No
UA/ Lufthansa	Chicago-Frankfurt* Washington-Frankfurt*	U.S. POS, all local O&D traffic	5/96 – 12/10	No
UA/ Air Canada	Chicago-Toronto# San Francisco-Toronto#	U.S. POS, all local O&D traffic	9/97 -	Yes
UA/ Air New Zealand	Los Angeles-Auckland Los Angeles-Sydney	U.S. POS, time-sensitive travelers	4/01 -	Yes
UA/ CO/ LH/ Austrian/ TAP/ LOT/ Swiss/ Air Canada	New York-Copenhagen# New York-Lisbon# New York-Geneva# New York-Stockholm# Cleveland-Toronto# Houston-Calgary# Houston-Toronto# New York-Ottawa# U.S. – Beijing#	U.S. POS, all local O&D traffic	7/09 – 04/2011 7/09 – 3/2011 7/09 – 6/2011 7/09 – 4/2011 7/09 – 7/09 – 7/09 – 7/09 – 7/09 – 4/2011	No No** No No Yes Yes Yes Yes No

* Carve out ceases upon implementation of a joint venture.

** After the study was complete, it was learned that this carve-out is still in force. Making this change would have no effect on the results.

Carve out may be removed. If a new entrant initiates nonstop service in any of the subject markets and sustains that service with a minimum of 5 weekly roundtrip flights for more than nine months, the alliance may notify DOT in writing. If DOT takes no action, the carve-out is removed within 60 days of notice unless DOT objects in writing. *See* Order 2009-7-10 (July 10, 2009).

This list taken from alliance file located at: S/pubdocs/X-55/alliances & code shares/all immunized alliances. The source information is updated there.

Table A.6: Connecting Time Dummy Means

Dummies	mean
D_1998	0.0318
D_1999	0.0383
D_2000	0.0447
D_2001	0.0399
D_2002	0.0376
D_2003	0.0384
D_2004	0.0466
D_2005	0.0508
D_2006	0.0548
D_2007	0.0581
D_2008	0.0577
D_2009	0.0557
D_2010	0.0612
D_2011	0.0648
D_2012	0.0676
D_2013	0.0703
D_2014	0.0718
D_2015	0.0704
D_2016	0.0139
D_Q2	0.283
D_Q3	0.266
D_Q4	0.234

Table A.7: Connecting Year and Quarter Coefficients

VARIABLES	Economy	Business
D_1998	-0.0592**	0.000483
	(-23.14)	(0.0800)
D_1999	-0.0524**	0.0403**
	(-14.21)	(5.777)
D_2000	-0.0382**	0.0455**
	(-7.896)	(5.628)
D_2001	-0.0562**	0.0833**
	(-13.91)	(9.389)
D_2002	-0.0192**	0.104**
	(-4.051)	(11.65)
D_2003	0.0457**	0.157**
	(8.663)	(16.37)
D_2004	0.125**	0.203**
	(22.27)	(17.98)
D_2005	0.204**	0.238**
	(32.60)	(18.22)
D_2006	0.276**	0.233**
	(38.86)	(15.56)
D_2007	0.365**	0.284**
	(47.73)	(17.12)
D_2008	0.468**	0.366**
	(58.96)	(19.78)
D_2009	0.300**	0.273**
	(40.15)	(14.54)
D_2010	0.470**	0.338**
	(58.08)	(18.84)
D_2011	0.572**	0.386**
	(66.10)	(19.51)
D_2012	0.598**	0.423**
	(66.03)	(20.55)
D_2013	0.613**	0.366**
	(63.70)	(17.51)
D_2014	0.645**	0.336**
	(62.31)	(15.68)
D_2015	0.597**	0.258**
	(51.18)	(11.75)
D_2016	0.586**	0.219**
	(45.49)	(9.076)
D_Q2	0.0892**	-0.00955**
	(48.81)	(-3.818)
D_Q3	0.170**	-0.0358**
	(72.57)	(-12.68)
D_Q4	0.0512**	-0.00153
	(50.81)	(-0.577)

Clustered t-statistics in parentheses
** $p<0.01$, * $p<0.05$

Table A.8: GTG Time Dummy Means

Dummies	mean
D_1998	0.0375
D_1999	0.0407
D_2000	0.0436
D_2001	0.0414
D_2002	0.0362
D_2003	0.0371
D_2004	0.0407
D_2005	0.0457
D_2006	0.0498
D_2007	0.0559
D_2008	0.0552
D_2009	0.0523
D_2010	0.0583
D_2011	0.0682
D_2012	0.0666
D_2013	0.0671
D_2014	0.0741
D_2015	0.0809
D_2016	0.0193
D_Q2	0.2504
D_Q3	0.2505
D_Q4	0.2501

Table A.9: GTG Quarter, Year Coefficients (Economy)

VARIABLES	**coef**	**tstat**
D_Q2	0.0456**	9.751
D_Q3	0.107**	17.56
D_Q4	0.0348**	12.41
D_1998	-0.0896**	-9.519
D_1999	-0.100**	-8.765
D_2000	-0.0798**	-6.893
D_2001	-0.123**	-8.977
D_2002	-0.143**	-9.542
D_2003	-0.127**	-8.663
D_2004	-0.101**	-7.183
D_2005	-0.0606**	-4.081
D_2006	0.00473	0.321
D_2007	0.0437**	2.774
D_2008	0.104**	6.185
D_2009	-0.0184	-1.094
D_2010	0.133**	7.970
D_2011	0.184**	10.44
D_2012	0.220**	12.44
D_2013	0.224**	12.45
D_2014	0.243**	14.12
D_2015	0.191**	10.46
D_2016	0.162**	7.985
Constant	1.438**	11.19

Robust standard errors in parentheses

** $p<0.01$, * $p<0.05$