Firms' Markup, Cost, and Price Changes when Policymakers Permit Collusion: Does Antitrust Immunity Matter?

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Abstract

Airlines wanting to cooperatively set prices for their international air travel service must apply to the relevant authorities for antitrust immunity (ATI). Whether consumers, on net, benefit from a grant of ATI to partner airlines has caused much public debate. This paper investigates the impact of granting ATI to oneworld alliance members on their price, markup, and various measures of cost. The evidence suggests that implementation of the oneworld alliance without ATI did not have a statistically significant impact on the markup of products offered by the members, and there is no evidence that the subsequent grant of ATI to various members resulted in higher markups on their products. We find evidence suggesting that the grant of ATI facilitated a decrease in partner carriers' marginal and fixed costs. Furthermore, member carriers' price did not increase (decreased) in markets where their services do (do not) overlap, implying that consumers, on net, benefit from the grant of ATI in terms of price changes.

K*eywords:* Airline Competition; Strategic Alliances; Antitrust Immunity

JEL Classification codes: L13; L40; L93

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1. Introduction

The expansion of international airline alliances since the 1990s has drawn considerable attention of researchers and policymakers. The three major global airline alliances are: Star, SkyTeam, and oneworld. By joining a global alliance, an airline can leverage its partner carriers' route networks to extend its service to destinations in foreign countries that the airline could not otherwise serve using its own planes. Even though such interline service may be available to passengers without an alliance between the carriers, partner carriers in an alliance typically coordinate in an effort to make interline transfers seamless for passengers. In addition, partner carriers typically make their frequent-flyer programs reciprocal, thus allowing passengers with membership in any partner carrier's frequent-flyer program to accumulate and redeem frequent-flyer points across any carrier of the alliance.

Alliance partners often want to extend cooperation to revenue sharing, which effectively implies joint pricing of products. This type of cooperation in markets where the partners each offer substitute service is believed to harm competition and therefore violates antitrust laws. As such, alliance partners can only explicitly collude on price if the relevant authorities in each country exempt the partner carriers from prosecution under the country's antitrust laws – a grant of antitrust immunity.

To explicitly collude on price, airlines must first formally apply to the relevant authorities for antitrust immunity (ATI). The application process provides carriers with the opportunity to make their case to the relevant authorities that the level of cooperation that ATI would allow will yield net benefits to consumers. A grant of ATI is usually justified on grounds that the cooperative actions of partner carriers that are in violation of antitrust laws produce benefits to consumers that are sufficient to outweigh the cost of reduced competition. Furthermore, the relevant authorities can grant ATI with the restriction that antitrust immune partners cannot explicitly collude in certain markets, deemed carve-out markets, that the authorities believe will on net yield worse welfare outcomes due to reduced competition between the antitrust immune partners.[1]

There are numerous instances since the 1990s in which airlines have been successful in convincing the U.S. Department of Justice (DOJ) and U.S. Department of Transportation (DOT) that granting them ATI is, on net, beneficial for consumers. However, in recent time the DOJ has argued that ATI is not necessary for an alliance to yield net benefits for consumers and alliance carriers. In 2009 DOJ expressed this view in commenting on the joint application for antitrust immunity from five members of the oneworld alliance.[2] Furthermore, DOJ points out that granting these airlines antitrust immunity will reduce competition in origin-

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[1] See Gayle and Thomas (2016) for an empirical analysis of the effectiveness of carve-out policy.

[2] See: OST-2008-0252 – Public Version Comments of the Department of Justice. Document can be downloaded at: http://www.justice.gov/atr/public/comments/253575.htm.

destination markets between the U.S. and Europe where these carriers compete using nonstop flights.

Despite DOJ's concerns regarding granting ATI to these airlines, the DOT was convinced that there are sufficient efficiency gains associated with granting the carriers ATI, such that on net consumers would ultimately benefit. Since it is the DOT that has the statutory authority to approve and immunize from the U.S. antitrust laws agreements relating to international air transportation, DOT granted the carriers ATI in year 2010. Given the opposing positions that these two key government authorities took in this case, it is necessary to carefully study these issues to facilitate future policymaking decisions of this nature. As such, this paper has two main objectives: (1) investigate the effects of granting ATI on price, markup, and various categories of partner carriers' costs; and (2) investigate the relative effects of implementing an alliance without ATI versus an alliance with ATI.

There has been extensive work examining the airfare effect of alliances. Many studies find that airline cooperation due to an alliance puts downward pressure on fares in interline markets due to product complementarity and the mitigation of double marginalization.[3] However, as previously suggested, an alliance can also reduce competition in markets where the partners' route networks overlap (typically their interhub markets), which would put pressure on fares to rise in these markets. Zou, Oum and Yu (2011) argue that it is possible that an alliance causes fares to increase even in markets where the partners' route segments are complementary rather than overlapping, since the quality of interline connections improves with an alliance and consequently demand may increase owing to product quality improvements.

The arguments above describe situations in which an alliance may affect price via influencing the carriers' optimal choice of product price markup over marginal cost. So the predicted price effects based on the previously discussed arguments assume that marginal cost is unchanged. However, an alliance may influence partner carriers' marginal cost of transporting passengers. Specifically, by appropriately integrating their route networks, partner carriers can better fill their planes on a segment of an interline trip by channeling passengers from different origins through a common trip segment. Such cooperation enables carriers to exploit economies of passenger-traffic density, i.e., the marginal cost of transporting a passenger on a route is lower the more passengers that the airline transports on segments of the route [Brueckner and Spiller (1994); Brueckner (2001 and 2003); Gresik and Mansley (2001); and Keeler and Formby (1994)].

Gayle and Le (2013) argue that an alliance may not only influence partner carriers' marginal cost, but also their recurrent fixed and sunk market entry costs. A carrier's market entry cost may fall because the alliance effectively allows the carrier to enter several new origin-destination markets more cheaply by

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3 See Brueckner and Whalen (2000); Brueckner (2001 and 2003); Bamberger, Carlton and Neumann (2004); Ito and Lee (2007); Gayle (2008 and 2013); Gayle and Brown (2014); Whalen (2007); Zou, Oum, Yu (2011) among others.

leveraging its partners' network rather than having to exclusively use its own planes to enter these markets. They point out that a carriers' recurrent fixed cost may either rise or fall due to the alliance. For example, accommodating a higher volume of passengers may require partner carriers to acquire more airport gates and a larger airport staff to handle more intensive airport operations, which would increase partners' recurrent fixed cost. On the other hand, alliance partners often share their airport facilities (lounges, gates, check-in counters etc.), and ground and flight personnel, which may result in more efficient use of airport facilities and staff, and therefore effectively yield recurrent fixed cost savings [Park (1997)]. In their empirical investigation of the cost effects of the US domestic alliance between Delta, Continental and Northwest airlines, Gayle and Le (2013) find evidence that this alliance influenced the partner carriers' marginal, recurrent fixed, and sunk market entry costs.

It is important to note that the analysis in Gayle and Le (2013) focus on a US domestic airline alliance, which is not eligible to be granted ATI. In contrast to Gayle and Le (2013), our analysis focuses on an international alliance (a subset of the alliance members are distinct national carriers), which initially formed and operated for a number of years before ATI was granted to a subset of its member carriers. As such, unlike Gayle and Le (2013), we are able to separately analyze the impacts of ATI on prices, markups, and various types of costs. Since ATI allows carriers to explicitly cooperate on market transactions without fear of being in violation of antitrust laws due to such cooperation, we can expect greater cooperation between carriers that have ATI compared to carriers that do not have ATI. Greater cooperation can result in better route network integration across partner carriers, which may better enable partner carriers to exploit economies of passenger-traffic density to achieve lower per passenger cost. Lower costs may also be achieved if cooperation extends to ATI partner carriers' joint purchase of essential inputs such as fuel.

Gayle and Xie (2018) examine whether codesharing between market incumbents may serve to deter potential entrants to a market. The analytical setting and issues investigated in that paper differs from this paper in two important ways. First, Gayle and Xie (2018) examine how codesharing between alliance partners affects the market entry cost of other carriers that are potential competitors, while in this paper we examine whether the alliance partners' own market entry costs are influenced by operating within the alliance. Second, Gayle and Xie (2018) focus on US domestic airline alliances, which are not eligible to be granted ATI, while in the present paper we focus on an international alliance that is eligible for, and was granted, ATI.

Based on the preceding discussions, the effect of alliances on fares may depend on the relative magnitudes of cost-savings and optimal markup changes. A retrospective assessment of cost changes separate from markup changes associated with an alliance before and after antitrust immunity is granted may provide policymakers with some perspective on the efficacy of granting antitrust immunity. Our study focuses on identifying these effects in case of the oneworld alliance.

Researchers have investigated the relative effects of a codeshare alliance with and without ATI. For example, Bruckner (2003) finds that the effect of codesharing on fares is smaller than the effect of ATI, while Whalen (2007) finds a similar result and additionally finds that prices for immunized alliance service are equal to online service. Bruckner, Lee and Singer (2011) show that codesharing, alliance service, and ATI each separately reduces fares below the traditional interline level, while Bilotkach (2005) shows that granting ATI pushes up fares for non-stop trips between hub airports and does not generate any additional benefits to interline passengers, as compared with alliances without immunity.

None of the studies separately identify the effects of an alliance and ATI on markup versus cost, which is essential to better understand the efficacy of granting ATI. Therefore, a key distinguishing feature of our study from others in the literature is that we use a structural model to disentangle markup changes from cost changes associated with an alliance and ATI.

Even though Gayle and Thomas (2016) also provide a structural econometric analysis of international airline alliances, their analysis focuses on the effectiveness of carve-out policy in particular, while our analysis more broadly examines the impacts of airlines being granted ATI. Furthermore, unlike Gayle and Thomas (2016), our structural econometric model incorporates a dynamic entry/exit game. The dynamic entry/exit game allows us to examine the impacts of ATI on recurrent fixed costs and sunk market entry costs, which are types of costs not considered in Gayle and Thomas (2016). Using existing market data for price, markup and marginal cost analysis is typically most useful to capture shorter horizon price, markup and marginal cost impacts conditional on existing market structure. However, one way to think about the importance of considering ATI's impacts on recurrent fixed costs and sunk market entry costs, is that these costs are more relevant in determining the medium to long run structure of a market, which ultimately impacts future prices and more importantly welfare.

The following is a brief description of our research methodology. We first specify and estimate air travel demand using a discrete choice model. Then, for the short-run supply-side, we assume that multiproduct airlines set prices for their differentiated products according to a Nash equilibrium price-setting game. The Nash equilibrium price-setting assumption allows us to derive product-specific markups and recover product-level marginal costs. With the estimated marginal costs in hand, we are able to specify and estimate a marginal cost function. The marginal cost specification allows us to estimate marginal cost changes for the alliance members across pre-post periods of implementation of the alliance without ATI. Similarly, we are able to estimate marginal cost changes for the alliance members across pre-post periods of obtaining ATI. With product-level markup estimates in hand, we then separately specify and estimate markup equations that identify changes in the alliance members' markup across pre-post periods of alliance implementation and pre-post periods of obtaining ATI, respectively.

Next, we compute firm-level variable profits using the derived product markups and product quantities sold. With data on markets in which each firm is active or not during specific time periods, as well as our estimates of their variable profits when they are active in markets, we are able to estimate a dynamic entry/exit game. The dynamic entry/exit game allows us to estimate recurrent fixed cost and market entry cost functions. These functions are specified to identify changes in alliance partners' recurrent fixed and market entry costs across pre-post periods of alliance implementation and pre-post periods of obtaining ATI, respectively.

Our econometric estimates suggest the following. First, implementation of the oneworld alliance did not have a statistically significant impact on the markup of products offered by the members, and there is no evidence that the subsequent grant of ATI to various members resulted in higher markups on their products. Second, we did not find any evidence that implementation of the oneworld alliance created marginal cost efficiencies, but we do find evidence suggesting that the subsequent grant of ATI to some oneworld members is associated with a reduction in these members' marginal costs. So the evidence does support the argument that granting of ATI better enables members to achieve cost efficiency gains, perhaps due to more effective cooperation between these members. Third, the dynamic entry/exit part of the model did not produce any statistically discernible evidence that implementation of the oneworld alliance influenced members recurrent fixed or market entry costs, but reveals evidence that the subsequent grant of ATI to some oneworld members is associated with fixed cost efficiency gains, but no evidence of market entry cost changes for these ATI members.

Last, we find evidence suggesting that the grant of ATI to various members is associated with a decline in their price in markets where their services do not overlap. Furthermore, the evidence suggest that prices did not increase in markets where their services do overlap.

The remainder of this paper is organized as follows. Section 2 provides relevant background information on the oneworld alliance and subsequent grant of ATI to various members of the alliance. We define some relevant concepts and discuss the data in section 3. In section 4 we present our econometric model. In section 5 we discuss estimation procedures. Estimation results are presented and discussed in section 6. Section 7 concludes.

2. Background Information on oneworld Alliance and Antitrust Immunity

On September 21, 1998, American Airlines, British Airways, Canadian Airlines[4], Cathay Pacific, and Qantas unveiled the formation of oneworld, one of the world's three largest global airline alliances. The other two major global alliances are Star Alliance and SkyTeam. The oneworld alliance was officially launched and started its operation on February 1, 1999. Since its inception, several airlines have joined the alliance. Table A1 in Appendix A lists members of the alliance at the beginning of 2013. A few more airlines are expected to enter the alliance in 2013-2014. The central office for the alliance is based in New York City, New York, in the U.S.

The oneworld alliance global airline network provides services to more than 800 destinations in over 150 countries.[5] It is argued that flying with oneworld allows passengers to enjoy multiple privileges. For example, a passenger who is a member of the frequent-flyer program (FFP) offered by a oneworld carrier is able to earn and redeem frequent-flyer points across other oneworld partner carriers. Second, smooth transfer between partner airlines brings more convenience and reduces layover time for passengers.[6]

Foreign and major U.S. airlines may request a grant of immunity from the U.S. antitrust laws to operate certain commercial alliances. Airlines with immunity can coordinate their fares, services, and capacity as if they were a single carrier in origin-destination markets. Table A2 in Appendix A lists airline alliances operating with antitrust immunity. On August 14, 2008, five members of the oneworld alliance, American Airlines; British Airways; Finnair; Iberia; and Royal Jordanian Airlines, jointly applied for antitrust immunity for a set of bilateral and multilateral alliance agreements. The DOT tentatively approved and granted antitrust immunity to alliance agreements between and among the five airlines on February 13, 2010,[7] and issued a final order of approval on July 20, 2010.

As part of the approval, American, British Airways and Iberia can implement a joint business venture (JBA) to connect their transatlantic flight services more closely. However, the grant of immunity is subject to a slot remedy. A "slot" is the name given to an airline's right to land and takeoff at a given airport. The slot remedy requires the airlines to transfer four slot pairs at London Heathrow to competitors for a period of at least 10 years.[8] The rationale put forth by the DOT is that this slot remedy will sufficiently lower market entry

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[4] Canadian Airlines was acquired by Air Canada in 2000 and then exited oneworld alliance.

[5] Oneworld at a glance http://www.oneworld.com/news-information/oneworld-fact-sheets/oneworld-at-a-glance

[6] This information is attained from http://www.oneworld.com/ffp/.

[7] Order 2010-2-13 found at http://www.airlineinfo.com/ostdocket2010/order20100208.html

[8] Order 2010-7-8 - American, British Airways, Finnair, Iberia and Royal Jordanian - Final Order - Antitrust Immunity. Issued by United States Department of Transportation. Document can be downloaded at: http://www.airlineinfo.com/ostdocket2010/order20100708.html

barriers for potential competitors, and therefore effectively constrain anticompetitive behavior of the antitrust immune carriers. [9]

American Airlines, which serves 273 cities in 51 countries, is one of the largest carriers in the world with total revenues of about $25 billion in 2013.[10] American's primary hubs are based in Dallas, Chicago, and Miami. British Airways, which is also among the world's largest international airlines, is the flag carrier airline of the United Kingdom and has its main hub at London Heathrow Airport. In addition, British Airways serves 190 cities in 89 countries. Iberia, the largest airline of Spain, merged with British Airways on November 29, 2010. These three airlines provide the vast majority of oneworld service between the U.S. and Europe and they codeshare[11] among each other. Finnair and Royal Jordanian provide a very limited amount of transatlantic service.

The application for ATI by oneworld members in 2008, which was eventually granted in 2010, was actually the third attempt by oneworld members to seek ATI. The previous two attempts were unsuccessful. The first of the previous two attempts came in 1997 when American and British Airways applied for ATI, but the DOT dismissed the application due to failure of the liberalization of the Bermuda II Treaty.[12] In 2001, the carriers again requested antitrust immunity and DOT issued a show cause order to grant immunity conditionally. However, American and British Airways withdrew their application.

In their application of 2008, the five oneworld alliance applicants claim that they seek antitrust immunity in order to better compete with SkyTeam and Star alliances, which both had received immunity. The oneworld alliance applicants stated that: "The recent expansion of Star and SkyTeam makes the proposed alliance necessary to maintain inter-alliance competition and to achieve the full benefits of U.S. – EU Open Skies."[13,14] They believe that the transatlantic network integration from antitrust immunity and JBA could allow the applicants to provide services to more markets between oneworld hubs, Star and SkyTeam hubs, and spoke cities in Europe, thus facilitating the inter-alliance competition. In addition, the applicants assert that approval of the antitrust immunity and JBA will bring a number of benefits to both consumers and the

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9 Order 2010-2-8 issued by the United Sates Department of Transportation. Document can be downloaded at: http://www.mainjustice.com/files/2010/02/DOT-BA-AA-Approval.pdf

10 Oneworld at a glance at http://www.oneworld.com/news-information/oneworld-fact-sheets/oneworld-at-a-glance

11 Codeshare is the name given to agreements between partner carriers that allow a carrier to market and sell tickets to consumers for seats on its partners' plane.

12 Bernuda II treaty was a bilateral air transport agreement between the governments of the United States and the United Kingdom signed on 23 July 1977.

13 In 2007, the United States and the European Union signed a new "open skies" to replace Bermuda II.

14 For summary of arguments that applicants made in their joint application see: OST-2008-0252 – Public Version Comments of the Department of Justice. Document can be downloaded at: http://www.justice.gov/atr/public/comments/253575.htm.

applicants' employees and shareholders.

In response to the application, DOJ issued a recommendation report on the possible market effects of granting antitrust immunity.[15] DOJ strongly believes that granting antitrust immunity would harm competition in transatlantic markets. Specifically, DOJ argues that the reduction in number of nonstop competitors caused by granting immunity would likely result in significant fare increases. In addition, DOJ believes that entry is difficult in hub-to-hub routes and thus is unlikely to inhibit price increases. Moreover, DOJ suggests that immunity is not required to achieve the benefits claimed in the application.

3. Definitions and Data

3.1 Definitions

We now define some important concepts that are used throughout this paper. A market is defined as directional pair of origin and destination airports during a particular time period. For example, irrespective of intermediate stop(s), one market constitutes air travel from Los Angeles International airport to London Heathrow airport during the first quarter of 1998. A flight itinerary is a detailed plan for roundtrip air travel that includes all airport stops from origin to destination and back to origin.

Each segment of a trip (air travel between two airports) has a ticket coupon. For each coupon there is an operating carrier and a ticketing carrier. The operating carrier is the airline that actually uses its own plane to transport passengers, while the ticketing carrier, also referred to as marketing carrier, is the airline that sells tickets for seats on the operating carrier's plane. A product is defined as a combination of itinerary, ticketing carrier, and operating carrier(s) for all segments of the trip. We only focus on products with the same ticketing carrier for all trip segments, but operating carriers may differ across trip segments.

We classify characteristics of a travel itinerary for each direction of air travel on the itinerary into the following categories: (1) Pure Online; (2) Traditional Codeshare Type I; (3) Traditional Codeshare Type II; and (4) Virtual Codeshare. Table 1 provides examples of these categories for an itinerary that uses two segments (i.e. requires one intermediate stop) for the given direction[16] of air travel being classified. We independently classify each direction of air travel on a given itinerary, and therefore the classification category for the going (or outbound) segment(s) of the trip may be different from the classification category on the coming back (or inbound) segment(s) of the trip.

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[15] See OST-2008-0252 – Public Version Comments of the Department of Justice. Document can be downloaded at: http://www.justice.gov/atr/public/comments/253575.htm.

[16] Direction of air travel here means either going to the destination or coming back from the destination.

The segment(s) of an itinerary that the passenger uses for travel in a given direction is defined as pure online if the same carrier serves as both the operating and ticketing carrier for all segments of the itinerary. For the example in the table, Delta Airlines (DL) is the ticking carrier for the first and second segments of the trip, denoted by DL: DL. Moreover, Delta is also the operating carrier for these two segments.

The segment(s) of an itinerary that the passenger uses for travel in a given direction is defined as codeshare when operating carrier(s) differ from ticketing carrier. Codeshare itineraries may either be Traditional Type I; Traditional Type II; or Virtual. The segments of air travel in a given direction on an itinerary are classified as Traditional Type I if operating carriers across the segments differ, and the ticketing carrier is one of the distinct operating carriers, but Traditional Type II if the ticketing carrier is not one of the distinct operating carriers. Table 1 shows carrier information for a given direction of air travel on an itinerary that is Traditional Type I since the operating carriers are Sabena Belgian World Airlines (SN) and Austrian Airlines (OS), and the ticketing carrier is Sabena Belgian World Airlines. The table also shows that the classification would instead be Traditional Type II if the ticketing carrier is Delta Airlines (DL) rather than Sabena Belgian World Airlines.

Last, the segment(s) of an itinerary for a given direction of air travel is (are) classified as virtual codeshare if the segment(s) use(s) the same operating carrier, but the ticketing carrier is different. The virtual codeshare example in the table indicates that Delta is the ticking carrier, but Sabena Belgian World Airlines operates on all segments of the trip.

Table 1
Examples of Itinerary Categories for a given Direction of Air Travel

Itinerary Category	Ticking Carrier	Operating Carriers
Pure Online	DL:DL	DL:DL
Traditional Type I	SN:SN	SN:OS
Traditional Type II	DL:DL	SN:OS
Virtual	DL:DL	SN:SN

3.2 Data

The source of data used in our study is the International Passenger Airline Origin and Destination Survey (DB1B) collected by the Office of Airline Information of the Bureau of Transportation Statistics. The database comes from a quarterly survey of ten percent of the passengers traveling through at least one route segment that is flown by a U.S. carrier. Since each ticket in the data needs at least one segment operated by a US carrier, then the representativeness of this dataset varies across markets due to the missing part relating to services provided by only non-US airlines. Each observation represents an itinerary that was purchased at a specific price by a given number of passengers during a quarter. Information provided by each observation includes: (1) the number of passengers paying the given fare during the quarter; (2) mileage flown for each itinerary segment; (3) numeric codes identifying each airport, city, and country on the itinerary; and (4) identity of operating and ticketing carriers on the itinerary. In addition, turnaround points in the itinerary can be identified by the trip break code. The trip break code is useful for identifying the origin and destination.

We compiled two separate data samples from the database. One sample, which we refer to as the "oneworld Event Sample", is compiled specifically for studying market effects associated with implementation of the oneworld alliance. The "oneworld Event Sample" covers periods before and after implementation of the oneworld alliance. As we previously stated, the oneworld alliance was officially launched and started its operation on February 1, 1999. The pre-alliance periods in the "oneworld Event Sample" are quarters 1 and 2 of 1998, while the post-alliance periods are quarters 1 and 2 of 2001. The reason we use quarters 1 and 2 of 2001 as the post-alliance periods is to avoid capturing the impacts that the terrorist attack of 9-11 had on air travel, which would confound identifying the pure effects of implementing the oneworld alliance.

The other data sample, which we refer to as the "ATI Event Sample", is compiled specifically for studying market effects associated with the granting of ATI to various members of the oneworld alliance. The "ATI Event Sample" covers periods before and after ATI was granted. As we previously stated, on August 14, 2008, five members of the oneworld alliance jointly applied for ATI, but it was not until July 20, 2010 that the DOT issued a final order of approval for ATI. The pre-ATI periods in the "ATI Event Sample" are quarters 2 and 3 of 2008, while the post-ATI periods are quarters 2 and 3 of 2011.

Note that American Airlines, British Airways, Cathay Pacific, and Qantas are founders of oneworld alliance, but Iberia and Finnair entered the alliance in the same year of alliance formation, and LAN joined the alliance in year 2000. Therefore, we only consider these seven airlines as oneworld alliance members in the "oneworld Event Sample". In the "ATI Event Sample", American Airlines, British Airways, Iberia, Finnair, and Royal Jordanian are the oneworld members that were granted ATI.

It is important to note that the names we use to label these data samples do not imply that the only airlines in each sample are members of the oneworld alliance. The name given to a data sample purely relates to the event that the data sample is used to study. Therefore, each sample comprises a wide array of airlines. There are 65 ticketing carriers in the "oneworld Event Sample", while the "ATI Event Sample" contains 72 ticketing carriers. Table A3 and Table A4 in Appendix A list all the ticketing carriers in each data sample respectively.

We apply several restrictions to "clean" the raw data. First, observations in which itineraries have more than 8 coupons are eliminated. Second, we only keep observations with roundtrip itineraries, so the starting and ending airports are the same. Third, itineraries that are cheaper than $100 or more expensive than $10,000 are deleted. Fourth, origin airports must be located in the 48 main land states of the U.S., while destination airports are located in other countries. However, itineraries with origin airport outside the U.S. and destination airport within the U.S. are not included because it is difficult to collect demographic data (e.g. population size) for cities of origin airports located outside the United States. We need data on population size in origin cities in order to measure potential market size and to compute observed product shares in our study.

The data that remain after applying the restrictions above do have repeated observations of products that have different prices and numbers of passengers within each quarter. During each quarter we compute the average price and aggregate the number of passengers associated with unique products (itinerary-airline(s) combination), then collapse the data in each quarter by only keeping unique products. In the end, we have 164,908 products (observations) across 55,641 markets in the collapsed "oneworld Event Sample", and 333,450 products across 84,740 markets in the collapsed "ATI Event Sample".

In the "oneworld Event Sample" and the "ATI Event Sample", there are respectively 142 and 181 destination countries across six world continents. Table 2 and Table 3 respectively list destination countries in each dataset for which the percent of products that have the country as a destination is at least 1 percent. In the "oneworld Event Sample", among 142 destination countries, only 26 of them are destinations for a sufficiently large number of itineraries that satisfy the "at least 1 percent of products" threshold. However, the percent of products in the "oneworld Event Sample" with air travel to these 26 countries is almost 80 percent. In the "ATI Event Sample" there are only 21 destination countries out of 181 that satisfy the "at least 1 percent of products" threshold, but the percent of products in this sample with air travel to these 21 countries is around 72 percent.

Based on the collapsed datasets, we create additional variables needed in our study. These variables are constructed to capture various non-price characteristics of air travel products. The reader will observe in subsequent sections of the paper that our model of demand and short-run supply requires data on product characteristics for econometric estimation.

Table 2
List of most frequent destination countries in the "oneworld Event Sample"

Destination countries	**Percent of products offered**	**Destination countries**	**Percent of products offered**
Canada	15.34	Hong Kong	1.41
Mexico	13.18	Philippines	1.38
United Kingdom	6.40	Switzerland	1.38
Germany	6.12	Dominican Republic	1.24
France	5.01	Netherlands Antilles	1.21
Bahamas	3.27	Australia	1.18
Japan	3.17	Cayman Islands	1.15
Italy	2.54	South Korea	1.07
Netherlands	2.01	Aruba	1.03
Brazil	1.86	Belgium	1.03
Jamaica	1.84	India	1.03
Spain	1.72	Thailand	1
Costa Rica	1.48	Others	20.50
China	1.45	Total	100

Table 3
List of most frequent destination countries in the "ATI Event Sample"

Destination countries	Percent of products offered	Destination countries	Percent of products offered
Mexico	13.16	Costa Rica	1.62
Canada	12.53	Brazil	1.62
United Kingdom	6.52	Netherlands	1.55
Germany	5.47	Ireland	1.49
Italy	4.22	India	1.30
France	3.65	Switzerland	1.19
Bahamas	2.89	Aruba	1.15
Spain	2.88	South Korea	1.07
China	2.52	Australia	1.04
Dominican Republic	2.13	Other countries	27.96
Japan	2.06	Total	100
Jamaica	1.98		

As in Gayle and Thomas (2016), we define origin presence variables from two different perspectives. The variable *Opres_demand* is a count of the number of different airports to which the airline has nonstop flights leaving from the relevant origin airport for which variable *Opres_demand* is being used to measure the size of the airline's presence. On the other hand, *Opres_cost* counts the number of airports within the United States from which the airline provides nonstop flights going to the relevant origin airport for which *Opres_cost* is being used to measure the size of the airline's presence. Effectively, *Opres_demand* is measured from the perspective of an airline's distinct "outbound" activities from an origin airport of a market, while *Opres_cost* is measured from the perspective of an airline's "inbound" activities to the origin airport of a market.[17]

Opres_demand is constructed to help explain variations in demand across carriers for the products offered to consumers at the consumers' origin airport, i.e., this variable helps explain consumers' choice between airlines at the consumer's origin airport. The presumption here is that a consumer is more likely to choose the airline that offers nonstop service to more cities from the consumer's origin airport. On the other hand, *Opres_cost* is intended to help capture airlines' cost effects. The idea is that the larger is an airline's *Opres_cost* measure at the origin of a market, the larger the volume of passengers the airline is likely to channel through the market and therefore the airline is expected to have lower marginal cost of transporting a passenger in this market due to economies of passenger-traffic density.

Nonstop_going and *Nonstop_coming* are dummy variables we construct to equal to 1 if the product uses nonstop itinerary for departing and returning legs of the trip, respectively. The variables *Distance_going* and *Distance_coming* respectively measure the market miles flown between origin and destination for departing and returning trips.

Routing_quality_going (*Routing_quality_coming*) is a variable that constitutes a flying distance-based measure of routing quality, or "directness" of routing, on the going (coming) portion of the product itinerary. It is computed as the minimum flying distance going to (coming from) the destination airport in the origin-destination market as a percentage of the actual flying distance on the going (coming) portion of the itinerary for the product for which the routing quality is being measured. If *Routing_quality_going* (*Routing_quality_coming*) takes on the maximum value of 100, then in terms of flying distance this is the most travel-convenient routing offered in the market for the going (coming) portion of the trip.[18]

Observed product share, S_j, is computed by dividing quantity of product j sold by origin city population, i.e. $S_j = {q_j}/{POP}$.[19] The population data are obtained from the population estimates of United States Census Bureau.

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[17] As discussed in Gayle and Thomas (2016), an airline's inbound and outbound nonstop service activities at an airport need not be symmetrical in terms of the number and/or identity of endpoint cities from which its inbound flights come compared to the number and/or identity of endpoint cities to which it provides nonstop outbound service. A reason for the potential asymmetry is that the plane used to provide inbound nonstop service to the relevant airport for a subset of passengers on the plane, may not contain nonstop passengers for the outbound service from the relevant airport to possibly a different city. As such, while variables *Opres_demand* and *Opres_cost* are likely positively correlated, they need not be perfectly correlated.

[18] See Chen and Gayle (2018) for a detailed discussion of this distance-based measure of routing quality.

[19] Due to the fact that population magnitudes are significantly larger than quantity sold for any given air travel product, observed product shares, computed as described above, are extremely small numbers. We therefore scale up all product shares in the data by a common factor. The common factor is the largest integer such that the outside good share ($S_0 = 1 - \sum_{j=1}^{J} S_j$) in each market

To properly identify codeshare products, we appropriately recode the feeder/regional airlines to their matching major airlines since we only consider codesharing between major carriers. For example, SkyWest (OO) operates on a regional airline level, and feeds passengers to United Airlines (UA), US Airways (US), and Delta Airlines (DL). Therefore, SkyWest needs to be recoded to take the code of the major airline to which it feeds passengers for the itinerary under consideration. We do this recoding to all operating carriers that are feeder, regional, or subsidiary airlines for each coupon in the datasets. Even though this is a tedious process that takes time, doing so lets us accurately identify codeshare products between major carriers. The summary statistics of above-mentioned variables are shown in Table 4. We use the consumer price index with a base year of 2005 to convert prices into constant year 2005 dollars.

Table 4
Summary Statistics

Variables	"oneworld Event Sample"				"ATI Event Sample"			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Fare[a]	1,025.298	1043.988	110.003	11,997.06	1,094.031	1,012.379	86.240	8,992.601
Quantity (q_j)	6.495	38.496	1	3,210	5.401	38.477	1	3,279
Opres_demand	25.007	33.258	0	186	30.482	45.248	0	261
Opres_cost	25.002	28.861	0	143	26.354	33.908	0	172
Nonstop_going	0.047	0.212	0	1	0.041	0.199	0	1
Nonstop _coming	0.049	0.215	0	1	0.039	0.195	0	1
Distance _going	4,016.996	2,462.371	96	16,619	4,121.875	2,455.821	96	17,801
Distance _coming	4019.531	2,465.869	96	13,933	4,126.352	2,458.620	96	17,457
Routing_quality_going	94.398	8.808	42.634	100	94.076	9.086	39.362	100
Routing_quality_ coming	94.350	8.878	35.616	100	93.962	9.205	35.859	100
Traditional_I_going	0.157	0.364	0	1	0.173	0.378	0	1
Traditional_II_going	1.88E-04	0.014	0	1	0.003	0.054	0	1
Traditional_I_coming	0.156	0.363	0	1	0.175	0.380	0	1
Traditional_II_coming	3.58E-04	0.019	0	1	0.003	0.057	0	1
Virtual_going	0.015	0.123	0	1	0.019	0.137	0	1
Virtual_coming	0.016	0.126	0	1	0.022	0.147	0	1
Observed Product Shares (S_j)	0.003	0.012	2.27E-05	0.924	0.001	0.004	7.52E-06	0.437
Number of products	164,908				333,450			
Number of markets	55,641				84,740			

Notes: [a] The variable "Fare" in both samples is measured in constant year 2005 dollars based on the consumer price index.

remains positive. The common factor that satisfies these conditions is 183 in the "oneworld Event Sample" and 62 in the "ATI Event Sample".

3.3 Results from a Reduced-form Price Regression

To help motivate the need for our subsequent structural econometric model, we now examine price effects associated with: (*i*) various features of airline markets and air travel products; (*ii*) implementation of the oneworld alliance; and (*iii*) the grant of ATI to various members of the oneworld alliance. Price effects are identified within a reduced-form price regression framework. One attractive feature of a reduced-form price regression is that its specification and estimation do not require the strong assumptions on optimizing behavior of market participants as are required for specification and estimation of a structural model. However, unlike a structural model, a reduced-form price regression cannot separately identify changes in markup versus changes in marginal cost, which are two key distinct aggregate components of equilibrium price. Understanding how various market and product features influence markup and marginal cost is crucial for understanding the economic mechanisms through which these features impact prices.

Table 5 presents the estimation results of a reduced-form price regression. In both the "oneworld Event Sample" and "ATI Event Sample", the coefficient estimate on *Opres_cost* is positive, but the coefficient estimate on *Opres_cost_square* is negative. This sign pattern of these coefficient estimates suggests that an airline's size of presence at the origin airport has a positive price effect at relatively low levels of its airport presence, but a negative price effect at relatively high levels of its presence at the origin airport. One can reasonably argue that these estimated price effects are likely driven by the impacts an airline's size of presence at the origin airport has on its marginal cost. Specifically, once an airline's airport presence increases beyond a certain threshold, then the airline is better able to exploit economies of passenger-traffic density, causing downward pressure on its marginal cost, which in turn causes downward pressure on its fares. This is an example in which we need the structural model to properly disentangle the sources (markup versus cost) of key driving forces of the estimated price effects.

The coefficient estimates on the nonstop variables suggest that products that require flying nonstop between the origin and destination tend to have relatively higher fares. The higher fares associated with nonstop products can be due to these products having higher markup, higher marginal cost, or a combination of both. Estimation results from the structural model will shed more light on markup and marginal cost reasons why nonstop products tend to have relatively higher fares.

Coefficient estimates on the routing quality variables suggest that products with more travel-convenient routing, as measured by the product's flying distance relative to the minimum flying distance needed, tend to have relatively higher fares. These results are consistent with the argument that a more travel-convenient itinerary is associated with higher passenger utility, a demand result that can explicitly be tested within the structural demand model framework we subsequently specify and estimate.

As expected, the estimated coefficients on the flying distance variables suggest that longer itinerary distances are associated with higher product price. This result makes sense since it is likely that itinerary flying distance is positively related to marginal cost.

Table 5
Reduced-form Price Equation Estimation

Variables	"oneworld Event Sample" Coefficient Estimates	"oneworld Event Sample" Std. Error	"ATI Event Sample" Coefficient Estimates	"ATI Event Sample" Std. Error
Opres_cost	3.016***	0.414	3.655***	0.229
Opres_cost_square	-0.004	0.003	-0.014***	0.002
Nonstop_going	59.601***	15.896	17.501	11.082
Nonstop_coming	0.681	15.208	22.503*	11.534
Routing quality_going	1.398**	0.607	1.372***	0.357
Routing_quality_coming	2.287***	0.604	1.315***	0.351
Distance_going	0.056***	0.022	0.044***	0.013
Distance_coming	0.094***	0.022	0.033***	0.013
Close_comp_going	0.319	0.921	-0.351	0.322
Close_comp_coming	-0.921	0.920	-0.084	0.322
Traditional_I_going	6.279	14.464	39.772***	8.949
Traditional_II_going	672.564**	330.111	-24.579	44.212
Traditional_I_coming	40.065***	13.798	87.016***	8.736
Traditional_II_coming	171.489	157.115	34.892	41.630
Virtual_going	-8.901	22.225	-1.901	14.676
Virtual_coming	62.332***	22.954	103.286***	14.848
$T_{post-Event}$	-152.044***	6.051	15.362***	4.439
Event_Members	13.503	89.004	17.887	44.852
$T_{post-Event} \times$ Event_Members	24.817**	11.037	-29.351***	10.686
Market_Overlap_ATI_carriers	-	-	-10.241**	4.615
$T_{post-Event} \times$ Event_Members $\times$ Market_Overlap_ATI_carriers	-	-	13.295	10.520
Constant	1447.753***	511.662	528.932***	168.787
Operating carrier group fixed effects	YES		YES	
Season fixed effect	YES		YES	
Market Origin fixed effect	YES		YES	
Market Destination fixed effect	YES		YES	
R-squared	0.2365		0.2786	

Notes: Equations estimated using ordinary least squares. *** statistically significant at 1%; ** statistically significant at 5%; and * statistically significant at 10%

For the given product under consideration, the variables *Close_comp_going* and *Close_comp_coming* measure the number of competing products offered by other carriers with equivalent number of intermediate stops on the departing and returning portions of the trip respectively. We expect that the measure of each of these variables for a given product is positively correlated with the level of competition this product faces in the market. However, there is no evidence in the reduced-form price regression that these variables influence price.

The coefficient estimates on the zero-one codeshare dummy variables provide a comparison with respect to pure online products. The reduced-form price regression results reveal that these coefficient estimates are positive whenever they are statistically significant, suggesting that codeshare itineraries are associated with higher price relative to pure online itineraries. At this point it is not clear whether the relatively higher price of codeshare itineraries is driven by relatively higher markup or higher marginal cost.

$T_{post-Event}$ is a time period zero-one dummy variable that equals 1 only during time periods after occurrence of the relevant event under consideration, where the event is either the implementation of the oneworld alliance, or the grant of ATI to various members of the oneworld alliance; and $Event\_Member$ is a zero-one airline dummy variable that equals 1 when the airline is a direct member of the event being analyzed. In the "oneworld Event Sample" the coefficient estimate on $T_{post-Event}$ is negative and statistically significant, suggesting that across the pre-post periods of implementation of the oneworld alliance, carriers that are not members of this alliance, on average, decreased the price of their products. Interestingly, the coefficient estimate on $T_{post-Event} \times Event\_Members$ is positive and statistically significant, but in absolute terms the coefficient estimate on $T_{post-Event}$ is larger. As such, across the pre-post periods of implementation of the oneworld alliance, members of this alliance, on average, also decreased the price of their products, but by a smaller magnitude compared to other carriers. This evidence of differential changes in price for oneworld alliance members compared to other carriers suggests that implementation of the alliance is not associated with partner carriers charging lower prices, and may even have led to partner carriers' prices being higher than would otherwise be, a result that is contrary to findings in Brueckner, Lee and Singer (2011).

In the "ATI Event Sample" we include the dummy variable $Market\_Overlap\_ATI\_carriers$, which equals to 1 for markets in which there exists substitute products that are both ticketed and operated by at least two distinct ATI carrier members, i.e., markets in which the ATI members' service overlap. First, the coefficient estimate on $T_{post-Event}$ is positive and statistically significant, suggesting that prices charged by carriers other than oneworld ATI members, on average, increased over the pre-post periods of granting ATI to some oneworld members. However, the coefficient estimate on $T_{post-Event} \times Event\_Member$ is negative, statistically significant, and in absolute terms larger than the coefficient estimate on $T_{post-Event}$. As such, the evidence suggests that in markets where oneworld ATI members' services did not overlap, prices charged by these ATI members decreased over the pre-post periods of granting them ATI. Furthermore, since the coefficient estimate on $T_{post-Event} \times Event\_Member \times Market\_Overlap\_ATI\_tkcarriers$ is statistically insignificant, there is no evidence that granting ATI resulted in these carriers raising their price in their overlap markets. Therefore, the evidence suggests that granting Antitrust Immunity brought benefits to consumers in terms of lower fares, a result that is consistent with findings in Brueckner, Lee and Singer (2011) and much of the previous literature on the price effects ATI.

We now turn to specifying the structural econometric model used for decomposing the estimated price effects discussed above into demand effects, markup effects, and cost effects. The subsequent structural econometric analyses enable readers to better understand the economic market forces associated with alliance implementation with and without granting ATI.

4. Model

4.1 Demand

We model air travel demand using a random coefficients logit model. [20] Suppose in a market there are *J* differentiated air travel products, *j = 1,…,J*, and one outside good/option, *j = 0*, e.g. driving, taking a train, or not traveling at all. Products may be purchased by *POP* potential consumers. Each potential consumer, indexed by *c*, chooses the travel option that gives him the highest utility, that is, we assume each potential consumer solves the following discrete choice optimization problem:

$$\max_{j\epsilon\{0,\dots,J\}}\{U_{cj} = x_j\phi_c^x + \phi_c^p p_j + \xi_j + \varepsilon_{cj}^d\} \quad (1)$$

where U_{cj} is the value of travel option *j* to consumer *c*; x_j is a vector of non-price characteristics of product *j*; ϕ_c^x is a vector of consumer-specific marginal utilities (assumed to vary randomly across consumers) associated with non-price characteristics in x_j; p_j is the price the consumer must pay to obtain product *j*; ϕ_c^p is the consumer-specific marginal utility of price, which is assumed to vary randomly across consumers; ξ_j capture product characteristics that are observed by consumers and airlines, but not observed by us the researchers; and ε_{cj}^d is a mean-zero random component of utility.

The random coefficients vary across consumers based on the following specification:

$$\begin{pmatrix}\phi_c^p\\ \phi_c^x\end{pmatrix} = \begin{pmatrix}\phi^p\\ \phi^x\end{pmatrix} + \begin{pmatrix}\phi_p^I\\ \phi_1^I\\ .\\ .\\ \phi_L^I\end{pmatrix} \times I_c + \begin{pmatrix}\phi_p^v & 0 & 0 & 0 & 0\\ 0 & \phi_1^v & 0 & 0 & 0\\ 0 & 0 & . & 0 & 0\\ 0 & 0 & 0 & . & 0\\ 0 & 0 & 0 & 0 & \phi_L^v\end{pmatrix} \times \begin{pmatrix}v_{cp}\\ v_{c1}\\ .\\ .\\ v_{cL}\end{pmatrix} \quad (2)$$

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[20] See Peters (2006) and Berry and Jia (2010) for similar modeling approach of air travel demand with the exception that these papers use a nested logit model.

where ϕ^p is the mean (across consumers) marginal utility of price; ϕ^x is a vector of mean marginal utilities for respective non-price product characteristics; $\phi^I = (\phi_p^I, \phi_1^I, \dots, \phi_L^I)$ is a set of parameters that measure consumer income-induced taste variation for respective product characteristics; I_c is a variable that measures consumer income, which has a mean of zero across consumers since this variable measures the deviation of consumer *c*'s income from the mean income of consumers in the relevant market; $\phi^v = (\phi_p^v, \phi_1^v, \dots, \phi_L^v)$ is a set of parameters that measure variation across consumers in random taste shocks for respective product characteristics; and $v_c = (v_{cp}, v_{c1}, \dots, v_{cL})$ is a set of consumer *c*'s random taste shocks for respective product characteristics. We assume that v_c follows a standard normal probability distribution across consumers.

We follow much of the literature on discrete choice demand model and assume that ε_{cj}^d in equation (1) is governed by an independent and identically distributed extreme value probability density[see Nevo (2000)]. As such, the probability that product *j* is chosen, or equivalently the predicted market share of product *j* is:

$$s_j(x_j, p_{j,}\xi_j; \phi^x, \phi^p, \phi^I, \phi^v) = \int \frac{\exp(\delta_j + \mu_{cj})}{1 + \sum_k^J \exp(\delta_k + \mu_{ck})} d\hat{G}(I) dG(v) \tag{3}$$

where $\delta_j = x_j\phi^x + \phi^p p_j + \xi_j$ is the mean utility obtained across consumers who choose product *j*; $\mu_{cj} = \phi_p^I p_j I_c + \sum_{l=1}^L \phi_l^I x_{jl} I_c + \phi_p^v p_j v_{cp} + \sum_{l=1}^L \phi_l^v x_{jl} v_{cl}$ is a consumer-specific deviation from the mean utility level; $\hat{G}(\cdot)$ is the empirical distribution of consumer incomes in the market; and $G(\cdot)$ is the standard normal distribution function for the taste shocks. Since there is no closed-form solution for the integral in equation (3), this integral is approximated numerically using random draws from $\hat{G}(I)$ and $G(v)$. [21]

We further attempt to disentangle ξ_j into two components, Υ_j and $\Delta\xi_j$, where Υ_j is a component that captures the extent to which consumers' product choice behavior is influenced by cooperative agreements (Alliance and ATI) between airlines, and $\Delta\xi_j$ is a composite of product characteristics that are observed by consumers and airlines, but not observed by us the researchers. In particular, we specify that $\xi_j = \Upsilon_j + \Delta\xi_j$, where

$$\Upsilon_j = \gamma_1 T_{post-Event} + \gamma_2 Event\_Member + \gamma_3 T_{post-Event} \times Event\_Member. \tag{4}$$

As previously defined, $T_{post-Event}$ is a time period zero-one dummy variable that equals 1 only during time periods after occurrence of the relevant event under consideration, where the event is either the implementation of the oneworld alliance, or the grant of ATI to various members of the oneworld alliance; and $Event\_Member$ is a zero-one airline dummy variable that equals 1 when the airline is a direct member of the event being analyzed. Substituting for ξ_j and Υ_j in the mean utility function yields the following expression

[21] We use 200 random draws from $\hat{G}(I)$ and $G(v)$ for the numerical approximation of $s_j(\cdot)$.

for the mean utility function:

$$\delta_j = x_j\phi^x + \phi^p p_j + \gamma_1 T_{post-Event} + \gamma_2 Event\_Member + \gamma_3 T_{post-Event} \times Event\_Member + \Delta\xi_j \tag{5}$$

Key parameters of interest in equation (5) are: γ_1, γ_2 and γ_3. γ_1 measures the extent to which mean utility changes across pre-post event periods for products offered by airlines that are not direct members of the event. γ_2 measures whether products offered by event members yield persistently different mean utility to consumers, irrespective of the event, compared to the mean utility yielded from products offered by other airlines. Last, across the pre-post event periods, γ_3 measures the difference in changes of the mean utility obtained from consuming products offered by event members relative to products offered by other airlines. Therefore, γ_3 captures how the event differentially influences mean utility, and consequently demand for event members' products.

The demand, d_j, for product j is simply given by:

$$d_j = s_j(p, x, \Delta\xi; \Phi^{\mathrm{d}}) \times POP, \tag{6}$$

where *POP* is a measure of market size, which we assume to be the total number of potential consumers (measured by population) in the origin city, and $s_j(p, x, \Delta\xi; \Phi^{\mathrm{d}})$ is the predicted product share function given in equation(3). $\Phi^{\mathrm{d}} = (\phi^p, \phi^x, \gamma_1, \gamma_2, \gamma_3, \phi^I, \phi^v)$ is the vector of demand parameters to be estimated.

4.2 Supply

Codeshare agreements commonly require that the ticketing carrier markets and sets the final price for the round-trip ticket and compensates the operating carrier for operating services provided. However, partner airlines do not publicize what mechanism they use for compensating each other for transportation services provided on codeshare products. Furthermore, agreed upon compensation mechanisms may even vary across partners. Therefore, the challenge we face as researchers is to specify a modeling approach that captures our basic understanding of what is commonly known about how a codeshare agreement works without imposing too much structure on a contracting process about which we have few facts.

We follow Chen and Gayle (2007), Gayle (2013) and Gayle and Thomas (2016) and specify a codeshare agreement as a privately negotiated pricing contract between partners (w, Γ), where w is a per-passenger price the ticketing carrier pays over to an operating carrier for transporting the passenger, while Γ represents a potential lump-sum transfer between partners that determines how the joint surplus of a codeshare product is distributed. For the purpose of this paper, we do not need to econometrically identify an equilibrium value of Γ. However, in describing the dynamic part of the model, we do show where Γ enters the model.

Suppose that the final price of a codeshare product is determined within a sequential price-setting game. In the first stage of the sequential process the operating carrier sets price for transporting a passenger, w, and privately makes this price known to its partner ticketing carrier. In the second stage, given the price w that will be paid to the operating carrier, the ticketing carrier sets the final round-trip price p for the codeshare product. The final subgame in this sequential price-setting game is played between ticketing carriers, and yields the final ticket prices observed by consumers.

Let each airline/ticketing carrier offer a set B_{imt} of products for sale to consumers in market *m* during period *t*. Across these products, airline *i* effectively solves the following optimization problem:

$$\max_{p_{jmt}\,\forall j\in B_{imt}} VP_{imt} = \max_{p_{jmt}\,\forall\, j\in B_{imt}} \left[\sum_{j\in B_{imt}} (p_{jmt} - mc_{jmt})q_{jmt}\right], \qquad (7)$$

where VP_{imt} is the variable profit carrier i obtains in market *m* during period *t*, and p_{jmt}, q_{jmt}, and mc_{jmt} represent, respectively, price, quantity sold, and effective marginal cost of product *j* in market *m* during period *t*.

Let $f = 1, \dots, F$ index the corresponding operating carriers and O^j the set of operating carriers, excluding the ticketing carrier, that use their own planes to transport consumers of product j. If product j is a traditional codeshare product, then $mc_{jmt} = c^i_{jmt} + \sum_{f\in O^j} w^f_{jmt}$, where c^i_{jmt} is the marginal cost that ticketing carrier i incurs by using its own plane to transport passengers on some segment(s) of the trip needed for product j, while w^f_{jmt} is the price ticketing carrier i pays to operating carrier f for transportation services carrier *f* provides on a subset of the remaining trip segment(s). If ticketing carrier i does not provide any transportation service to traditional codeshare product *j*, then $c^i_{jmt} = 0$. If instead product j is a virtual codeshare product, then $mc_{jmt} = w^f_{jmt}$, where w^f_{jmt} is the price the ticketing carrier pays to operating carrier f for its exclusive transportation services in the provision of product j.[22] Last, if product j is a pure online product, then $mc_{jmt} = c^i_{jmt}$. In the case of a pure online product, the ticketing carrier is also the sole operating carrier of product j, i.e., $i = f$.

Note that c^i_{jmt} is the per-passenger expenses directly incurred by ticketing carrier i when it uses its own plane(s) to transport passengers on a subset of the trip segments of product j, while w^f_{jmt} is positively correlated with per-passenger expenses incurred by operating carrier f when it contributes operating services to product *j*. In the first stage of the sequential price-setting game, operating carriers each optimally choose

[22] We implicitly assume here that the ticketing carrier of a virtual codeshare product only incurs fixed expenses in marketing the product to potential passengers.

w^f_{jmt} , i.e., each operating carrier f solves the following profit maximization problem: $\underset{w^f_{jmt}\ \forall\ j\in A_f}{\text{Max}} \left[\sum_{j\in A_f}(w^f_{jmt} - c^f_{jmt})q_{jmt}\right]$, where A_f is the set of products in the market to which carrier f contributes its transportation services, while c^f_{jmt} is the marginal cost that carrier f incurs by using its own plane to provide transportation services to product j. In equilibrium, the profit maximizing choice of w^f_{jmt} across competing operating carriers yields a positive correlation between w^f_{jmt} and c^f_{jmt}. Therefore, both c^i_{jmt} and w^f_{jmt} are a function of factors that influence the marginal cost of operating carriers. As such, when we subsequently specify a parametric marginal cost function for econometric estimation, mc_{jmt} will be a function of factors that influence the marginal cost of operating carriers.

In equilibrium, the amount of product *j* an airline sells is equal to the quantity demanded, that is, $q_{jmt} = s_{jmt}(p, x, \xi; \Phi^{\mathrm{d}}) \times POP$. The optimization problem in (7) yields the following set of *J* first-order conditions – one for each of the *J* products in the market:

$$s_j + \sum_{k\in B_i}(p_k - mc_k)\frac{\partial s_k}{\partial p_j} = 0 \ \ for\ all\ j = 1, \dots, J. \qquad (8)$$

We have dropped the time and market subscripts in equation (8) only to avoid a clutter of notation. Using matrix notation, the system of first-order conditions in equation (8) is represented by:

$$s + (\Omega .* \Delta) \times (p - mc) = 0, \qquad (9)$$

where s, *p*, and *mc* are $J\times 1$ vectors of predicted product shares, product prices, and marginal costs respectively. Ω is a $J\times J$ matrix of appropriately positioned zeros and ones that describes ticketing carriers' ownership structure of the *J* products, where element $\Omega_{jk} = 1$ when $j = k$ or when $j \neq k$ but distinct products *j* and *k* are "owned" by the same ticketing carrier, otherwise element $\Omega_{jk} = 0$. $.*$ is the operator for element-by-element matrix multiplication, and Δ is a $J\times J$ matrix of first-order derivatives of product market shares with respect to prices, where element $\Delta_{jk} = \frac{\partial s_k}{\partial p_j}$. Because the ticketing carrier is considered the "owner" of a product, in the discussion that follows, "airline" is synonymous with ticketing carrier.

Note that the structure of matrix Ω effectively determines groups of products in a market that are jointly priced. If distinct airlines that offer products in a market non-cooperatively set their product prices, then the structure of Ω is determined by B_i for all *i* in market *m*. However, if subsets of these airlines have ATI, then ATI partners will jointly/cooperatively set prices in the market, and consequently the structure of Ω is based on product-groupings according to subsets of ATI partners rather than B_i. During various periods in our data, members of SkyTeam and Star alliances have ATI, and the structure of Ω takes this into account.[23] Of course

[23] Carve-outs are markets in which authorities forbid joint pricing of products by ATI members. We assume that ATI members do

Ω also takes into account that oneworld alliance members presumably non-cooperatively priced their products during periods before ATI was granted to them, but cooperatively priced their products after ATI is granted.

Re-arranging equation (9), we can obtain a vector of product markups:

$$mkup(x, \Delta\xi; \Phi^{\mathrm{d}}) = p - mc = -(\Omega.* \Delta)^{-1} \times s. \tag{10}$$

Using the estimated product-level markups from equation (10), product-level marginal costs are recovered by:

$$\widehat{mc} = p - \widehat{mkup}, \tag{11}$$

where $\widehat{mc}$ is the vector of estimated marginal costs for all products.

Finally, with the estimated markups from equation (10), firm-level variable profits can be computed by:

$$VP_{imt} = \sum_{j \in B_{imt}} mkup_{jmt}(x, \Delta\xi; \widehat{\Phi^{\mathrm{d}}}) q_{jmt}. \tag{12}$$

4.3 Dynamic Entry/Exit Game

In the dynamic entry/exit game, at the end of every period, airlines decide on the set of markets in which to offer products during the next period. Airlines make such forward-looking and strategic decisions to maximize their expected discounted inter-temporal profits in each market:

$$E_t\left(\sum_{r=0}^{\infty} \beta^r \Pi_{im,t+r}\right), \tag{13}$$

where $\beta \in (0,1)$ is the discount factor, and $\Pi_{im,t+r}$ is the per-period profit of airline i in origin-destination market *m*. Per-period profit is equal to variable profit minus per-period fixed cost of being active in a market, and minus the one-time entry cost of starting to offer products in a market for the first time:

$$\Pi_{imt} = a_{im,t-1} VP_{imt} - a_{imt}\left\{FC_{imt} + \epsilon_{imt}^{FC} + \left(1 - a_{im,t-1}\right)\left[EC_{imt} + \epsilon_{imt}^{EC}\right]\right\}, \tag{14}$$

where a_{imt} is a zero-one indicator variable that equals 1 only if airline *i* makes decision in period *t* to be active in market *m* during period *t+1*; and VP_{imt} is the variable profit of airline i in origin-destination market *m* during period *t* that is computed from the Nash equilibrium price-setting game discussed previously. An airline is viewed as active in a market when it actually sells products to consumers even though a subset of those products may use the operating services of the airline's partner carriers.

FC_{imt} and EC_{imt} are deterministic parts of the fixed cost and entry cost functions, respectively. These deterministic parts of the cost functions are common knowledge for all airlines. ϵ_{imt}^{FC} and ϵ_{imt}^{EC} represent private information shocks to fixed and entry costs respectively. The composite shock $\varepsilon_{imt} = \epsilon_{imt}^{FC} +$

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not jointly price in carve-out markets, and therefore Ω takes carve-out markets into account.

$(1 - a_{im,t-1})\epsilon_{imt}^{EC}$ is assumed to be independent and identically distributed *(i.i.d)* over airlines, markets, and time period based on a specific probability distribution function, which we assume is the type 1 extreme value distribution.

The deterministic portions of fixed and entry costs are specified as:

$$FC_{imt} = \theta_0^{FC} + \theta_1^{FC} Opres\_cost_{imt} + \theta_2^{FC} T_{post-Event} + \theta_3^{FC} Event\_Member_{imt} + \theta_4^{FC} T_{post-Event} \times Event\_Member_{imt} \quad (15)$$

$$EC_{imt} = \theta_0^{EC} + \theta_1^{EC} Opres\_cost_{imt} + \theta_2^{EC} T_{post-Event} + \theta_3^{EC} Event\_Member_{imt} + \theta_4^{EC} T_{post-Event} \times Event\_Member_{imt} \quad (16)$$

where $T_{post-Event}$ is a time period zero-one dummy variable that equals 1 only during time periods after occurrence of the event, where the event is either the implementation of the oneworld alliance, or the grant of ATI to various members of the oneworld alliance; and $Event\_Member_{imt}$ is a zero-one airline dummy variable that equals 1 when the airline is a member of the event being analyzed.

The vector of parameters to be estimated in the dynamic model is as follows:

$$\theta = \{\theta_0^{FC}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}\}', \quad (17)$$

where θ_0^{FC} and θ_0^{EC} respectively measure mean fixed and entry costs across airlines, markets and time;[24] θ_1^{FC} and θ_1^{EC} respectively measure the effect that origin airport presence has on fixed and entry costs; θ_2^{FC} and θ_2^{EC} respectively measure the extent to which fixed and entry cost change across pre-post event periods for airlines that are not members of the event; while θ_3^{FC} and θ_3^{EC} respectively measure the extent to which event members fixed and entry costs persistently differ from other airlines' fixed and entry costs. Across the pre-post event periods, θ_4^{FC} measures the difference in changes of mean fixed costs of event members relative to other airlines, while θ_4^{EC} measures the difference in changes of mean entry costs of event members relative to other airlines. Therefore, θ_4^{FC} and θ_4^{EC} capture how the event differentially influences mean fixed and entry costs respectively.

Note that the mean recurrent fixed cost parameter θ_0^{FC} may comprise fixed expenses incurred by a ticketing carrier when the carrier markets a codeshare product to potential consumers. We previously stated that (w, Γ) represents a privately negotiated codeshare contract between partner carriers, where w is a per-

[24] We do not estimate airline-specific effects in the fixed and entry cost functions. One reason is that adding individual airline fixed effects substantially increases the number of parameters to be estimated, which substantially increases computation time to estimate the dynamic model. It takes about two weeks for our program to optimize the dynamic estimation even with only 10 parameters to be estimated in our specifications. However, the fixed and entry cost functions do capture some heterogeneity across airlines via the airline-specific variable $Opres\_cost_{imt}$.

passenger price the ticketing carrier pays over to an operating carrier for transporting the passenger, while Γ represents a potential lump-sum transfer between partners that determines how the joint surplus is distributed. Our previous discussion also shows that w enters the effective marginal cost of the ticketing carrier. However, the lump-sum transfer between partners, Γ, is nested in θ_0^{FC}, but we do not attempt to separately identify Γ since knowing its value is not essential for the purposes of our paper.

Reducing the dimensionality of the state space

Let

$$R_{imt}^{*} = a_{im,t-1} VP_{imt}. \tag{18}$$

The (x, ξ) in equation (12) are state variables that will be present in the dynamic entry/exit game. As Aguirregabiria and Ho (2012) points out, R_{imt}^{*} aggregates these state variables through equation (12) and (18) so that these state variables do not need to enter the dynamic game individually, which considerably reduces the dimensionality of the state space. Therefore, following Aguirregabiria and Ho (2012), we just treat R_{imt}^{*} as a firm-specific state variable, rather than treating x and ξ separately.

The payoff-relevant information of airline i in origin-destination market m during period t will be the following:

$$y_{imt} \equiv \{a_{im,t-1}, R_{imt}^{*}, Opres\_cost_{imt}, T_{post-Event}\}. \tag{19}$$

Value Function and Bellman Equation

Let $\sigma \equiv \{\sigma_{im}(y_{imt}, \varepsilon_{imt}), i = 1,2,..,N; m = 1,2,\dots,M\}$ be a set of strategy functions, one for each airline. σ is a Markov Perfect Equilibrium (MPE) if the profile of strategies in σ maximizes the expected profit of airline i at each possible state $(y_{imt}, \varepsilon_{imt})$ given the opponent's strategy.

Let $V_i^{\sigma}(y_t, \varepsilon_{it})$ be the value function for airline i given that the other airlines behave according to their respective strategies in σ. The value function is the unique solution to the Bellman equation:

$$\begin{aligned} V_i^{\sigma}(y_t, \varepsilon_{it}) = \ & \underset{a_{it}\in\{0,1\}}{\text{Max}} \{\Pi_{it}^{\sigma}(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ & + \beta \int V_i^{\sigma}(y_{t+1}, \varepsilon_{it+1})\, dG_i(\varepsilon_{it+1}) F_i^{\sigma}(y_{t+1}|a_{it}, y_t)\}, \end{aligned} \tag{20}$$

where $\Pi_{it}^{\sigma}(a_{it}, y_t)$ and $F_i^{\sigma}(y_{t+1}|a_{it}, y_t)$ are the expected one-period profit and expected transition of state variables, respectively, for airline i given the strategies of the other airlines. A MPE in this model is a set of strategy functions σ such that for any airline i and at every state:

$$\begin{aligned} \sigma_i(y_t, \varepsilon_{it}) = arg\underset{a_{it}}{\max}\{ & \Pi_{it}^{\sigma}(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ & + \beta \int V_i^{\sigma}(y_{t+1}, \varepsilon_{it+1})\, dG_i(\varepsilon_{it+1}) F_i^{\sigma}(y_{t+1}|a_{it}, y_t)\}. \end{aligned} \tag{21}$$

Transition rules for state variables are described in Appendix B. In Appendix C we illustrate that the MPE can also be represented as a vector of conditional choice probabilities (CCPs) that solves the fixed point problem $\boldsymbol{P} = \psi(\boldsymbol{P}, \theta)$, where $\mathbf{P} = \{P_i(\mathbf{y})\text{: for every firm and state } (i, \boldsymbol{y})\}$. $\boldsymbol{P} = \psi(\boldsymbol{P}, \theta)$ is a vector of best response probability mapping, where $\psi(\cdot)$ is the CDF of the type 1 extreme value distribution.

5. Estimation

5.1 Demand Estimation

The demand model is estimated using Generalized Methods of Moments (GMM). Following Berry (1994), Berry, Levinsohn, and Pakes (1995), and Nevo (2000), we can solve for $\Delta\xi_j$ as a function of demand parameters and the data, where $\Delta\xi_j = \delta_j - x_j\phi^x - \gamma_1 T_{post-Event} - \gamma_2 Event\_Member - \gamma_3 T_{post-Event} \times Event\_Member$. $\Delta\xi_j$ is the error term used to formulate the GMM optimization problem:

$$\min_{\Phi^d} \Delta\xi' Z^d W Z^{d\prime} \Delta\xi \tag{22}$$

where Z^d is the matrix of instruments that are assumed orthogonal to the error vector $\Delta\xi$, while W is the standard weighting matrix, $W = \left[\frac{1}{n} Z^{d\prime}\Delta\xi\Delta\xi' Z^d\right]^{-1}$. Since parameters ϕ^p, ϕ^x, γ_1, γ_2 and γ_3 enter the error term linearly, we can restructure the GMM optimization problem in (22) such that the search to minimize the objective function, $\Delta\xi' Z^d W Z^{d\prime} \Delta\xi$, is done exclusively over parameter vector ϕ^I and ϕ^v, i.e., the GMM optimization problem reduces to $\min_{\phi^I, \phi^v} \Delta\xi' Z^d W Z^{d\prime} \Delta\xi$. Once the optimization over ϕ^I and ϕ^v is complete, we can recover estimates of ϕ^p, ϕ^x, γ_1, γ_2 and γ_3.[25]

In using GMM to estimate the demand parameters, we take into account that p_{jmt} is endogenous. The endogeneity problem exists because the product price, p_{jmt}, is correlated with the error term $\Delta\xi_{jmt}$. Therefore, an application of valid instruments is necessary. Valid instruments should be correlated with p_{jmt}, but uncorrelated with $\Delta\xi_{jmt}$.

Instruments for endogenous variables in demand equation

The instruments used in the demand estimation for "oneworld Event Sample" and "ATI Event Sample" are: (1) the number of competing products offered by other carriers with equivalent number of intermediate stops on the departing and returning legs of the trip respectively; (2) the interaction between jet fuel price[26]

[25] For details of this estimation algorithm of a random coefficients logit model, see Nevo (2000).

[26] The jet fuel price we use is U.S. Gulf Kerosene-Type Jet Fuel Spot Price FOB from U.S. Energy Information Administration.

and itinerary distance for the departing and returning legs of the trip respectively; and (3) itinerary distance for the departing and returning legs of the trip respectively. These instruments are similar to those used in Gayle (2013).

Instrument (1) measures the degree of market competition facing a product, which affects the size of its price-cost markup. The rationale for instrument (2) and (3) is due to the fact that jet fuel price and itinerary distance are correlated with marginal cost of providing the product, which in turn affect its price.

Validity of the instruments rely on the fact that the menu of products offered by airlines in a market is predetermined at the time of shocks to demand, which implies that the instruments are uncorrelated with $\Delta\xi_{jmt}$. Furthermore, unlike price, the menu of products offered and their associated non-price characteristics are not routinely and easily changed during a short period of time, which mitigates the influence of demand shocks on the menu of products offered and their non-price characteristics.[27]

5.2 Marginal Cost Function Estimation

Our specification of the marginal cost function is as follows:

$$\widehat{mc_{jmt}} = \tau_0 + \tau_1 W_{jmt} + \tau_2 T_{post-Event} + \tau_3 Event_{Members} + \tau_4 T_{post-Event} \times Event_{Members} + opcarrier_j + Quarter_t + Origin_m + Dest_m + \eta_{jmt}, \quad (23)$$

where the dependent variable, $\widehat{mc_{jmt}}$, is first recovered based on the Nash equilibrium price-setting game by subtracting estimated product markups from prices (see equations (10) and (11)); W_{jmt} is a vector of variables that shift marginal cost; $opcarrier_j^{mc}$ is an airline-specific component of marginal cost captured by operating carrier group fixed effect; and η_{jmt} is an unobserved component of marginal cost. We estimate the marginal cost function using ordinary least squares.

Given that $T_{post-Event}$ is a zero-one time period dummy variable that equals 1 only during post-event time periods, parameter τ_2, which is the coefficient on $T_{post-Event}$, measures how marginal cost changes across pre-post event periods for products offered by airlines that are not direct members of the event. Parameter τ_3, which is the coefficient on *Event_Members,* measures whether products offered by event members have persistently different marginal cost, irrespective of the event, compared to the marginal cost of products offered by other airlines. Last, across the pre-post event periods, parameter τ_4 measures the difference in changes of mean marginal costs of providing event members products relative to products

[27] The frequency with which airlines change their menu of product offerings in a market likely differ across markets. In principle, our instruments are stronger in markets where most airlines infrequently change their menu of product offerings, but weaker in markets where most airlines routinely change their menu of product offerings.

provided by other airlines. Therefore, τ_4 captures how the event differentially influences marginal cost of event members' products.

5.3 Dynamic Model Estimation

The datasets used for estimating the short-run demand and supply are at the product-market-time period level. However, for estimating the dynamic entry/exit model, the data need to be aggregated up to the airline-market-time period level. Since the datasets contain too many airlines for the dynamic model to handle, we need to appropriately group some airlines to make estimation of the dynamic model feasible. For the "oneworld Event Sample", some airlines are grouped resulting into the following 7 distinct entry/exit decision-making units in the dynamic model: oneworld alliance members; Continental; Delta; Northwest; United; US Airways; and all other airlines. For the "ATI Event Sample", we have the following 6 distinct entry/exit decision-making units: oneworld ATI members, Continental, Delta, United, US Airways, all other airlines.

In order to estimate the dynamic entry/exit model we need to know whether an airline is effectively active or not in each market. Similar to Aguirregabiria and Ho (2012), a number-of-passengers threshold is used to determine activity of each airline in each market. We define an airline to be active in an origin-destination market during a quarter if the airline's number of passengers in the quarter averages to at least 1 passenger per week.[28] Based on this defined market activity information, we are able to identify the markets that each carrier enters and exits during the quarter. Knowing the entry and exit decisions is essential for us to estimate fixed and entry costs in the sense that the dynamic model is based on the assumption that potential entrants decide to enter a market only when the one-time entry cost is less than the expected discounted future stream of profits, and incumbents decide to exit the market when per-period fixed cost exceeds the per-period variable profit and thus the expected discounted future stream of profits are not positive.

To estimate the dynamic model, we consider the following pseudo log likelihood function:

$$Q(\theta, \boldsymbol{P}) = \sum_{m=1}^{M} \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ \begin{array}{c} a_{imt} ln \left[\psi \left(\tilde{Z}_{imt}^{P}(y) \times \theta + \tilde{e}_{imt}^{P}(y) \right) \right] \\ +(1 - a_{imt}) ln \left[\psi \left(-\tilde{Z}_{imt}^{P}(y) \times \theta - \tilde{e}_{imt}^{P}(y) \right) \right] \end{array} \right\}, \quad (24)$$

where the conditional choice probabilities (CCPs) in vector **P**, which are used for computing $\tilde{Z}_{imt}^{P}(y)$ and $\tilde{e}_{imt}^{P}(y)$ (see Appendix C), are arbitrary and do not represent the equilibrium probabilities associated with θ in the model.

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[28] Aguirregabiria and Ho (2012) define the airline to be active in a market each quarter when the number of passengers is 260 or more in a non-directional market per quarter (20 passengers per week).

We apply the Nested Pseudo Likelihood (NPL) estimation algorithm discussed in Aguirregabiria and Ho (2012) and Aguirregabia and Mira (2002 and 2007), but we begin with the Pseudo Maximum Likelihood (PML) estimation procedure. The PML estimation algorithm requires two steps. In step 1, we estimate relevant state transition equations and compute nonparametric estimates of the choice probabilities $\widehat{\mathbf{P}}_0$. By estimating the state transition equations, we are able to construct state transition probability matrices $\mathbf{F}_{iy}^{\mathbf{P}}(1)$ and $\mathbf{F}_{iy}^{\mathbf{P}}(0)$. Nonparametric probability estimates are used to construct consistent estimates of $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$ as described in Appendix C. With $\mathbf{F}_{iy}^{\mathbf{P}}(1)$, $\mathbf{F}_{iy}^{\mathbf{P}}(0)$, $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$, we can construct the pseudo log likelihood function, $Q(\theta, \widehat{\mathbf{P}}_0)$.

In step 2, the vector of parameters $\hat{\theta}_{PML}$ is estimated by:

$$\hat{\theta}_{PML} = \arg\max_{\theta} \; Q(\theta, \widehat{\mathbf{P}}_0) \,. \tag{25}$$

Step 2 is computationally straightforward since it only involves estimation of a standard discrete choice logit model. In addition, the PML algorithm does not require solving for an equilibrium in the dynamic game, which reduces computational burden. However, the nonparametric estimation of $\widehat{\mathbf{P}}_0$ might be inconsistent due to serial correlation or time invariant unobserved heterogeneity [Aguirregabiria and Ho (2012)]. In addition, the expected value of the nonlinear objective function of $\widehat{\mathbf{P}}_0$ is not equal to the value of the objective function evaluated at the expected value of $\widehat{\mathbf{P}}_0$, leading to bias of the two-step estimator $\hat{\theta}_{PML}$. So we next implement the NPL algorithm, which is designed to reduce the bias of the two-step PML estimator.

The NPL algorithm applies a recursive K-step extension of the PML estimation. Since we have the two-step estimator $\hat{\theta}_{PML}$ and the initial nonparametric estimates of CCPs, $\widehat{\mathbf{P}}_0$, we can construct new CCP estimates, $\widehat{\mathbf{P}}_1$, using the best response CCPs equation $\widehat{\mathbf{P}}_1 = \Psi(\widehat{\mathbf{P}}_0, \hat{\theta}_{PML})$. We then maximize the pseudo log likelihood function, where the function is constructed using $\widehat{\mathbf{P}}_1$, i.e. we solve the following problem: $\hat{\theta}_2 = \arg\max_{\theta} \; Q(\theta, \widehat{\mathbf{P}}_1)$. This process is repeated K times to obtain $\hat{\theta}_K = \arg\max_{\theta} \; Q(\theta, \widehat{\mathbf{P}}_{K-1})$ and $\widehat{\mathbf{P}}_K = \Psi(\widehat{\mathbf{P}}_{K-1}, \hat{\theta}_K)$. The algorithm comes to an end on the K^{th} iteration in which the choice probability vector $\widehat{\mathbf{P}}_K$ is sufficiently close to $\widehat{\mathbf{P}}_{K-1}$ based on a tolerance level that we chose. To assess robustness of parameter convergence in our application of the NPL estimation algorithm, we have tried starting the algorithm at several distinct initial sets of θ and find that the NPL algorithm converged to qualitatively similar θ on each run of the estimation algorithm. Aguirregabiria and Mira (2002, 2007) show that the NPL algorithm reduces the finite sample bias of the two-step PML estimator.

6. Results from Estimation

6.1 Results from Demand Estimation

Table 6A and 6B report demand estimation results for the "oneworld Event Sample" and "ATI Event Sample" respectively. We begin by estimating a standard logit specification of the demand model, which is more restrictive than the random coefficients logit model. Each table reports both ordinary least squares (OLS) and two-stage least squares (2SLS) estimates of the standard logit demand model. As discussed previously, it is likely that the variable *Fare* (p_j) is endogenous. Even though the coefficient estimate on *Fare* has the expected negative sign for both OLS and 2SLS estimation of the model, the substantial difference in magnitude of the OLS and 2SLS coefficient estimate on *Fare* is evidence suggestive of *Fare* being endogenous.

To formally investigate if *Fare* is endogenous, we implement a Hausman test. Based on the results of the Hausmam test shown in each table, we easily reject that *Fare* is exogenous at conventional levels of statistical significance. We also evaluate whether the instruments have statistically significant explanatory power in explaining variations in *Fare*. First-stage reduced-form regressions in which *Fare* is the dependent variable yield R-squared values of 0.23 and 0.26 for the "oneworld Event Sample" and "ATI Event Sample" respectively. An *F*-test of the joint statistical significance of the instruments in the first-stage reduced-form regressions yield *F*-statistic values of $F(6, 164901) = 1429.98$ and $F(6, 332332) = 133.40$, each with a corresponding *p*-value of 0.000 for the "oneworld Event Sample" and "ATI Event Sample" respectively. These results suggest that the instruments do have statistically significant explanatory power of variations in *Fare*.

The discussion of demand results in Table 6A and Table 6B focuses on the less restrictive random coefficients logit model. The upper panel of each table reports the mean marginal (dis)utilities for each product characteristic (ϕ^p and ϕ^x), while the lower panel of each table reports the parameter estimates that measure income-induced and random taste variations across consumers for respective product characteristics (ϕ^I and ϕ^v) .

We find a negative coefficient estimate for variable *Fare* in both datasets, implying that price has a negative effect on consumers' mean utility. This is expected because, assuming all non-price product characteristic are held constant, passengers should prefer itineraries with a lower price. Furthermore, a positive income-induced taste variation parameter estimate, which is the coefficient estimate on the interaction of *Fare* with *Income*, suggests the intuitively appealing result that higher income consumers display lower sensitivity to price changes.

It is estimated that *Opres_demand* has a positive effect on consumers' utility. This estimated marginal effect is expected since travelers are likely to prefer using the airline that provides services to more destinations from the travelers' origin airport. The intuition is that the value of an airline's frequent-flyer program (FFP) to residents of an origin city increases as the number of destinations to which the airline offers nonstop flight leaving from the travelers' origin airport increases, thus increasing loyalty to the airline.

The coefficient estimates associated with *Nonstop_going* and *Nonstop_coming* are positive and statistically significant, implying passengers prefer flying nonstop to their destination and flying nonstop from their destination back to their origin. Moreover, as expected, *Routing_quality_going* and *Routing_quality_coming* are estimated to have positive effects on consumers' utility, implying that passengers are more likely to choose the itinerary that uses the most convenient routing in terms of travel distance covered.

Table 6A
Demand Estimation using the "oneworld Event Sample"

	Standard Logit Model				Random Coefficients Logit Model	
	OLS Estimation		2SLS Estimation		GMM Estimation	
Variables in the mean utility function: Associated parameters, ϕ^p and ϕ^x.	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error
Fare	-0.026***	0.002	-1.062***	0.033	-2.085***	0.216
Opres_demand	0.002***	0.0001	0.005***	0.0002	0.004***	2.73E-04
Nonstop_going	0.707***	0.02	0.701***	0.024	0.768***	0.035
Nonstop_coming	0.631***	0.019	0.570***	0.023	0.688***	0.034
Routing_quality_going	0.990***	0.037	1.081***	0.052	1.126***	0.068
Routing_quality_coming	1.086***	0.037	1.137***	0.052	1.220***	0.063
Traditional_I_going	-0.257***	0.007	-0.243***	0.013	-0.249***	0.017
Traditional_II_going	-0.765***	0.088	-0.237	0.346	-0.241	0.480
Traditional_I_coming	-0.263***	0.007	-0.217***	0.012	-0.212***	0.016
Traditional_II_coming	-0.670***	0.076	-0.636***	0.139	-0.631***	0.245
Virtual_going	-0.628***	0.020	-0.647***	0.030	-0.649***	0.042
Virtual_coming	-0.610***	0.019	-0.555***	0.030	-0.656***	0.042
$T_{post-Event}$	-0.009*	0.005	-0.152***	0.008	-0.162***	0.011
Event_Member	0.841***	0.115	0.826***	0.142	0.846***	0.194
$T_{post-Event} \times$ Event_Member	-0.014	0.012	0.014	0.016	0.029	0.026
Spring (Summer)	0.035***	0.005	0.012*	0.007	0.075***	0.015
Constant	-9.466***	0.163	-6.505***	0.556	-7.219***	1.111
Tkcarriers fixed effects	YES		YES		YES	
Market Origin fixed effects	YES		YES		YES	
Market Destination fixed effects	YES		YES		YES	
Variables that measure taste heterogeneity across Consumers: Associated parameters, ϕ^I and ϕ^v.						
$v \times$ Constant	-	-	-	-	-1.354	244.39
$v \times$ Fare	-	-	-	-	-8.431	66.988
$Income \times$ Fare	-	-	-	-	0.861***	0.094
R-squared	0.610				-	
GMM Objective Function Value					1406.984	
Test of Endogeneity: Ho: Fare is Exogenous Robust Score Chi-sq (1)	2400.97 (P-Value = 0.0000)					
Robust regression F(1, 163938)	2580.20 (P-Value = 0.0000)					

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level. For the Standard Logit Model, the well-known linear equation used for estimating the parameters is: $ln(S_j) - ln(S_0) = x_j\phi^x - \phi^p p_j + \cdots + \xi_j$, where S_j is the observed share of product j, $S_0 = 1 - \sum_{j=1}^{J} S_j$ is the observed share of the outside good, and ξ_j is the error term of the equation.

Table 6B
Demand Estimation using the "ATI Event Sample"

	Standard Logit Model				Random Coefficients Logit Model	
	OLS Estimation		2SLS Estimation		GMM Estimation	
Variables in the mean utility function: Associated parameters, ϕ^p and ϕ^x.	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error
Fare	-0.007***	0.001	-1.926***	0.080	-4.169	2.846
Opres_demand	0.001***	0.00005	0.004***	0.0002	0.004***	3.088E-04
Nonstop_going	0.832***	0.013	0.815***	0.023	0.853***	0.054
Nonstop_coming	0.850***	0.014	0.827***	0.024	0.852***	0.038
Routing_quality_going	0.655***	0.021	0.729***	0.042	0.742***	0.054
Routing_quality_coming	0.743***	0.021	0.900***	0.042	0.970***	0.073
Traditional_I_going	-0.217***	0.004	-0.084***	0.015	-0.105***	0.029
Traditional_II_going	-0.281***	0.018	-0.190***	0.067	-0.276*	0.152
Traditional_I_coming	-0.230***	0.004	-0.020	0.016	-0.077*	0.077
Traditional_II_coming	-0.308***	0.017	-0.145***	0.060	-0.129	0.085
Virtual_going	-0.484***	0.011	-0.405***	0.029	-0.354***	0.050
Virtual_coming	-0.479***	0.010	-0.176***	0.032	-0.212***	0.055
$\mathrm{T}_{\mathrm{post-Event}}$	-0.050***	0.003	-0.050***	0.008	0.008	0.034
Event_Member	0.278	0.307	1.131***	0.393	0.399	0.376
$\mathrm{T}_{\mathrm{post-Event}} \times$ Event_Member	-0.003	0.009	-0.016	0.017	0.007	0.030
Spring (Summer)	-0.032***	0.003	0.043***	0.007	0.044***	0.018
Constant	-9.578***	0.316	-8.220***	0.447	-5.570***	1.759
Tkcarriers fixed effects	YES		YES		YES	
Market Origin fixed effects	YES		YES		YES	
Market Destination fixed effects	YES		YES		YES	
Variables that measure taste heterogeneity across Consumers: Associated parameters, ϕ^I and ϕ^v.						
$v \times$ Constant	-	-	-	-	0.052	4.618
$v \times$ Fare	-	-	-	-	0.718	1.248
$Income \times$ Fare	-	-	-	-	1.109***	0.469
R-squared	0.680				-	
GMM Objective Function Value					220.526	
Test of Endogeneity: Ho: Fare is Exogenous						
Robust Score Chi-sq (1)	2831.59 (P-Value = 0.0000)					
Robust regression F(1, 332336)	3055.26 (P-Value = 0.0000)					

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level. For the Standard Logit Model, the well-known linear equation used for estimating the parameters is: $ln(S_j) - ln(S_0) = x_j\phi^x - \phi^p p_j + \cdots + \xi_j$, where S_j is the observed share of product j, $S_0 = 1 - \sum_{j=1}^{J} S_j$ is the observed share of the outside good, and ξ_j is the error term of the equation.

The coefficient estimates on the codeshare dummy variables provide a comparison with respect to pure online products. Across both data samples these coefficient estimates are negative when statistically significant, implying that consumers less prefer codeshare itineraries to pure online itineraries. Evidently, consumers view pure online products to be of higher quality than codeshare products. Since traditional codeshare itineraries require partner operating carriers to coordinate interline flight connections, the apparent relatively higher quality of pure online itineraries may in part be driven by any given airline being better able to organize its own flights to streamline connection schedules and arrange gates to reduce layover time. In other words, even though traditional codeshare partners try to organize and coordinate their gates and flight schedules, the estimates suggest that they do not perform as well as pure online providers. In case of the comparison between pure online and virtual codeshare itineraries, the apparent relatively higher perceived quality of pure online itineraries may in part be due to a rationale posited by Ito and Lee (2007). They argue that passengers perceive a virtual codeshare product as an inferior substitute to an otherwise equivalent pure online product since frequent-flyer programs often do not allow upgrade of a virtual codeshare ticket to first class.

For the "oneworld Event Sample", the coefficient estimate on $T_{post-Event}$ is negative and statistically significant, but the coefficient estimate on $T_{post-Event} \times Event\_Member$ is not statistically significant at conventional levels of statistical significance. These coefficient estimates therefore suggest that, on average, there is a decline in demand for products provided by all carriers during periods subsequent to implementation of the oneworld alliance relative to periods prior. Furthermore, over the pre-post alliance implementation periods, the decline in demand experienced by oneworld alliance members was not systematically different than the decline in demand experienced by other airlines. As such, we do not find evidence that formation of the oneworld alliance systematically influenced demand for the alliance members' products.

In the "ATI Event Sample", the coefficient estimates on $T_{post-Event}$ and $T_{post-Event} \times Event\_Member$ are not statistically significant at conventional levels of statistical significance. These coefficient estimates therefore suggest that demand for products provided by all carriers did not systematically change over the pre-post periods of granting ATI to some oneworld members. As such, we do not find evidence that granting ATI to some oneworld members systematically influenced demand for the ATI members' products.

The mean own-price elasticity estimates that the demand model yields are -2.12 in the "oneworld Event Sample" and -3.66 in the "ATI Event Sample". Own-price elasticity estimates from our model are in the "ballpark" and consistent with estimates from other airline industry studies. For example, Oum, Gillen and Noble (1986) and Brander and Zhang (1990) find own-price elasticity in the airline industry ranging from -

1.2 to -2.0, Berry and Jia (2010) find own-price elasticity estimates ranging from -1.89 to -2.10 in their year 2006 sample, while Peters (2006) study of the airline industry produces own-price elasticity estimates ranging from -3.2 to -3.6.[29]

6.2 Computed Markups and Variable Profits

Information with regards to marginal costs, prices, markups, and variable profits may allow for drawing useful inference on market competitiveness. Based on equation (10), combined with demand parameter estimates shown in Table 6A and Table 6B respectively, product markups can be computed and then marginal costs consequently recovered by subtracting markups from prices.

Recall that all monetary variables in both datasets are measured with respect to year 2005 constant dollars. The mean prices are \$1,025.30 and \$1,094.03 in the "oneworld Event Sample" and "ATI Event Sample" respectively, while mean product markups are \$486.35 and \$278.89 respectively.[30] The relatively lower markup in the "ATI Event Sample" is not surprising since demand is more elastic in the "ATI Event Sample" than in the "oneworld Event Sample". The Lerner Index, which is the ratio of product markup to price, is a well-known measure of market power. The overall mean Lerner Indexes are 72.88% in the "oneworld Event Sample" and 37.71% in the "ATI Event Sample".

As previously discussed, to facilitate studying two distinct events that occurred during separate periods of time, the two data samples cover very different time periods - the "oneworld Event Sample" comprises data in years 1998 and 2001, while the "ATI Event Sample" comprises data in years 2008 and 2011. As such, various market conditions may differ across these distinct time periods, which may explain the contrast in demand elasticity, and airlines' markup behavior across the two data samples, i.e., in more recent years apparently consumers are relatively more price sensitive and airlines have relatively less market power. Interestingly, the structural model plays an important role in revealing these market changes even though mean

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[29] For comparative purposes it is worth pointing out that the standard logit version of our demand model generates own price elasticity estimates of -1.09 in the "oneworld Event Sample" and -2.11 in the "ATI Event Sample". These own price elasticity estimates, reported in Table A5 in Appendix A, are consistently lower than those generated by our random coefficients logit demand model, and among the lower end of what other researchers have estimated in the literature.

[30] For comparative purposes it is worth pointing out that the standard logit version of our demand model generates mean product markups of \$952.71 in the "oneworld Event Sample" and \$521.47 in the "ATI Event Sample". These product markup estimates, reported in Table A5 in Appendix A, are consistently and substantially higher than those generated by our random coefficients logit demand model. The substantially higher product markups generated from the standard logit model are driven by the relatively low demand elasticity estimates associated with the standard logit model. As further shown in Table A5 in Appendix A, the higher product markups associated with the standard logit model results in higher variable profits. Inaccurate estimates of variable profits will distort results from the dynamic entry/exit model.

prices did not change much over time.

We implement a counterfactual experiment in which the markups are re-calculated based on the assumption that ATI was not granted to the oneworld members, i.e., members cannot cooperatively price their products in a given market. The counterfactual experiment focuses on the markets where ATI carrier members each sell substitute products, i.e., markets in which air travel services they sell overlap. Comparing actual markups in the post-ATI period to the counterfactual ones, we find that the mean markup of products offered by the ATI members would only be 0.15% lower if cooperative pricing among the members were forbidden. Such small changes in markups make us believe that the approval of ATI for the oneworld members has not resulted in significant competitive harm.

The quarterly market-level variable profits of each airline can be computed using equation (12). Since variable profit is a state variable in our dynamic entry/exit model, it is essential to have variation of this variable. We find that product markups do not vary much across airlines, but we do have cross-airline variation in market-level variable profits. The sources of the cross-airline variation in variable profits are the cross-airline variation in number of passengers per product, as well as cross-airline variation in number of products sold per market. The overall mean quarterly airline market-level variable profit is $19,648.82 in the "oneworld Event Sample", and $31,752.06 in the "ATI Event Sample", and the overall median variable profits are $7,158.19 and $11,755.13 in the "oneworld Event Sample" and "ATI Event Sample" respectively.

It is useful at this point to put in context the magnitudes of quarterly market-level variable profit estimates. Recall that the original database, before any cleaning, is only a 10% sample of air travel tickets sold. This implies that the magnitudes of variable profit estimates are at most roughly 10% of actual variable profits.

6.3 Results from Markup function and Marginal Cost function Estimation

Table 7 presents the OLS estimates of an equation in which we regress computed product markups on various determinants of product markup. The coefficient estimate on *Opres_demand* has the expected positive sign with statistical significance. A rationale for this estimated effect is that an airline usually has greater market power at its hub airport where it typically has large presence.

For both datasets, it is estimated that the nonstop dummy variables are associated with higher markups, which is what we expect because consumers prefer nonstop flight to get to their destination and back, and therefore are willing to pay higher price for this itinerary travel convenience. When the coefficient estimates on the routing quality variables are statistically significant, the estimated effect of routing quality on markup is positive as expected. These results largely suggest that airlines are more likely to charge higher markups when itineraries use more convenient routing for passengers in terms of miles flown relative to the possible minimum flight miles needed.

As previously defined, *Close_comp_going* and *Close_comp_coming* measure the number of competing products offered by other carriers with equivalent number of intermediate stops for the departing and returning legs of the trip respectively. We find that only *Close_comp_coming* has a statistically significant coefficient estimate for the "ATI Event Sample". The estimated negative effect on markup is consistent with expectation because these variables measure the level of market competition a product faces, i.e., products that face more competition will have relatively lower markup, ceteris paribus.

Table 7
Markup Function Estimation

Variable	"oneworld Event Sample" Coefficient Estimates	"oneworld Event Sample" Std. Error	"ATI Event Sample" Coefficient Estimates	"ATI Event Sample" Std. Error
Opres_demand	0.105***	0.003	0.069***	0.002
Nonstop_going	7.388***	0.806	1.794***	0.564
Nonstop_coming	7.191***	0.788	1.743***	0.595
Routing_quality_going	0.020**	0.009	0.022**	0.009
Routing_quality_coming	0.004	0.009	0.029***	0.009
Close_comp_going	-0.033	0.024	-0.006	0.016
Close_comp_coming	-0.036	0.025	-0.034**	0.016
Traditional_1_going	-1.047***	0.140	2.700***	0.307
Traditional_2_going	-2.055*	1.09	0.545	1.362
Traditional_1_coming	-0.567***	0.135	3.786***	0.292
Traditional_2_coming	-2.137**	0.840	4.150***	1.355
Virtual_going	-5.261***	0.394	0.049	0.643
Virtual_coming	-4.951***	0.388	5.456***	0.798
$T_{post-Event}$	1.094***	0.093	0.077	0.171
Event_Member	-3.954*	2.253	10.864*	6.588
$T_{post-Event} \times$ Event_Member	-0.485	0.459	-0.372	0.324
Market_Overlap_ATI_tkcarriers	-	-	2.726***	0.556
$T_{post-Event} \times$ Event_Member $\times$ Market_Overlap_ATI_tkcarriers	-	-	-1.395*	0.840
Constant	483.678***	2.992	261.914***	7.725
Ticketing carriers fixed effects	YES		YES	
Season/Quarter effect	YES		YES	
Market Origin fixed effect	YES		YES	
Market Destination fixed effect	YES		YES	
R-squared	0.1612		0.2038	

Notes: *** statistically significant at 1% level; ** statistically significant at 5% level;
* statistically significant at 10% level.

Examining the effect of codeshare on markups, we notice that the coefficient estimates of these variables in Table 7 are surprisingly different across the two samples: negative in the “oneworld Event Sample”, but positive in the “ATI Event Sample”. The results suggest that, compared to markups charged on pure online products, airlines charge relatively lower markups for codeshare products in years 1998 and 2001, but charge relatively higher markups for codeshare products in years 2008 and 2011. Since on average consumers less prefer codeshare products to pure online products, this suggests airlines are likely to charge relatively lower markups on codeshare products, which is consistent with the negative coefficient estimates on the codeshare variables in the “oneworld Event Sample”. However, in the case of traditional codeshare products, at least two distinct partner carriers are involved in pricing this type of product, and as Gayle (2013) argues and shows evidence of, even when the partner carriers jointly price the codeshare product optimally, double markups may not be eliminated resulting in these products having higher markups than pure online products. The positive coefficient estimates on the traditional codeshare variables in the “ATI Event Sample” are consistent with arguments and results in Gayle (2013). It is more difficult to rationalize the positive coefficient estimates on the virtual codeshare variables for the “ATI Event Sample”.

The coefficient estimate on interaction variable $T_{post-Event} \times Event\_Member$ is not statistically significant in the “oneworld Event Sample”, suggesting that the implementation of oneworld alliance did not influence market power of the oneworld members. In the “ATI Event Sample”, we include the dummy variable $Market\_Overlap\_ATI\_tkcarriers$, which equals to 1 for markets in which at least two ATI carrier members each sell substitute products, i.e., markets in which air travel services sold by ATI members overlap. First, the coefficient estimate on $T_{post-Event}$ is statistically insignificant, suggesting that markups charged by carriers other than oneworld ATI members did not change over the pre-post periods of granting ATI to some oneworld members. In addition, the coefficient estimate on $T_{post-Event} \times Event\_Member$ is also statistically insignificant, suggesting that in markets where air travel services sold by oneworld ATI members did not overlap, markups charged by oneworld ATI members did not change over the pre-post periods of granting them ATI. The coefficient estimate on the three-way interaction variable $T_{post-Event} \times Event\_Member \times Market\_Overlap\_ATI\_tkcarriers$ is negative, but only statistically significant at the 10 percent level. Therefore, there is no evidence that granting ATI to oneworld members caused oneworld members to increase markups in markets where air travel services they sell overlap.

Table 8 provides estimation results for the marginal cost regression based on equation (23). The variable *Opres_cost* has a positive coefficient estimate in both samples, while the coefficient estimate on *Opres_cost_square* is negative but only statistically significant in the “ATI Event Sample”. Such sign pattern of these two size-of-presence variables indicates that the size of an airline’s origin airport presence has a positive marginal effect on the airline's marginal cost at relatively low levels of its origin airport presence, but a negative marginal effect on the airline's marginal cost at relatively high levels of its origin airport presence. This result suggests that cost efficiency gains due to economy of passenger-traffic density can only be achieved when the size of an airline's airport presence surpasses a certain level. Because an increase in an airline's origin airport presence facilitates the airline channeling more of its passengers through these airports, we believe that economy of passenger-traffic density is a key driver of the estimated impacts on marginal cost of the size-of-presence variables. The evidence we find suggesting the presence of economy of passenger-traffic density is consistent with findings in Brueckner and Spiller (1994).

Table 8
Marginal Cost Function Estimation

	"oneworld Event Sample"		"ATI Event Sample"	
Variables	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error
Opres_cost	2.765***	0.413	3.537***	0.221
Opres_cost_square	-0.002	0.003	-0.014***	0.002
Nonstop_going	58.599***	14.125	25.895***	9.444
Nonstop_coming	10.368	13.579	26.730***	9.924
Distance_going	0.060***	0.013	0.038***	0.007
Distance_coming	0.082***	0.013	0.026***	0.007
Traditional_I_going	5.186	14.435	39.040***	8.602
Traditional_II_going	667.082**	329.366	-22.456	42.740
Traditional_I_coming	39.611***	13.774	83.826***	8.384
Traditional_II_coming	175.439	157.028	32.607	39.961
Virtual_going	-4.917	22.167	-0.491	14.147
Virtual_coming	68.440***	22.876	99.793***	14.315
$T_{post-Event}$	-154.566***	6.014	13.859***	4.292
Event_Members	3.916	91.901	13.485	40.959
$T_{post-Event} \times$ Event_Members	23.512**	11.043	-19.859**	8.078
Constant	1417.599***	510.342	598.926***	161.759
Operating carrier group fixed effects	YES		YES	
Season/Quarter effect	YES		YES	
Market Origin fixed effect	YES		YES	
Market Destination fixed effect	YES		YES	
R-squared	0.2370		0.2773	

Notes: Equations estimated using ordinary least squares. *** statistically significant at 1%; ** statistically significant at 5%.

The coefficient estimates suggest that the nonstop product characteristic of travel itineraries positively affects marginal cost of providing the air travel product. It is possible that the relatively higher marginal cost for nonstop itineraries is in part driven by the fact that products with intermediate stop(s) are better able to exploit economies of passenger-traffic density, especially when an intermediate stop is at a carrier's hub airport.

As expected, the coefficient estimates on flying distance variables are positive and statistically significant. The estimated positive marginal effects of flying distance on marginal cost may simply be capturing the fact that covering longer distances require more fuel.

In both the "oneworld Event Sample" and the "ATI Event Sample", codeshare variables are either positively correlated with, or not related to, marginal cost. In other words, relative to pure online itineraries, codeshare itineraries seem more costly for the airlines to provide. A possible reason for the higher marginal cost is that airlines that offer traditional codeshare products find it costly to coordinate schedules and gates for connecting flights with their codeshare partners. The evidence apparently suggests that there also exists some costly coordination between operating and ticketing carriers when offering virtual codeshare products.

In the "oneworld Event Sample" the coefficient estimate on $T_{post-Event}$ is negative and statistically significant, suggesting that across the pre-post periods of implementation of the oneworld alliance, carriers that are not members of this alliance experienced a decrease in marginal cost of providing their products. Interestingly, the coefficient estimate on $T_{post-Event} \times Event\_Members$ is positive and statistically significant, but in absolute terms the coefficient estimate on $T_{post-Event}$ is larger. As such, across the pre-post periods of implementation of the oneworld alliance, members of this alliance also experienced a decrease in marginal cost of providing their products, but the magnitude of the decrease is smaller than what was experienced by other carriers. This evidence of differential changes in marginal cost for oneworld alliance members compared to other carriers suggests that implementation of the alliance is not associated with marginal cost efficiencies for the partner carriers, and may even have generated marginal cost inefficiencies for the partner carriers.

In contrast to marginal cost effects findings associated with implementation of the oneworld alliance, coefficient estimates in the "ATI Event Sample" suggest that granting some oneworld members ATI is associated with marginal cost efficiency gains for these ATI members. Specifically, in the "ATI Event Sample" the coefficient estimate on $T_{post-Event}$ is positive and statistically significant, suggesting that across the pre-post periods of granting ATI to some oneworld members, carriers that are not members of this ATI group experienced an increase in marginal cost of providing their products. However, the coefficient estimate on $T_{post-Event} \times Event\_Members$ is negative and statistically significant, and in absolute terms is larger than the coefficient estimate on $T_{post-Event}$. As such, across the pre-post periods of granting ATI to some oneworld members, these ATI members experienced a decrease in marginal cost of providing their products, which is in contrast to the increase in marginal cost experienced by other carriers. In their joint application for ATI, the oneworld members did suggest that the greater network integration and cooperation that ATI permits will result in efficiency gains. We therefore find evidence in support of these arguments.

Our results are consistent with the finding of Oum, Park, Kim, and Yu (2004) that airlines tend to enjoy higher productivity gains and profitability when they form alliances at high-level cooperation than when alliances are at low-level cooperation. This implies that there might be no productivity gains when the cooperation is too low. Oneworld alliance without ATI involves less cooperation among the members than oneworld alliance with ATI in the sense that, without ATI, members are not allowed to jointly set prices and share revenues.

In summary, this study has useful findings for policymakers in terms of effects on marginal costs, markups, and prices of alliance implementation with and without ATI. The evidence suggests that implementation of the oneworld alliance without ATI did not yield cost efficiencies for the members. However, the subsequent grant of ATI to various members of the oneworld alliance is associated with cost efficiency gains for the oneworld ATI members, perhaps owing to the greater network integration and cooperation that ATI permits. Importantly, there is no evidence that granting ATI caused ATI members to increase markups or prices in markets where services they sell overlap. In fact, as revealed in the reduced-form price regression results reported in Table 5, the evidence is consistent with the granting of ATI causing ATI members to decrease their prices in markets where their services did not overlap.

6.4 Results from the Dynamic Model

Table 9 and Table 10 report our recurrent fixed and market entry cost estimation results for the "oneworld Event Sample" and the "ATI Event Sample" respectively. The quarterly discount factor, β, is fixed at 0.99, which implies an annual discount factor of 0.96. All the estimated fixed and entry cost parameters are measured in ten thousands of annual 2005 dollars.

We begin by discussing the fixed cost results and then turn to discussing the entry cost results for both samples. The parameter estimates in the fixed cost functions for "oneworld Even Sample" are unreasonably small and not precisely estimated. As such, we cannot draw reliable inferences about size of fixed cost in this data sample. However, we find statistical significance among fixed cost parameter estimates in the "ATI Event Sample". As such, our discussion of fixed cost parameter estimates focus on the statistically significant parameter estimates.

The mean fixed cost across all carriers is $7,282 in the "ATI Event Sample". Based on our Nash equilibrium price-setting game previously discussed, the overall mean quarterly variable profits in a directional origin-destination market is estimated to be $31,752.06 in the "ATI Event Sample". As a result, it takes airlines slightly less than one fourth of a quarter of variable profits to pay for their quarterly market fixed cost.

ATI is a zero-one dummy variable that equals to 1 only if the carrier is a oneworld ATI member. The positive fixed cost coefficient estimate on this variable suggests that mean fixed cost for oneworld ATI members is persistently higher than the mean fixed cost of other airlines.

Table 9
Estimates of Parameters in Fixed and Entry Cost Functions
for the "oneworld Event Sample"

	Parameter Estimates (In ten thousand $)	Std. Error	T-stat
Fixed Cost Function			
Mean fixed cost across all carriers	0.0014	0.043	0.0329
$Opres\_cost_{imt}$	-1.57E-06	0.0003	-0.0046
$T_{post-Alliance}$	-0.0012	0.0519	-0.0229
$Alliance\ Member$	0.0005	0.0595	0.0081
$T^{alliance}$ × Alliance	-0.0005	0.1014	-0.0047
Entry Cost Function			
Mean entry cost across all carriers	4.2187***	0.0529	79.6977
$Opres\_cost_{imt}$	-0.0078***	0.0004	-17.6321
$T^{alliance}$	0.0421	0.0674	0.6246
$Alliance\ Member$	-0.7123***	0.0778	-9.1512
$T^{alliance}$ × Alliance	-0.0989	0.1344	-0.7354

Notes: *** statistically significant at 1%; * statistically significant at 10%.

Table 10
Estimates of Parameters in Fixed and Entry Cost Functions
for the "ATI Event Sample"

	Parameter Estimates (In ten thousand $)	Std. Error	T-stat
Fixed Cost Function			
Mean fixed cost across all carriers	0.7282***	0.0305	23.8515
$Opres\_cost_{imt}$	-0.0042***	2.03E-04	-20.839
T^{ATI}	0.0369	0.0340	1.0837
ATI	0.1089**	0.0471	2.3102
T^{ATI} × ATI	-0.1458*	0.0815	-1.79
Entry Cost Function			
Mean entry cost across all carriers	3.4021***	0.0387	87.8913
$Opres\_cost_{imt}$	-0.0037***	2.91E-04	-12.6037
T^{ATI}	0.6319***	0.0556	11.3635
ATI	-0.3003**	0.0665	-4.5159
T^{ATI} × ATI	0.0703	0.1283	0.5479

Notes: *** statistically significant at 1%; ** statistically significant at 5%; * statistically significant at 10%.

The fixed cost coefficient estimate on variable T^{ATI} in Table 10 measures the extent to which fixed costs of carriers other than oneworld ATI members change over the pre and post-ATI periods. This coefficient estimate is statistically insignificant, suggesting that fixed cost of carriers other than oneworld ATI members, on average, did not change over the pre-post periods of granting ATI to some oneworld members. However, the fixed cost coefficient estimate on interaction variable $T^{ATI} \times ATI$ is negative, which suggests that granting oneworld members ATI reduced these airlines quarterly fixed cost in the origin-destination markets they serve. Therefore, there is evidence of fixed cost efficiency gains associated with the grant of immunity.

Finding evidence of fixed cost efficiency gains is not trivial since such gains ultimately results in higher profits for ATI partner carriers than would otherwise be the case. An implication of fixed cost efficiency gains being associated with the grant of immunity is that the governmental policy decision to grant alliance carriers immunity may result in an unintended consequence of providing an opportunity for some less efficient carriers to sustain operations in markets that they might have exited had it not been for the grant of immunity. As such, the grant of immunity can have medium to long run consequences for market structure.[31]

We now turn to discussing results for the entry cost functions. All variables that enter the entry cost functions are the same as in the fixed cost functions. The mean entry cost across all carriers is $42,187 in the "oneworld Event Sample" and $34,021 in the "ATI Event Sample". The overall mean quarterly variable profits in a directional origin-destination market are estimated to be $19,648.82 in the "oneworld Event Sample" and $31,752.06 in the "ATI Event Sample". As such, in the "oneworld Event Sample" it takes airlines about two quarters of variable profits to recoup their one-time sunk market entry cost investment, while in the "ATI Event Sample" it takes airlines just over one quarter of variable profits to recoup their one-time sunk market entry cost investment.

The variable $Opres\_cost_{imt}$ measures the size of an airline's presence at the origin airport of the market based on the number of other U.S. domestic airports from which the airline has nonstop flight going to the origin airport. The entry cost function coefficient estimate on $Opres\_cost_{imt}$ in Table 9 and Table 10 are both negative and statistically significant, suggesting that an airline's entry cost to a market declines the larger is the airline's presence at the origin airport of the market. This result is consistent with how the literature believes airline markets work [see Berry (1992); Goolsbee and Syverson (2008); Gayle and Wu (2014) among others].

The coefficient estimates on variables $T^{alliance}$ and T^{ATI} in the entry cost functions respectively measure how market entry costs of non-oneworld alliance and non-oneworld ATI member airlines change between pre-post alliance and pre-post ATI periods, respectively. Coefficient estimates on these time dummy variables suggest that non-oneworld alliance airlines' market entry cost did not change between the pre and

[31] We thank an anonymous referee for pointing out this market structure implication of the empirical results.

post-alliance periods, while the entry cost of non-oneworld ATI airlines increased by $6,319 in the post-ATI period relative to pre-ATI period.

Lastly, we are interested in knowing how forming oneworld alliance and granting of ATI affect the entry costs of alliance members and ATI members, respectively. The coefficient estimates on $T^{alliance} \times Alliance$ and $T^{ATI} \times ATI$ are not statistically significant, suggesting that neither the implementation of oneworld alliance in year 1999, nor the subsequent grant of antitrust immunity to some members in year 2010, had a statistically discernible impact on the members' market entry costs.

In summary, we did not find any statistically discernible evidence that implementation of the oneworld alliance in year 1999 influenced members recurrent fixed or market entry costs, but our model reveals evidence that the subsequent grant of ATI in year 2010 to some oneworld members is associated with fixed cost efficiency gains, but no evidence of market entry cost changes for these ATI members.

7. Concluding Remarks

As airline alliance members increasingly seek to achieve greater cooperation and consolidation of their networks, granting antitrust immunity to alliance members has become a controversial issue and raises much concern in policy making. For example, the United States Department of Justice (DOJ) expressed concerns that the grant of antitrust immunity will reduce competition in markets where the member carriers each offer substitute service (their overlap markets). Furthermore, the DOJ takes the position that immunity is not required for an alliance to yield benefits to consumers and partner carriers. On the contrary, the United States Department of Transportation (DOT) takes the position that there are sufficient efficiency gains associated with granting carriers antitrust immunity such that, on net, consumers would ultimately benefit.

Even though the literature on the price effects of granting airlines antitrust immunity is extensive, immunity's separate impacts on partner carriers' cost and markup have received little analysis. However, to better evaluate the opposing policy positions taken on granting immunity, it is necessary to disentangle the cost effects from the markup effects. This paper uses a structural econometric model to empirically investigate the impacts of implementation of an international airline alliance, and the subsequent grant of antitrust immunity on price, markup, and various measures of cost.

One of our key findings of interest to policymakers is that implementation of the oneworld alliance did not have a statistically significant impact on markup of products offered by the alliance members, and there is no evidence that the subsequent grant of ATI to various members resulted in higher markups on their products. Furthermore, our empirical results suggest that implementation of the oneworld alliance did not yield marginal cost efficiencies, but the subsequent grant of ATI to various oneworld members facilitated them generating marginal cost efficiencies. The reduction in marginal costs of oneworld ATI members puts downward pressure on prices in the short-run. In particular, the grant of ATI to various members is associated with a decline in their price in markets where their services do not overlap. Furthermore, the evidence suggest that prices did not increase in markets where their services do overlap. These findings provide better support for the DOT's policy position than they do for the DOJ's policy position.

In addition, results from the dynamic entry/exit part of the model did not produce any statistically discernible evidence that implementation of the oneworld alliance in year 1999 influenced members recurrent fixed or market entry costs, but reveals evidence that the subsequent grant of ATI in year 2010 to some oneworld members is associated with fixed cost efficiency gains, but no evidence of market entry cost changes for these ATI members. Finding evidence of fixed cost efficiency gains is not trivial since such gains ultimately results in higher profits for ATI partner carriers than would otherwise be the case. An implication of fixed cost efficiency gains being associated with the grant of immunity is that the governmental policy decision to grant alliance carriers immunity may result in an unintended consequence of providing an opportunity for some less efficient carriers to sustain operations in markets that they might have exited had it not been for the grant of immunity. As such, the grant of immunity can have medium to long run consequences for market structure.

Since firms typically can adjust their prices in the short term, while cost changes are typically linked to medium and longer term adjustments that includes seamless route network integration across partner carriers, then a reasonable hypothesis is that the impacts of ATI should more quickly be reflected in prices compared to costs. Given the relatively short post-event time span of our data, this may in part explain why we did not find any evidence of market entry cost effects. To properly explore appropriate lag effects of ATI requires a more extensive time span of the data, which would increase the size of the data sample and significantly challenge feasibility of estimating the structural model we use. However, investigation of appropriate lag effects of ATI is a fruitful topic for future research.

In summary, evidence from evaluating the oneworld alliance suggests that the grant of antitrust immunity matters, and on net consumers seem to benefit.

Appendix A

Table A1

Oneworld Alliance Members

Members	Carrier Code	Year carrier joined the alliance
Air Berlin	AB	2012
American Airlines	AA	Founder(1999)
British Airways	BA	Founder(1999)
Cathay Pacific	CX	Founder(1999)
Finnair	AY	1999
Iberia	IB	1999
Japan Airlines	JL	2007
LAN	LA	2000
Qantas	QF	Founder(1999)
Royal Jordanian	RJ	2007
S7 Airlines	S7	2010
Mexicana	MX	2009

Table A2

Timeline of Antitrust Immunity by U.S. Carriers

U.S. Carriers	ATI partners	Active time period	Carve-out [3]
Aloha	Hawaiian	9/2002 - 5/2007	
America West	Royal Jordanian	1/2005 - 5/2007	
American	Canadian International	7/1996 - 6/2007[1]	New York-Toronto
	LAN	9/1999 - present	Miami-Santiago
	Swissair	5/2000 - 11/2001	Chicago-Brussels
	Sabena	5/2000 - 3/2002	Chicago-Zurich
	Finnair Swiss International Air Lines	7/2002 - present 11/2002 - 8/2005	
	SN Brussels LAN and LAN-Peru*	4/2004 - 10/2009 10/2005 -present	 Miami-Lima
	British Airways, Iberia, Finnair and Royal Jordanian*	7/2010 - present	
	Japan Airlines	11/2010 -present	
Delta	Austrian Airlines, Sabena and Swissair	6/1996 -5/2007[2]	Atlanta-Zurich, Atlanta-Brussels, Cincinnati-Zurich, New York-Brussels, New York-Vienna, New York-Geneva and New York-Zurich
	Air France, Alitalia, Czech Airlines	1/2002 - present	Atlanta-Paris and Cincinnati-Paris
	Korean Air Lines, Air France, Alitalia and Czech Airlines*	6/2002 - present	
	Virgin Blue Group	6/2011	
Delta and Northwest	Air France, KLM, Alitalia, Czech Airlines*	5/2008 - present	Atlanta-Paris and Cincinnati-Paris carve-outs removed

*indicates an expansion of previous ATI decisions.

1. Although not officially closed until 2007, this alliance ended on June 1, 1996.

2. Although not officially closed until 2007, this alliance ended on August, 6, 2000.

3. Carve-outs are markets in which authorities forbid joint pricing of products by ATI members.

Table A2.cont.

Timeline of Antitrust Immunity by U.S. Carriers

U.S. Carriers	ATI partners	Active time period	Carve-out
Northwest	KLM	1/1993	
	KLM and Alitalia*	12/1999 -10/2001	
United	Lufthansa	5/1996	Chicago-Frankfurt and Washington D.C.-Frankfurt
	Lufthansa and SAS*	11/1996 - present	
	Air Canada	9/1997 - present	Chicago-Toronto and San Francisco-Toronto
	Air New Zealand	4/2001 - present	Los Angeles-Auckland and Los Angeles-Sydney
	Austrian Airlines, Lufthansa and SAS*	1/2001 present	
	Copa Airlines	5/2001 - present	
	British Midland, Austrian Airlines, Lufthansa and SAS*,[4]	9/2007 - present	
	Asiana	5/2003 - present	
	Lufthansa, SAS, Austrian, British Midland, LOT, Swiss International Air Lines, TAP and Air Canada*	2/2007 - present	
	Brussels, Lufthansa, SAS, Austrian, British Midland, LOT, Swiss International Air Lines, TAP and Air Canada*	7/2009 - present	
	ANA	11/2010 - present	

4. British Midland did not operate in the alliance beyond 4/2012.

Table A3

List of Ticking Carriers in "oneworld Event Sample"

Airline Name	Code	Airline Name	Code	Airline Name	Code
American Airlines Inc.	AA	Hawaiian Airlines Inc.	HA	Qantas Airways Ltd.	QF
Air Canada	AC	America West Airlines Inc.	HP	Reno Air Inc.	QQ
Compagnie Nat'l Air France	AF	Iberia Air Lines Of Spain	IB	Varig S. A.	RG
Aeromexico	AM	Midway Airlines	JI	Alia-(The) Royal Jordanian	RJ
Aloha Air Cargo	AQ	TAM Airlines	JJ	South African Airways	SA
Alaska Airlines Inc.	AS	Japan Air Lines Co. Ltd.	JL	Scandinavian Airlines Sys.	SK
Royal Air Maroc	AT	Air Jamaica Limited	JM	Sunworld International Airlines	SM
Finnair Oy	AY	Aero California	JR	Sabena Belgian World Air.	SN
Alitalia	AZ	Korean Air Lines Co. Ltd.	KE	Swissair Transport Co. Ltd.	SR
British Airways Plc	BA	Klm Royal Dutch Airlines	KL	Sun Country Airlines	SY
Eva Airways Corporation	BR	Lan-Chile Airlines.	LA	Taca International Airlines	TA
Caribbean Airlines Limited	BW	Lufthansa German Airlines	LH	Thai Airways International Ltd.	TG
Air China	CA	Polskie Linie Lotnicze	LO	Turk Hava Yollari A.O.	TK
China Airlines Ltd.	CI	Lacsa	LR	Tap-Portuguese Airlines	TP
Continental Air Lines Inc.	CO	Malev Hungarian Airlines	MA	Transbrasil S.A.	TR
Canadian Airlines	CP	China Eastern Airlines	MU	Trans World Airways LLC	TW
Continental Micronesia	CS	Compania Mexicana De Aviaci	MX	ATA Airlines d/b/a ATA	TZ
China Southern Airlines	CZ	Northwest Airlines Inc.	NW	United Air Lines Inc.	UA
Delta Air Lines Inc.	DL	Air New Zealand	NZ	US Airways Inc.	US
Tower Air Inc.	FF	Czech Airlines	OK	Aeropostal Alas De Venezuel	VH
AirTran Airways Corporation	FL	Austrian Airlines	OS	Republic Airlines	YX
Gulf Air Company	GF	Asiana Airlines Inc.	OZ		

Table A4

List of Ticketing Carriers in "ATI Event Sample"

Airline Name	Code	Airline Name	Code	Airline Name	Code
LAN Argentina	4M	Aer Lingus Plc	EI	Air New Zealand	NZ
Jet Airways (India) Limited	9W	Emirates	EK	Olympic Airlines	OA
Aegean Airlines	A3	Etihad Airways	EY	Czech Airlines	OK
American Airlines Inc.	AA	Frontier Airlines Inc.	F9	Austrian Airlines	OS
Air Berlin PLC and CO	AB	Icelandair	FI	Asiana Airlines Inc.	OZ
Air Canada	AC	AirTran Airways Corporation	FL	Qantas Airways Ltd.	QF
Compagnie Nat'l Air France	AF	Gulf Air Company	GF	Qatar Airways	QR
Aeromexico	AM	Hawaiian Airlines Inc.	HA	Alia-(The) Royal Jordanian	RJ
Aeromexpress	AP	Iberia Air Lines Of Spain	IB	South African Airways	SA
Alaska Airlines Inc.	AS	TAM Airlines	JJ	Scandinavian Airlines Sys.	SK
Royal Air Maroc	AT	Spanair S.A.	JK	Sabena Belgian World Air.	SN
Finnair Oy	AY	Japan Air Lines Co. Ltd.	JL	Sun Country Airlines	SY
Alitalia	AZ	Korean Air Lines Co. Ltd.	KE	TAP Portugal	TP
JetBlue Airways	B6	Klm Royal Dutch Airlines	KL	ATA Airlines	TZ
British Airways Plc	BA	Lan-Chile Airlines.	LA	USA3000 Airlines	U5
British Midland Airways Ltd.	BD	Lufthansa German Airlines	LH	United Air Lines Inc.	UA
Eva Air (Taiwan)	BR	Polskie Linie Lotnicze	LO	US Airways Inc.	US
China Airlines Ltd.	CI	Lan Peru	LP	Air Europa	UX
Compania Panamena (Copa)	CM	Swiss International Airlines	LY	Virgin Australia	VA
Continental Air Lines Inc.	CO	Malév Hungarian Airlines	MA	Vietnam Airlines	VN
Cathay Pacific	CX	Compania Mexicana De Aviaci	MX	Virgin Atlantic Airways	VS
China Southern Airlines	CZ	North American Airlines	NA	ACES Colombia	VX
Delta Air Lines Inc.	DL	All Nippon Airways Co.	NH	West Jet	WS
EOS Airlines, Inc.	E0	Spirit Airlines	NK	Republic Airlines	YX

Table A5 Comparison of Standard Logit Demand Model and Random Coefficients Logit Demand Model on Select Predicted Market Outcomes			
	"oneworld Event Sample"		
	Standard Logit Model Predicted Estimates [mean; (std. error)]	Random Coefficients Logit Model Predicted Estimates [mean; (std. error)]	Difference in Predicted Estimates Between the two Models [mean; (std. error)]
Own Price Elasticity (%)	[-1.09; (0.0027)]	[-2.12; (0.0052)]	[1.03; (0.0025)]
Product Level Markups ($)	[952.71; (0.126)]	[486.35; (0.064)]	[466.37; (0.063)]
Quarterly Variable Profits[a] ($)	[66,066.39; (2,599.6)]	[19,648.82; (772.84)]	[46,417.57; (1,826.76)]
	"ATI Event Sample"		
Own Price Elasticity (%)	[-2.11; (0.0034)]	[-3.66; (0.0042)]	[1.56; (0.0012)]
Product Level Markups ($)	[521.47; (0.0213)]	[278.89; (0.0747)]	[242.58; (0.0755)]
Quarterly Variable Profits[a] ($)	[36,498.57; (587.63)]	[31,752.06; (511.21)]	[4,746.51; (76.42)]

[a] Quarterly variable profits are measured at the origin-destination market-level for an airline.

Appendix B

Recall that the vector of state variables shown in equation (16) is:

$$y_{imt} \equiv \{s_{imt}, R^*_{imt}, Opres\_cost_{imt}, T_t^{Alliance/ATI}\}$$

Transition rules for state variables are as follows:

$$s_{im,t+1} = a_{it} \tag{B1}$$

$$R^*_{im,t+1} = a_{imt}(\alpha_0^R + \alpha_1^R R^*_{imt} + \zeta^R_{imt}) \tag{B2}$$

$$Opres\_cost_{im,t+1} = \alpha_0^{Opres\_cost} + \alpha_1^{Opres\_cost} Opres\_cost_{imt} + \zeta_{imt}^{Opres\_cost} \tag{B3}$$

where ζ^R_{imt} and $\zeta_{imt}^{Opres\_cost}$ are assumed to be normally distributed.

The joint transition probabilities of the state variables are determined by:

$$F_i^{\sigma}(y_{t+1}|a_{it,}y_t) = \begin{cases} 1\{s_{i,t+1} = 1\} * \Pr_R * \Pr_{Opres\_cost} * Pr\left(T_t^{Alliance/ATI} = 1|y_t\right) * \Pr_{comp} \\ 1\{s_{i,t+1} = 0\} * \Pr_R{}' * \Pr_{Opres\_cost} * Pr\left(T_t^{Alliance/ATI} = 1|y_t\right) * \Pr_{comp} \end{cases} \tag{B4}$$

where

$$\Pr_R = F_R\left(R^*_{i,t+1}|R^*_{it}\right) * \prod_{j\neq i} F_R\left(R^*_{jt+1}|R^*_{jt}\right) \tag{B5}$$

$$\Pr_{Opres\_cost} = F_{Opres\_cost}(Opres\_cost_{it+1}|Opres\_cost_{it}) * \prod_{j\neq i} F_{Opres\_cost}\left(Opres\_cost_{jt+1}|Opres\_cost_{jt}\right) \tag{B6}$$

$$\Pr_R{}' = 1\{R^*_{it+1} = 0\} * \prod_{j\neq i} F_R\left(R^*_{jt+1}|R^*_{jt}\right) \tag{B7}$$

$$Pr(T_t^{Alliance/ATI} = 1|y_t) = \Phi(\alpha_0^T + \alpha_1^T s_{it} + \alpha_2^T R^*_{it} + \alpha_3^T Opres\_cost_{it}) \tag{B8}$$

$$\Pr_{comp} = \prod_{j\neq i} Pr\left(s_{jt+1} = \sigma_j\left(y_{jt}, \varepsilon_{jt}\right)|y_{jt}\right) \tag{B9}$$

Appendix C: Representation of Markov Perfect Equilibrium (MPE) using Conditional Choice Probabilities (CCPs)

Recall that the expected one-period profit function for airline i is as follows:

$$\Pi_{imt}(a_{it}, y_t) = R^*_{imt} - a_{imt}(FC_i + (1 - s_{imt})EC_i) \qquad \text{(C1)}$$

Based on equation (C1), note that $\Pi_{imt}(0, y_t) = R^*_{imt}$ and $\Pi_{imt}(1, y_t) = R^*_{imt} - FC_i - (1 - s_{imt})EC_i$.

Following Aguirregabiria and Ho (2012), we represent the MPE as a vector of conditional choice probabilities (CCPs), P = {$P_i(y)$: *for every firm and state* (i, y)}, where P solves the fixed point problem $P = \psi(P, \theta)$. $P = \psi(P, \theta)$ is a vector of best response mapping:

$$\{\psi\left(\tilde{Z}_i^P(y)\frac{\theta}{\sigma_\varepsilon} + \tilde{e}_i^P(y)\right): for\ every\ firm\ and\ state\ (i, y)\} \qquad \text{(C2)}$$

where $\psi(.)$ is the *CDF* of the type 1 extreme value distribution, and

$$\tilde{Z}_i^P(y) = Z_i(1, y) - Z_i(0, y) + \beta[F^P_{i,y}(1) - F^P_{i,y}(0)] \times w^P_{z,i} \qquad \text{(C3)}$$

$$\tilde{e}_i^P(y) = \beta[F^P_{i,y}(1) - F^P_{i,y}(0)] \times w^P_{e,i} \qquad \text{(C4)}$$

$$w^P_{z,i} = (1 - \beta * \overline{F^P_{i,y}})^{-1} \times \{P_i(y) * Z_i(1, y) + [1 - P_i(y)] * Z_i(0, y)\} \qquad \text{(C5)}$$

$$w^P_{e,i} = (1 - \beta * \overline{F^P_{i,y}})^{-1} \times [P_i(y) * e_i^P] \qquad \text{(C6)}$$

and

$$\overline{F^P_{i,y}} = [P_i(y) \times 1'_M) * F^P_{i,y}(1) + \left(\left(1 - P_i(y)\right) \times 1'_M\right) * F^P_{i,y}(0)] \qquad \text{(C7)}$$

$$\overline{F^P_{i,y}} = [P_i(y) \times 1'_M) * F^P_{i,y}(1) + \left(\left(1 - P_i(y)\right) \times 1'_M\right) * F^P_{i,y}(0)] \qquad \text{(C8)}$$

$w^P_{z,i}$ and $w^P_{e,i}$ are vectors of valuations that depend on CCPs and transition probabilities, but not on the dynamic parameters being estimated. Since ε_{imt} is assumed type 1 extreme value distributed, e_i^P is a function vector equal to $e_i^P = \gamma - ln\left(P_i(y)\right)$, where $\gamma = 0.5772$ is Euler's constant.

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