ESSAYS ON ECONOMICS OF AIRLINE ALLIANCES

by

XIN XIE

B.A., Wuhan University of Technology, 2006
M.B.A., Pittsburg State University, 2008

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2014

Abstract

This dissertation constitutes two essays in the field of industrial organization. Specifically, the research focuses on empirically assessing the market effects of airline alliances.

The first essay examines how codesharing, a form of strategic alliances, by airlines affects market entry decisions of potential competitors. Researchers have written extensively on the impact that strategic alliances between airlines have on airfare, but little is known of the market entry deterrent impact of strategic alliances. Using a structural econometric model, this essay examines the market entry deterrent impact of codesharing between incumbent carriers in U.S. domestic air travel markets. We find that a specific type of codesharing between market incumbents has a market entry deterrent effect to Southwest Airlines, but not other potential entrants. Furthermore, we quantify the extent to which market incumbents' codesharing influences market entry cost of potential entrants.

The second essay examines the effects of granting Antitrust Immunity (ATI) to a group of airlines. Airline alliance partners often want to extend cooperation to revenue sharing, which effectively implies joint pricing of their products (explicit price collusion). To explicitly collude on price, airlines must apply to the relevant government authorities for ATI (U.S. Department of Justice and Department of Transportation in the case of air travel markets that have a U.S. airport as an endpoint), which effectively means an exemption from prosecution under the relevant antitrust laws. Whether consumers, on net, benefit from a grant of ATI to partner airlines has caused much public debate. This essay specifically investigates the impact of granting ATI to oneworld alliance members on their price, markup, and various measures of cost. The evidence suggests that the grant of ATI facilitated a decrease in partner carriers' marginal cost, and increased (decreased) their markup in markets where their service do (do not) overlap. Furthermore, member carriers' price did not change (decreased) in markets where their services do (do not) overlap, implying that consumers, on net, benefit in terms of price changes.

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Chapter 1 - Entry Deterrence and Strategic Alliances

1. Introduction

In recent years, strategic alliances between airlines have become increasingly popular. The format of a strategic alliance between airlines can vary from a limited marketing arrangement, for example an arrangement between partner carriers that only makes their frequent-flyer programs reciprocal, [1] to more extensive arrangements that include reciprocal frequent-flyer programs as well as codesharing. Reciprocal frequent-flyer programs effectively allow passengers that hold frequent-flyer membership with one carrier in the alliance to earn and redeem frequent-flyer points across any partner carrier in the alliance. A codeshare arrangement effectively allows each carrier in the alliance to sell tickets for seats on its partners' airplane, i.e., partners essentially share certain facilities, in this case airplanes, that are solely owned by one of the partners.

Researchers have written extensively on the impact that strategic alliances have on airfare [Brueckner and Whalen (2000); Brueckner (2001 and 2003); Bamberger, Carlton and Neumann (2004); Ito and Lee (2007); Gayle (2008 and 2013); Gayle and Brown (2012) among others]. [2] However, there is a paucity of work that examines the impact that strategic alliances may have on deterring potential competitors from entering a relevant market. This is a particularly interesting aspect of strategic alliances to study since a substantial amount of these alliances are formed between traditional major/legacy carriers, who may face increasingly stiff competition from the growing prominence of low-cost-carriers (LCCs). Some researchers argue that hub-and-spoke network carriers form and use strategic codeshare alliances to better compete with low-cost-carriers, [Mantovani and Tarola (2007)]. So the following series of relevant questions

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[1] Membership in an airline's frequent-flyer program allows the passenger to accumulate points each time the passenger flies on the airline. The frequent-flyer program allows the passenger to be eligible for various rewards once the passenger accumulates points beyond certain pre-determine thresholds. As such, frequent-flyer programs are designed to build customer loyalty to the carrier that offers the program.

[2] Earlier contributions to this literature include: Oum and Park (1997); Park (1997); Park and Zhang (1998); and Park and Zhang (2000).

need careful study. First, does the evidence support the argument that strategic alliances between major airlines, among achieving other goals, serve to deter entry of potential entrants to a relevant market? Second, if an entry-deterrence effect is evident, is there a particular type of practice among alliance partners that is most effective at deterring entry? Third, is there a particular type of airline that seems to be more deterred via such practice by alliance partners? [3]

Chen and Ross (2000) theoretically explore the anticompetitive effect of a particular type of strategic alliance, by which the partner airlines share important facilities such as airplanes, terminals etc. They argue that this type of alliance can forestall a complete and competitive entry by another firm, that is, such alliances can have an entry-deterrent effect. The mechanism through which Chen and Ross envisioned that a strategic alliance may deter a complete and competitive entry is as follows. An incumbent offers to form a strategic alliance with a potential entrant, which takes the form of the incumbent willing to share its facility with the potential entrant in order to discourage the potential entrant from building its own facility and entering on a larger, more competitive scale. In the context of a codeshare alliance, this would translate into the incumbent offering to let a potential entrant sell tickets for seats on the incumbent's plane in order to discourage the potential entrant from putting its own plane on the route. So based on Chen and Ross's argument, entry-deterrent codesharing should primarily take place between a market incumbent and the potential entrant the incumbent is intending to deter.

Lin (2005) uses a theoretical model to show that incumbents can use codeshare alliances as a credible threat to deter the entry of potential entrants who do not have significant cost advantage. The author uses the model to show that, owing to joint profit maximizing behavior between allied airlines, there exists an equilibrium in which the joint profit of two allied airlines is higher than the sum of their individual profits if they were not allied. In addition, this higher joint profit of the allied airlines comes at the expense of lower profit for a new non-allied entrant. This equilibrium implies that if market entry cost is sufficiently high, such that entry in the

[3] In a separate, but related airline entry-deterrence literature, Oum, Zhang and Zhang (1995); Hendricks, Piccione and Tan (1997); Berechman, Poddar and Shy (1998); Aguirregabiria and Ho (2010) among others have argued that hub-and-spoke route networks adopted by many legacy carriers do give these carriers an incentive and the ability to deter entry of other carriers that do not use hub-and-spoke route network, which include many low-cost-carriers. But this literature focuses on the entry deterrence effect of hub-and-spoke networks rather than more specifically on the entry deterrence effect of codeshare alliances.

presence of an alliance between market incumbents is unprofitable for the new non-allied entrant, but profitable if incumbents were not allied, then formation of the alliance can be done to strategically deter entry. [4]

In addition to Chen and Ross (2000) and Lin (2005) arguments why codeshare alliances may deter entry, we posit yet another mechanism through which a codeshare alliance may deter potential entrants from entering a market. The idea is that codeshare partner carriers typically make their frequent-flyer programs reciprocal. This has the effect of making frequent-flyer membership of each partner carrier more valuable to customers due to the increased opportunities for customers to accumulate and redeem frequent-flyer miles across partner carriers. In other words, the alliance partners' loyal-customer base in a market is likely to expand with a codeshare alliance. Consistent with this argument, Lederman (2007) provides econometric evidence suggesting that enhancements to frequent-flyer partnerships are associated with increased demand for partners' air travel services. An increase in alliance partners' loyal-customer base makes it increasingly difficult for potential entrants to enter the market and amass a sufficiently large customer base to make entry profitable. This increased difficulty that potential entrants face to steal customers upon entry, is likely to be reflected as relatively higher entry cost to these codeshare markets.

Via reduced-form econometric regressions, Goetz and Shapiro (2012) empirically test for the presence of entry-deterrence motives behind codesharing alliances, and find that an incumbent is approximately 25% more likely than average to codeshare when facing the threat of entry by low-cost carriers. However, Goetz and Shapiro (2012) did not investigate whether the entry-deterrence effect they found depends on the type of codesharing (Traditional versus Virtual) [5] employed by incumbent partner airlines. In addition, they did not fully investigate whether the entry-deterrence effect of codesharing depends on the identity of the carrier that is threatening to enter the relevant market.

Previous studies have argued that Southwest Airlines, if not the most formidable LCC in U.S. domestic air travel markets, is certainly among the most formidable LCCs in these markets.

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[4] Lin (2008) extends this model to consider situations in which an incumbent has a relatively large hub-and-spoke network and entry has positive spillover network effects for the incumbent.

[5] In the Definition and Data section of the paper we define and distinguish Traditional and Virtual codesharing.

As such, many studies have treated Southwest separately than other LCCs, or focused on Southwest as the sole LCC [for example see Morrison (2001), Goolsbee and Syverson (2008), Brueckner, Lee and Singer (2012) among others]. Brueckner, Lee and Singer (2012) find that the presence of potential competition from Southwest reduces fares by 8 percent, while potential competition from other LCCs has no fare effect. Mason and Morrison (2008) find significant differences between low-cost carriers in their business models. Therefore, we are encouraged to investigate whether any possible entry-deterrent effect of codesharing depends on whether the potential entrant is Southwest versus other low-cost carriers.

While Goetz and Shapiro (2012) use a reduced-form regression analysis to empirically test whether domestic codesharing alliances are motivated by an entry-deterrence purpose, to the best of our knowledge, there is no other empirical analysis of this issue. We believe a structural econometric analysis of this issue is needed to take us a step further in examining the evidence on this type of strategic behavior by airlines. One advantage of using a structural econometric model is that we are able to quantify, in monetary terms, possible market entry barriers associated with codesharing.

Therefore, the main objective of our paper is to use a structural econometric model to investigate: (1) whether codesharing between airlines in domestic air travel markets, a form of strategic alliance, has a deterrent effect on the entry of potential competitors; (2) whether there is a particular type of codesharing among alliance partners that is most effective at deterring entry; and (3) whether there is a particular type of airline that seems to be more deterred via such type of codesharing between alliance partners.

To assess the deterrent effect of codesharing on market entry of potential competitors, we proceed as follows. First, we estimate a discrete choice model of air travel demand. Second, 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 use them to compute firm-level variable profits, which are subsequently used in a dynamic market entry/exit game. Third, we specify a dynamic market entry/exit game played between airlines in which each airline chooses markets in which to be active during specific time periods in order to maximize its expected discounted stream of profit. Per-period profit comprises variable profit less per-period fixed cost and a one-time entry cost if the airline will serve the relevant market in the next period but not currently serving the market. The dynamic entry/exit game allows us to estimate fixed and entry costs by exploiting previously computed variable profits from the Nash equilibrium price-setting game along with observed data on airlines' decisions to enter and exit certain markets. It is the estimated effect that codesharing between incumbents have on the entry cost of potential entrants that allows us to evaluate whether codeshairng has an entry deterrent effect.

We specify entry cost functions such that we can identify whether or not the extent of codesharing by incumbent airlines in a market influences the market entry cost of potential entrants, and whether this influence differs by type of potential entrant. A potential entrant can fall into one of three categories: (1) legacy carriers; (2) Southwest Airlines; or (3) other LCCs. Since the majority of codesharing in U.S. domestic air travel markets occurs between legacy carriers, this implies that our entry cost function specification effectively allows us to explore whether codesharing between legacy carriers influences the market entry of: (1) other legacy carriers; (2) Southwest Airlines; (3) other LCCs; or some subset of the three carrier types.

An important aspect of our analysis is that we follow Ito and Lee (2007) and Gayle (2008) and decompose codesharing into two main types: (1) Traditional Codesharing; and (2) Virtual Codesharing. As such, we are able to investigate whether possible entry deterrent effects of codesharing depend on the type of codesharing.

Our econometric estimates from the entry cost function suggest that more traditional codesharing between incumbent carriers in a market puts Southwest at a relative disadvantage to enter the market compared to all other potential entrants (legacy carriers and other low-cost carriers). Specifically, each percentage point increase in traditional codeshare products offered by incumbents in a market raises market entry cost for Southwest by 0.3%, but reduces market entry cost by 0.6% and 0.7% for legacy and other low-cost carriers respectively. Therefore, traditional codesharing by market incumbent carriers has a relative market entry deterrent effect on Southwest. Furthermore, there is no evidence that virtual codesharing has a market entry deterrent effect.

We link the market entry deterrent effects inferred from our entry cost estimates to findings from our demand estimates. Estimates from our demand model suggest that incumbents' traditional codesharing has a larger demand-increasing effect for their products compared to virtual codesharing. Since the demand-side evidence is consistent with the argument that traditional codesharing better serves to expand the loyal customer base of market incumbents, then with more traditional codesharing by incumbents, a potential entrant will find it more costly (higher market entry cost) to build its own customer base upon entry, making entry less profitable in these high traditional codeshare markets. We argue that this entry deterrent effect is binding for Southwest but not for others due to evidence that the vast majority of codesharing is done between legacy carriers, and competition between Southwest and legacy carriers is stronger than competition between other low-cost carriers and legacy carriers. For example, as pointed out above, Brueckner, Lee and Singer (2012) provide evidence that incumbent legacy carriers do not cut fares in response to potential competition from other low-cost carriers, but cut fares by 8% in response to potential competition from Southwest.

The remainder of this paper is organized as follows. Next we define and discuss relevant concepts and terms used throughout this paper, and describe how we construct the dataset of our working sample. Our econometric model is presented in section 3. Section 4 discusses the estimation procedure and summarizes estimation results. Concluding remarks are offered in section 5.

2. Definitions and Data

2.1 Definitions

A market is defined as a directional pair of origin and destination cities during a particular time period. For example, air travel from New York to Dallas is a different market than air travel from Dallas to New York. Treating markets in a direction-specific manner better enables our model to account for the impact that heterogeneity in demographics across origin cities has on air travel demand.

An itinerary is a detailed plan of a journey from an origin to destination city, so it consists of one or more flight coupons depending on whether or not intermediate stops are required. Each coupon typically represents travel on a particular flight. Each flight has a ticketing carrier and an operating carrier. The ticketing carrier, or sometimes referred to as the marketing carrier, is the airline selling the ticket for the seat, while the operating carrier is the airline whose plane actually transports the passenger. A product is defined as the combination of ticketing carrier, operating carrier(s) and itinerary.

A pure online product has an itinerary whose operating carrier for each flight coupon and ticketing carrier are the same. For example, a two-segment ticket with both segments operated and marketed by United Airlines (UA), i.e. (UA/UA → UA/UA). A flight is said to be codeshared when the operating and ticketing carriers for that flight differ. A traditional codeshared product is defined as an itinerary that has a single ticketing carrier for the trip, but multiple operating carriers, one of which is the ticketing carrier. For example, a connecting itinerary between Continental Airlines (CO) and Delta Airlines (DL), marketed solely by Delta (CO/DL → DL/DL) is a traditional codeshared product. A virtual codeshared product is defined as an itinerary that has the same operating carrier for all trip segments, but this operating carrier differs from the ticketing carrier. For example, a connecting itinerary operated entirely by United Airlines but marketed solely by US Airways (US) (UA/US→ UA/US), is a virtual codeshared product.[6]

2.2 Data

We use data from the Airline Origin and Destination Survey (DB1B) collected by the Office of Airline Information of the Bureau of Transportation Statistics. The DB1B survey is a 10% random sample of airline tickets from certified carriers in the United States. A record in this survey represents a ticket. Each ticket contains information on ticketing and operating carriers, origin and destination airports, fare, number of passengers, intermediate airport stops, market miles flown on the trip itinerary, nonstop miles between the origin and destination airports, and number of market coupons. Unfortunately, there is no passenger-specific information in the data, nor is there any information on ticket restrictions such as advance-purchase and length-of-stay requirements.

The data are quarterly, and our study uses data for the entire years of 2005, 2006 and 2007. Following Aguirregabiria and Ho (2012) among others, we select data on air travel between the 65 largest US cities. Some of the cities belong to the same metropolitan area and have multiple airports. Table 1.1 reports a list of the cities and the relevant airport groupings we use based on common metropolitan areas.

[6] Additional discussion and examples of pure online, traditional codeshare and virtual codeshare air travel products can be found in Ito and Lee (2007) and Gayle (2007, 2008 and 2013). In addition, see Gayle and Brown (2012).

Table 1.1 Cites, airports and population

City, State	Airports	City pop.		
		2005	2006	2007
New York-Newark-Jersey	LGA, JFK, EWR	8,726,847	8,764,876	8,826,288
Los Angeles, CA	LAX, BUR	3,794,640	3,777,502	3,778,658
Chicago, IL	ORD, MDW	2,824,584	2,806,391	2,811,035
Dallas, TX[a]	DAL, DFW	2,479,896	2,528,227	2,577,723
Phoenix-Tempe-Mesa, AZ	PHX	2,087,948	2,136,518	2,171,495
Houston, TX	HOU, IAH, EFD	2,076,189	2,169,248	2,206,573
Philadelphia, PA	PHL	1,517,628	1,520,251	1,530,031
San Diego, CA	SAN	1,284,347	1,294,071	1,297,624
San Antonio, TX	SAT	1,258,733	1,292,082	1,323,698
San Jose, CA	SJC	908,870	918,619	931,344
Detroit, MI	DTW	921,149	918,849	917,234
Denver-Aurora, CO	DEN	856,834	869,920	887,796
Indianapolis, IN	IND	789,250	792,619	796,611
Jacksonville, FL	JAX	786,938	798,494	805,325
San Francisco, CA	SFO	777,660	786,149	799,185
Columbus, OH	CMH	738,782	744,473	750,700
Austin, TX	AUS	708,293	730,729	749,120
Memphis, TN	MEM	680,515	682,024	679,404
Minneapolis-St.Paul, MN	MSP	652,481	652,003	656,659
Baltimore, MD	BWI	640,064	640,961	640,150
Charlotte, NC	CLT	631,160	652,202	669,690
El Paso, TX	ELP	587,400	595,980	600,402
Milwaukee, WI	MKE	601,983	602,782	602,656
Seattle, WA	SEA	575,036	582,877	592,647
Boston, MA	BOS	609,690	612,192	622,748

[a] includes Dallas, Arlington, Fort Worth and Plano

Table 1.1 Continued
Cites, airports and population

City, State	Airports	City pop.		
		2005	2006	2007
Louisville, KY	SDF	559,855	559,709	562,632
Washington, DC	DCA, IAD	582,049	583,978	586,409
Nashville, TN	BNA	579,748	586,327	592,503
Las Vegas, NV	LAS	544,806	552,855	559,892
Portland, OR	PDX	534,112	538,091	546,747
Oklahoma City, OK	OKC	532,006	539,001	545,910
Tucson, AZ	TUS	524,830	530,349	536,752
Albuquerque, NM	ABQ	497,543	508,486	517,162
Long Beach, CA	LGB	467,851	463,723	459,925
New Orleans, LA	MSY	455,188	208,548	288,113
Cleveland, OH	CLE	449,188	442,409	438,068
Sacramento, CA	SMF	448,842	449,658	455,760
Kansas City, MO	MCI	463,983	470,076	475,830
Atlanta, GA	ATL	483,108	498,208	519,569
Omaha, NE	OMA	432,148	437,523	442,452
Oakland, CA	OAK	392,112	392,076	397,441
Tulsa, OK	TUL	381,017	382,394	384,592
Miami, FL	MIA	390,768	412,460	424,662
Colorado Springs, CO	COS	393,804	398,778	399,751
Wichita, KS	ICT	354,524	356,592	360,897
St Louis, MO	STL	352,572	353,837	355,663
Santa Ana, CA	SNA	337,121	334,830	335,491
Raleigh-Durham, NC	RDU	553,294	574,065	596,049
Pittsburgh, PA	PIT	316,206	313,306	312,322
Tampa, FL	TPA	325,569	332,604	334,852
Cincinnati, OH	CVG	331,310	332,185	333,321
Ontario, CA	ONT	170,630	170,865	171,603
Buffalo, NY	BUF	277,998	274,740	272,492
Lexington, KY	LEX	278,313	283,324	287,263
Norfolk, VA	ORF	237,487	238,832	236,051

We eliminate tickets with nominal prices cheaper than $50 and more expensive than $2000, those with multiple ticketing carriers, and those containing more than 2 intermediate stops. Within each quarter, a given itinerary-airline(s) combination is repeated many times, each time at a different price, making the dataset extremely large. To make the data more manageable, we collapse the data based on our definition of product (unique itinerary-airline(s) combination) for each quarter. Before collapsing the data, we aggregated the number of passengers and averaged market fare over each defined product. This is the process by which each defined product's quantity and price are constructed. Products with quantity less than 9 passengers for the entire quarter are dropped from the data.[7] Also, we eliminate monopoly markets, i.e. markets in which only one carrier provides products. In the collapsed data set, we have 434,329 observations (products), each of them unique for each quarter, across 32,680 markets.

Other variables that capture air travel product characteristics are created for estimation. A measure of product *Inconvenience* is defined as market miles flown divided by nonstop miles between origin and destination. Thus, the minimum value for variable *Inconvenience*, which is equal to 1, implies the most convenient itinerary for a given market. The dummy variable *Nonstop* is equal to 1 if the product uses a nonstop itinerary.

We measure the size of an airline's presence at the endpoint cities of a market from different perspectives. The variable *Opres_out* is a count of the number of different cities that the airline offers nonstop flights to, leaving from the origin city. On the other hand, *Opres_in* counts the number of different cities that the airline provides nonstop flights from, going into the origin city of the market. We also construct a destination presence variable *Dpres_out,* which measures the number of distinct cities that the airline has nonstop flights to, leaving from the destination city.

Opres_out is intended to help explain consumers' choice between airlines at the consumer's origin city. 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 city. On the other hand, the *Opres_in* and *Dpres_out* may better explain an airline's cost of transporting passengers in a market. The argument is that due to possible economies of passenger-traffic density, an airline's marginal cost of transporting a passenger in a market is lower as the volume of passengers the airline channels through the market increases. An airline with large measures of *Opres_in* and *Dpres_out* for a given market, is likely to channel a large volume of passengers

[7] Berry (1992), Aguirregabiria and Ho (2012) among others use a similar, and sometimes more stringent, quantity threshold to help eliminate idiosyncratic product offerings that are not part of the normal set of products offered in a market.

through the market, and therefore is expected to have lower marginal cost of transporting a passenger in the market.

From the collapsed dataset, observed product market shares (subsequently denoted by upper case S_j) are created by dividing quantity of product j sold (subsequently denoted by q_j) by the geometric mean of the origin city and destination city populations (subsequently denoted by *POP*), i.e. $S_j = {}^{q_j}/_{POP}$.[8] *Traditional Codeshare* and *Virtual Codeshare* are dummy variables equal to 1 respectively when the itinerary is identified to be traditional codeshared and virtual codeshared. The variables *Percent Traditional for Airline* and *Percent Virtual for Airline* measure the percentage of an airline's products in a market that are traditional codeshare and virtual codeshare respectively.

We only identify codeshare products between major carriers, i.e. following much of the literature on airline codesharing, we do not consider products between regional and major carriers as codeshare. For example, a product that involves American Eagle (MQ) and American Airlines (AA), where one of them is the ticketing carrier and the other is an operating carrier, is still considered by us to be pure online since American Eagle is a regional airline that serves for American Airlines. Summary statistics of the variables used for estimation are presented in Table 1.2. The variable *Fare* is measured in constant year 1999 dollars. We use the consumer price index to deflate *Fare*.

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[8] POP is measured by: $POP = \sqrt{Origin\ Population \times Destination\ Population}$. 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 remains positive. The common factor that satisfies these conditions in the data set is 35.

Table 1.2 Summary Statistics for the Dataset

Variable	Mean	Std.Dev	Min	Max
Fare[a]	166.35	52.19	45.08	1,522.46
Quantity	149.57	508.25	9	11,643
Opres_out	29.05	28.35	0	177
Opres_in	29.03	28.30	0	177
Dpres_out	29.13	28.47	0	177
Nonstop	0.154	0.36	0	1
Market miles flown	1,542.34	695.27	67	4,156
Nonstop miles	1,371.42	648.60	67	2,724
Inconvenience	1.15	0.21	1	2.975
Traditional Codeshare	0.02	0.14	0	1
Virtual Codeshare	0.02	0.14	0	1
Percent Traditional for Airline	2.04	10.42	0	100
Percent Virtual for Airline	2.06	9.70	0	100
Observed Product Shares (S_j)	0.0067	0.02	5.45E-05	0.97
Number of Products	434,329			
Number of Markets	32,680			

Notes: [a] The variable "Fare" is measured in constant year 1999 dollars. We use the consumer price index to deflate "Fare".

Table 1.3 presents a list of ticketing carriers in the dataset according to type of products that each airline provides. The first two columns show that there are 21 airlines involved in pure online products. All airlines in the dataset provide pure online products. The next two columns in Table 1.3 show that, among all airlines in the dataset, 10 are involved in codeshare products and 7 of these airlines are the ones we classify as legacy carriers. The fifth column in Table 1.3 reports the percent of codeshare products in the sample that each carrier offers for sale to consumers. The data in this column reveal that the vast majority (approximately 83 percent) of codeshare products are provided by legacy carriers.

The last column in Table 1.3 reports the percent of each carrier's codeshare products that are codeshared with legacy carriers. Noticeably, almost all of each legacy carrier's codeshare products are codeshared with other legacy carriers, and moreover, ATA and Southwest Airlines, which are low-cost carriers, do not codeshare with legacy carriers. An exception to this pattern is Frontier Airlines, a low-cost carrier that has 91 percent of its codeshare products codeshared with a legacy carrier (typically with Alaska Airlines). However, the previous column shows that codeshare products offered by Frontier Airlines only account for 0.07 percent of total codeshare products offered. In summary, the data reveal that a substantial amount of codeshare alliances are formed between legacy carriers.

Table 1.3 List of Airlines in the Dataset by Product type they offer to Consumers

Airlines Involved in Pure online Products

Airlines Name	Code
American Airlines Inc.	AA
Aloha Airlines	AQ
Alaska Airlines Inc.	AS
JetBlue Airways	B6
Continental Air Lines Inc.	CO
Independence Air	DH
Delta Air Lines Inc.	DL
Frontier Airlines Inc.	F9
AirTran Airways	FL
Allegiant Air	G4
America West Airlines Inc.	HP
Spirit Air Lines	NK
Northwest Airlines Inc.	NW
Skybus Airlines, Inc.	SX
Sun Country Airlines	SY
ATA Airlines	TZ
United Air Lines Inc.	UA
US Airways Inc.	US
Southwest Airlines Co.	WN
ExpressJet Airlines Inc.	XE
Midwest Airlines	YX

Airlines that offer Codeshare Products to consumers

Airlines Name	Code	Percent of codeshare products in the sample	Percent of each carrier's codeshare products codeshared with legacy carriers
Legacy Carriers			
American Airlines Inc.	AA	13.47	98.87
Alaska Airlines Inc.	AS	7.87	100
Continental Air Lines Inc.	CO	5.76	100
Delta Air Lines Inc.	DL	4.76	99.88
Northwest Airlines Inc.	NW	10.03	100
United Air Lines Inc.	UA	28.75	100
US Airways Inc.	US	12.56	99.82
Sub-total		83.20	
Low Cost Carriers			
Southwest Airlines Co.	WN	9.28	0
ATA Airlines	TZ	7.45	0
Frontier Airlines Inc.	F9	0.07	91.67
Sub-total		16.80	
Total		100	

Notes: The carries we classify as Legacy carriers include: American Airline, Alaska Airlines, Continental Air, Delta Air Lines, Northwest Airlines, United Air Lines, and US Airways.

Table 1.4 summarizes our data according to the three types of products. Among codeshared products, the number of traditional codeshared products is slightly less than the number of virtual codeshared products, but twice as many passengers travel on virtual codeshared products compared to traditional codeshare products.

Table 1.4 Classification of Cooperative Agreement in Data Set

Classification	Observations/Products		Passengers	
	Frequency	Percent	Frequency	Percent
Pure online	416,537	95.90	64,150,292	98.75
Traditional Codeshare	8,847	2.04	254,065	0.39
Virtual Codeshare	8,945	2.06	558,095	0.86
Total	434,329	100.00	64,962,452	100.00

As we explain in subsequent sections of the paper, the short-run demand and supply sides of the model are estimated using the data at the product-market-time period level, while the dynamic entry/exit model is estimated using the data aggregated up to the airline-market-time period level. Since the data contain many more airlines than the dynamic entry/exit model can feasibly handle, at the stage of estimating the dynamic model, we impose additional restrictions to be able to estimate the dynamic model. A restrictive assumption we make is that a set of the airlines in our data can reasonably be lumped into an “Other low-cost carriers” category and treated as if the “Other low-cost carriers” is a single carrier. Similar to many studies in the literature [e.g. Brueckner, Lee and Singer (2012), Morrison (2001) among others], Southwest Airlines is the low-cost carrier that we treat separately than other low-cost carriers. So the “Other low-cost carriers” category includes all low-cost carriers except Southwest Airlines.

By using the number of passengers as a threshold to define whether or not an airline is active in a market, we are able to identify the number of markets that each airline has entered and exited. We define an airline to be active in a directional origin-destination market during a quarter if at least 130 passengers travel on products offered for sale by the airline in this market during the quarter.[9] Each airline's market entry and exit decisions contained in the data are crucial for us to be able to estimate fixed and entry costs, since the dynamic entry/exit model relies on the optimality assumption that potential entrants will only enter a market if the one-time entry cost is less than the expected discounted future stream of profits, and an incumbent will exit a market when per-period fixed cost becomes sufficiently high relative to per-period variable profits such that the expected discounted future stream of profits is non-positive. Therefore, it is useful to get a sense of the extent to which the data contain information relevant for identifying

[9] Our passenger threshold of 130 for a directional market is equivalent to the 260 for non-directional market used by Aguirregabiria and Ho (2012).

fixed and entry costs from the dynamic model. Table 1.5 reports the number of market entry and exit events by airline. The table shows that each airline has several market entry and exit events, but most airlines have more market entry than market exit events, and overall there are substantially more entry than exit events. This suggests that we might be better able to identify entry cost than fixed cost.

Table 1.5 Number of market entry and exit events by airline

Airlines	Number of market entry events	Number of market exit events
American Airlines Inc.	498	332
Continental Air Lines Inc.	372	303
Delta Air Lines Inc.	348	360
Northwest Airlines Inc.	323	309
United Air Lines Inc.	316	259
US Airways Inc.	655	151
Alaska Airlines Inc.	22	12
Southwest Airlines Co.	262	105
Other low cost carriers	368	625
Overall	3,164	2,456

3. Model

3.1 Demand

Demand is modeled using a nested logit model. There are *POP* potential consumers, who may either buy one of J air travel products, $j = 1,\ldots,J$, or otherwise choose the outside good (good 0), e.g. driving, taking a train, or not traveling at all. The nested logit model classifies products into G groups, and one additional group for the outside good. Products within the same group are closer substitutes than products from different groups. Groups are defined by ticketing carriers in this study, so products with the same ticketing carrier belong to the same group. The indirect utility of consumer c from purchasing product j is given by:

$$u_{cj} = \mu_j + \delta\zeta_{cg} + (1-\delta)\varepsilon_{cj}^{d} \qquad (1)$$

The first term, μ_j , is the mean valuation for product *j*, common to all consumers. The mean valuation of product *j* depends on its price, p_j, a vector x_j of observed characteristics of product *j*, and error term ξ_j reflecting unobserved (to researchers) product characteristics:

$$\mu_j = x_j\phi^x - \phi^p p_j + \xi_j \tag{2}$$

where ϕ^x and ϕ^p are parameters to be estimated.

The second term in equation (1), ζ_{cg}, is a random component of utility that is common to all products belonging to group g. The term ε_{cj}^d is consumer *c's* unobserved utility, specific to product j. The parameter δ lies between 0 and 1 and measures the correlation of the consumers' utility across products belonging to the same group. The correlation of preferences increases as δ approaches 1. At the other extreme, if $\delta = 0$, there is no correlation of preferences: consumers are equally likely to switch to products in a different group as to products in the same group in response to a price increase.

The nested logit model assumes that the random terms ζ_{cg} and ε_{cj}^d have distributions such that $\delta\zeta_{cg} + (1-\delta)\varepsilon_{cj}^d$ have the extreme value distribution. Normalizing the mean utility level for outside good to 0, i.e., $\mu_0 = 0$, the probability that a consumer chooses product *j* is as follows:

$$s_j = \frac{\exp(\frac{\mu_j}{1-\delta})}{D_g} \times \frac{D_g^{1-\delta}}{1 + \sum_{g=1}^{G} D_g^{1-\delta}} \tag{3}$$

where $D_g = \sum_{k \in G_g} \exp[\frac{\mu_k}{1-\delta}]$. The total quantity sold of product *j*, q_j, is simply specified to equal to the probability that a potential consumer chooses product *j* times the total number of potential consumers, *POP*:

$$q_j = s_j(p, x, \xi; \Phi^{\mathrm{d}}) \times POP \tag{4}$$

where $\Phi^{\mathrm{d}} = (\phi^p, \phi^x, \delta)$ is the vector of demand parameters to be estimated.

3.2 Supply

The ticketing carrier of a codeshare product markets and sets the final price for the round-trip ticket and compensates the operating carrier for operating services provided. Unfortunately for researchers, partner airlines do not publicize details of how they compensate each other on their codeshare flights. Therefore, our challenge 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. As such, we follow the modeling approach outlined in Chen and Gayle (2007) and Gayle (2013).

Chen and Gayle (2007) and Gayle (2013) suggest that for modeling purposes a codeshare agreement can be thought of 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 is distributed. For the purposes of this paper we do not need to econometrically identify an equilibrium value of Γ, but in describing the dynamic part of the model, we do show where Γ enters the model.

Suppose the final price of a codeshare product is determined within a sequential price-setting game, where in the first stage of the sequential process the operating carrier sets price, w, for transporting a passenger using its own plane(s), and privately makes this price known to its partner ticketing carrier. In the second stage, conditional on the agreed upon price w for services supplied by 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 produces the final ticket prices observed by consumers.

Each ticketing carrier i solves the following profit maximization problem:

$$\max_{p_{jmt}} VP_{imt} = \max_{p_{jmt}} \left[\sum_{j \in B_{imt}} (p_{jmt} - mc_{jmt}) q_{jmt} \right] \tag{5}$$

where VP_{imt} is the variable profit carrier i obtains in market m during period t by offering the set of products B_{imt} to consumers, q_{jmt} is the quantity of tickets for product j sold in market m, p_{jmt} is the price of product j, and mc_{jmt} is the effective marginal cost incurred by ticketing carrier i from offering product j.

Let $f = 1, \dots, F$ index the corresponding operating carriers. If product j is a traditional codeshare product, then $mc_{jmt} = c_{jmt}^{i} + w_{jmt}^{f}$, where c_{jmt}^{i} is the marginal cost that ticketing carrier i incurs by using its own plane to provide transportation services on some segment(s) of the trip needed for product j, while w_{jmt}^{f} is the price ticketing carrier i pays to operating carrier f for its transportation services on the remaining trip segment(s). If instead product *j* is a virtual codeshare product, then $mc_{jmt} = w_{jmt}^{f}$, where w_{jmt}^{f} is the price the ticketing carrier pays to operating carrier f for its exclusive transportation services in the provision of product j.[10] Last, if product j is a pure online product, then $mc_{jmt} = c_{jmt}^{i}$. In the case of a pure online product, the ticketing carrier is also the sole operating carrier of product j, i.e., $i = f$.

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 (5) yields the following set of *J* first-order conditions – one for each of the *J* products in the market:

$$\sum_{k \in B_i} (p_k - mc_k) \frac{\partial s_k}{\partial p_j} + s_j = 0 \;\; for\ all\ j = 1, \dots, J \tag{6}$$

We have dropped the market and time subscripts in equation (6) only to avoid a clutter of notation. The set of first-order conditions can be represented in matrix notation as follows:

$$(\Omega .\ast \Delta) \times (p - mc) + s = 0 \tag{7}$$

where *p*, *mc*, and *s* are $J \times 1$ vectors of product prices, marginal costs, and predicted product shares respectively, Ω is a $J \times J$ matrix of appropriately positioned zeros and ones that capture ticketing carriers' "ownership" structure of the *J* products in a market, $.\ast$ is the operator for element-by-element matrix multiplication, and Δ is a $J \times J$ matrix of own and cross-price effects, where element $\Delta_{jk} = \frac{\partial s_k}{\partial p_j}$. Since for purposes of the model the ticketing carrier is considered the "owner" of a product, in the discussion that follows, "airline" is synonymous with ticketing carrier.

Equation (7) can be re-arranged to yield a vector of product markups:

$$mkup(x, \xi; \Phi^{\mathrm{d}}) = p - mc = -(\Omega .\ast \Delta)^{-1} \times s \tag{8}$$

Based on equations (5) and (8), and with estimates of demand parameters in hand, $\widehat{\Phi^{\mathrm{d}}}$, firm-level variable profit can be recovered by:

[10] The implicit assumption here is that the ticketing carrier of a virtual codeshare product only incurs fixed expenses in marketing the product to potential passengers.

$$VP_{imt} = \sum_{j \in B_{imt}} mkup_{jmt}(x, \xi; \widehat{\Phi^{\mathrm{d}}}) q_{jmt} \quad (9)$$

3.3 Dynamic Entry/Exit Game

In the dynamic entry/exit game, each airline chooses markets in which to be active during specific time periods. An airline being active in a market means that the airline actually sells products to consumers in the market even though a subset of those products may use the operating services of the airline's codeshare partner carriers. Each airline optimally makes this decision in order to maximize its expected discounted stream of profit:

$$E_t \left(\sum_{r=0}^{\infty} \beta^r \Pi_{im,t+r} \right) \quad (10)$$

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*. Airline *i*'s per-period profit is:

$$\Pi_{imt} = a_{im,t-1} VP_{imt} - a_{imt} F_{imt} \quad (11)$$

where VP_{imt} represents the variable profit of airline *i* in origin-destination market *m* during period *t* that is computed from the previously discussed differentiated products Nash price-setting game; $a_{im,t-1}$ is a zero-one indicator that equals 1 only if airline *i* had made the decision in period *t-1* to be active in market *m* during period *t*, therefore $a_{imt} = 1$ only if airline *i* makes decision in period *t* to be active in market *m* during period *t+1*; and F_{imt} is the sum of fixed and entry costs of airline *i* in market *m* during period *t*.

Let F_{imt} be specified as:

$$F_{imt} = FC_{imt} + \epsilon_{imt}^{FC} + \left(1 - a_{im,t-1}\right)\left[EC_{imt} + \epsilon_{mt}^{Trad} + \epsilon_{mt}^{Virt} + \epsilon_{imt}^{EC}\right] \quad (12)$$

where FC_{imt} represents the deterministic part of per-period fixed cost of operating flights in origin-destination market *m*. The component ϵ_{imt}^{FC} represents a private firm-idiosyncratic shock to airline *i's* fixed cost. The fixed cost $FC_{imt} + \epsilon_{imt}^{FC}$ is paid now only if the airline decides to be active in market *m* next period, i.e., if $a_{imt} = 1$.

The entry cost $EC_{imt} + \epsilon_{mt}^{Trad} + \epsilon_{mt}^{Virt} + \epsilon_{imt}^{EC}$ has four components; EC_{imt} is a deterministic component, while ϵ_{mt}^{Trad}, ϵ_{mt}^{Virt}, and ϵ_{imt}^{EC} represent shocks to entry cost. Shocks

ϵ_{mt}^{Trad} and ϵ_{mt}^{Virt} only vary by market and time and are observed by firms, but not by us the researchers, while ϵ_{imt}^{EC} represents a private firm-idiosyncratic shock to airline *i's* entry cost. The entry cost is paid only when the airline is not active in market *m* at period *t* but it decides to be active in the market next period, i.e., if $a_{im,t-1} = 0$ and $a_{imt} = 1$.

Let the composite private firm-idiosyncratic shock to airline *i's* fixed and entry costs be denoted by ε_{imt}. Based on equation (12), $\varepsilon_{imt} = \epsilon_{imt}^{FC} + \left(1 - a_{im,t-1}\right)\epsilon_{imt}^{EC}$. We assume that the composite private information shock, ε_{imt}, is independently and identically distributed over firms, markets and time, and has a type 1 extreme value probability distribution function.

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

$$FC_{imt} = \theta_0^{FC} + \theta_1^{FC} Pres_{imt} \tag{13}$$

$$\begin{aligned} EC_{imt} = \theta_0^{EC} + \theta_1^{EC} Pres_{imt} \quad &+ \theta_2^{EC} Percent\_Trad_{mt} \\ &+ \theta_3^{EC} Percent\_Virtual_{mt} + \theta_4^{EC} Percent\_Trad_{mt} \\ &\times Southwest + \theta_5^{EC} Percent\_Virtual_{mt} \times Southwest \\ &+ \theta_6^{EC} Percent\_Trad_{mt} \times Other\_lcc \\ &+ \theta_7^{EC} Percent\_Virtual_{mt} \times Other\_lcc \end{aligned} \tag{14}$$

where $Pres_{imt}$ is the mean across size-of-presence variables *Opres_in* and *Dpres_out* for airline *i* at the endpoint cities of market *m*;[11] $Percent\_Trad_{mt}$ is the percent of products in market *m* during period *t* that are traditional codeshare; $Percent\_Virtual_{mt}$ is the percent of products in market *m* during period *t* that are virtual codeshare; *Southwest* is a zero-one dummy variable that equals to one only if the airline is Southwest; $Other\_lcc$ is a zero-one dummy variable that equals to one for low-cost carriers other than Southwest; and $\{\theta_0^{FC}, \theta_1^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}, \theta_5^{EC}, \theta_6^{EC}, \theta_7^{EC}\}$ is the set of structural parameters to be estimated.

$Percent\_Trad_{mt}$ and $Percent\_Virtual_{mt}$ measure the extent of codesharing that takes place in a market. While we do not explicitly model airlines' optimizing decision of whether or

[11] As we previously defined in the section, *Definitions and Data*, *Opres_in* is a variable that counts the number of different cities that the airline provides nonstop flights from, going into the origin city of the market, while variable *Dpres_out* counts the number of distinct cities that the airline has nonstop flights to, leaving from the destination city.

not to codeshare in a market, it is reasonable to conjecture that this optimizing decision is influenced by the effective cost an airline faces to use its own planes to begin providing service in the market (part of its market entry cost). This further suggests that shocks to market entry cost that are unobserved to us, ϵ_{mt}^{Trad} and ϵ_{mt}^{Virt}, are likely to influence $Percent\_Trad_{mt}$ and $Percent\_Virtual_{mt}$ respectively. As such, we formally specify the following equations:

$$Percent\_Trad_{mt} = Z_{mt}\gamma + \epsilon_{mt}^{Trad} \tag{15}$$

$$Percent\_Virtual_{mt} = Z_{mt}\lambda + \epsilon_{mt}^{Virt} \tag{16}$$

where Z_{mt} is a matrix of variables that influence the extent of traditional and virtual codesharing that takes place in a market; γ and λ are vectors of parameters associated with these variables in equations (15) and (16) respectively; while ϵ_{mt}^{Trad} and ϵ_{mt}^{Virt} are assumed to be independently and identically distributed normal random variables with mean zero and standard deviations σ^{Trad} and σ^{Virt} respectively. Therefore, the model accounts for the endogeneity of variables $Percent\_Trad_{mt}$ and $Percent\_Virtual_{mt}$ in the entry cost function.

The variables we include in Z_{mt} are: (1) the geometric mean of the origin city and destination city populations (*POP*), which is a measure of market size; (2) nonstop flight distance between the origin and destination; (3) one-period lag of the Herfindahl-Hirschman Index (HHI) computed based on the relative sizes of airlines' presence at the market endpoint cities, where an airline's size of city presence is measured by the previously defined variables, *Opres_in* and *Dpres_out*; [12] (4) origin city fixed effects; (5) destination city fixed effects; and (6) quarter fixed effects.

The set of structural parameters in the dynamic model to be estimated is $(\theta, \gamma, \lambda)$ where:

$$\theta = \{\theta_0^{FC}, \theta_1^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}, \theta_5^{EC}, \theta_6^{EC}, \theta_7^{EC}\}'. \tag{17}$$

θ_0^{FC} measures mean (across airlines, markets and time) fixed cost, while θ_1^{FC} measures the effect that size of an airline's city presence has on fixed cost. 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. In our previous discussion we define (w, Γ) as a privately negotiated codeshare contract between partner carriers, where w is a per-passenger

[12] *Opres_in* is a variable that counts the number of different cities that the airline provides nonstop flights from, going into the origin city of the market, while variable *Dpres_out* counts the number of distinct cities that the airline has nonstop flights to, leaving from the destination city.

price the ticketing carrier pays 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. It was shown 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.

θ_0^{EC} measures mean (across airlines, markets and time) entry cost – we also allow mean entry cost to differ by the three carrier-types we consider (*Legacy*, *Southwest* and *Other low cost carriers*), in which case θ_0^{EC} would be a vector containing three parameters; θ_1^{EC} measures the effect that size of an airline's city presence has on entry cost; θ_2^{EC} and θ_3^{EC} respectively measure the impact that traditional and virtual codesharing between incumbent airlines have on market entry costs of legacy carriers that are potential entrants to the relevant market, that is $\frac{\partial EC_{legacy}}{\partial Percent\_Trad} = \theta_2^{EC}$ and $\frac{\partial EC_{legacy}}{\partial Percent\_Virtual} = \theta_3^{EC}$; θ_4^{EC} and θ_5^{EC} measure the respective differential impacts that traditional and virtual codesharing between incumbent airlines have on market entry cost of Southwest when it is a potential entrant to the relevant market, relative to the entry cost impacts that these two types of codesharing have on potential entrants that are legacy carriers, that is $\frac{\partial EC_{Southwest}}{\partial Percent\_Trad} - \frac{\partial EC_{legacy}}{\partial Percent\_Trad} = \theta_4^{EC}$ and $\frac{\partial EC_{Southwest}}{\partial Percent\_Virtual} - \frac{\partial EC_{legacy}}{\partial Percent\_Virtual} = \theta_5^{EC}$; while θ_6^{EC} and θ_7^{EC} measure the respective differential impacts that traditional and virtual codesharing between incumbent airlines have on market entry cost of other low-cost carriers that are potential entrants to the relevant market, relative to the entry cost impacts that these two types of codesharing have on potential entrants that are legacy carriers, that is $\frac{\partial EC_{Other\_lcc}}{\partial Percent\_Trad} - \frac{\partial EC_{legacy}}{\partial Percent\_Trad} = \theta_6^{EC}$ and $\frac{\partial EC_{Other\_lcc}}{\partial Percent\_Virtual} - \frac{\partial EC_{legacy}}{\partial Percent\_Virtual} = \theta_7^{EC}$. For example, if $\theta_4^{EC} > 0$, then we can infer that traditional codesharing between incumbent carriers raises Southwest's entry cost to the relevant market, relative to the change in entry cost of potential entrant legacy carriers. Likewise, if $\theta_6^{EC} > 0$, then we can infer that traditional codesharing between incumbent carriers raises other low-cost carriers' entry cost to the relevant market, relative to the change in entry cost of potential entrant legacy carriers.

Our specified equations do not include a firm-specific component of fixed cost and entry cost for two reasons. First, estimation of the dynamic model is computationally quite intensive, and convergence is difficult to achieve when the number of parameters being optimized over is large. Even with the model restricted to 10 parameters and four quarters of data, optimization took approximately seven days of continuously running the computer program. Second, even without firm-specific parameters, the fixed and entry cost functions do capture some heterogeneity across firms via the firm-specific variable $Pres_{imt}$.

Reducing the dimensionality of the dynamic game

From the previously discussed Nash price-setting game, firm-level variable profit is: $VP_{imt}\left(x, \xi; \Phi^{\mathrm{d}}\right) = \sum_{j \in B_{imt}} mkup_{jmt}(x, \xi; \Phi^{\mathrm{d}}) * q_{jmt}$. Let

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

Note that (x, ξ) are state variables that are needed in the dynamic entry/exit game. As pointed out and discussed in Aguirregabiria and Ho (2012), R^*_{imt} aggregates these state variables in an economically meaningful way so that these state variables can enter the dynamic game through R^*_{imt}. Therefore, Aguirregabiria and Ho (2012) recommend treating R^*_{imt} as a firm-specific state variable, rather than treating x and ξ as separate state variables. This innovation substantially reduces the dimensionality of the state space. The payoff-relevant information of firm *i* in market *m* is:

$$y_{imt} \equiv \{s_{imt}, R^*_{imt}, Pres_{imt}, Percent\_Trad_{mt}, Percent\_Virtual_{mt}, \epsilon^{Trad}_{mt}, \epsilon^{Virt}_{mt}\}. \tag{19}$$

where $s_{imt} = a_{im,t-1}$.

Each airline has its own vector of state variables, y_{imt}, and airlines take into account these variables when making decisions. So it might seem that each airline does not take into account the strategies that other airlines adopt. However, an airline’s vector of state variables, y_{imt}, depends on previous period entry and exit decisions of other airlines. For example, the variable profit state variable, R^*_{imt}, depends on competition from other incumbents currently in the market, which implies that this state variable depends on the previous period’s entry/exit decisions of other airlines. Accordingly, our entry/exit model incorporates dynamic strategic interactions among airlines.

Let $\sigma \equiv \{\sigma_{im}(y_{imt}, \varepsilon_{imt}), i = 1,2,..,N; m = 1,2,\ldots,M\}$ 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 value of airline i at every state $(y_{imt}, \varepsilon_{imt})$ given the opponent's strategy.

Value Function and Bellman Equation

For notational convenience, we drop the market subscript. 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:

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

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. The profile of strategies in σ is a MPE if, for every airline *i* and every state (y_t, ε_{it}), we have:

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

The transition rules we use for state variables are described in Appendix A. In Appendix B 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.

4. Estimation and Results

4.1 Estimation of demand

It is well-known in the empirical industrial organization literature that in case of the nested logit model, the demand equation to be estimated takes the following linear functional form [see Berry (1994)]:

$$\ln\left(S_j\right) - \ln(S_0) = x_j\phi^x - \phi^p p_j + \delta \ln\left(S_{j|g}\right) + \xi_j \tag{22}$$

where S_j is the observed share of product j, S_0 is the share of the outside alternative for the market, and $S_{j|g}$ is the observed product share within group g.

Percent Traditional for Airline and *Percent Virtual for Airline* are two of the non-price product characteristic variables in x_j. Recall that variables *Percent Traditional for Airline* and *Percent Virtual for Airline* measure the percentage of an airline's products in a market that are traditional codeshare and virtual codeshare respectively. Since airlines optimally choose the extent to which to codeshare with others in a market, it is possible that these codeshare variables are correlated with shocks to demand captured in ξ_j, making *Percent Traditional for Airline* and *Percent Virtual for Airline* endogenous in the demand equation. In addition, it is well-known that p_j and $ln(S_{j|g})$ are correlated with ξ_j. Therefore, our estimation of the demand equation takes into account the endogeneity of p_j, $ln(S_{j|g})$, *Percent Traditional for Airline* and *Percent Virtual for Airline*. Specifically, we find instruments for these four variables and use two-stage-least squares (2SLS) to estimate the demand equation.

Instruments for endogenous variables in demand equation

To obtain valid instruments for price and within group product share, we exploit the fact that the menu of products offered by airlines in a market is predetermined at the time of shocks to demand. Furthermore, the non-price characteristics of an airline's products are primarily determined by the route network structure of the airline, and unlike price and within group product share, this network structure is 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 associated non-price characteristics.

The instruments we use for product price are: (1) number of competing products offered by other carriers with equivalent number of intermediate stops; (2) the squared deviation of a product's itinerary distance from the average itinerary distance of competing products offered by other airlines; (3) the number of other products offered by an airline in a market; (4) itinerary distance; and (5) the interaction between jet fuel price[13] and itinerary distance. The inclusion of these instruments is motivated by supply theory, which predicts that the price of a product will be influenced by changes in its markup and marginal cost.

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

The rationale for instruments (1) and (2) is that they are measures of the degree of competition that a product faces, which affects the size of a product's markup. Next, it is reasonable to assume that a multiproduct airline jointly sets the prices of its products in the market. Standard oligopoly theory tells us that the more substitutable products are, they will be priced higher if they are jointly priced by a single firm compared to if they are separately priced by different firms. This rationale leads us to believe that instrument (3) is correlated with product markup, and by extension product price. Instruments (4) and (5) should affect an airline's marginal cost of providing the product, which in turn influences the price of the product.

To instrument the log of within group product share, $ln(S_{j|g})$, we use the mean number of intermediate stops across products offered by an airline in a market. The rationale is that such an instrument is likely associated with passengers' preference for products offered by one airline relative to the products offered by another.

For the variables *Percent Traditional for Airline* and *Percent Virtual for Airline*, we adopt two instruments: (*i*) one-period lag of the squared deviation of an airline's size presence at the market endpoint cities from the average size presence of other airlines at the market endpoints; and (*ii*) the interaction of (*i*) with nonstop flight distance. The size of an airline's presence at the market endpoints is computed by averaging across variables *Opres_in* and *Dpres_out*, which are variables we defined in the *Definitions and Data* section. An airline's measures of *Opres_in* and *Dpres_out* at the endpoints of a market are more determined by the airline's extended route network structure rather than features of the given origin-destination market. Therefore, it is reasonable to assume that *Opres_in* and *Dpres_out* are uncorrelated with ξ_j. In addition, lower presence for an airline at the endpoints of a market makes it more likely that the airline will codeshare with others that are already serving the market. So *Opres_in* and *Dpres_out* are in principle good instruments for *Percent Traditional for Airline* and *Percent Virtual for Airline*. Last, we allow the influence of an airline's size of presence at the market endpoints on its extent of market codesharing to depend on the nonstop flight distance of the market. This explains the rationale for instrument (*ii*).

4.2 Results from demand estimation

We estimate the demand equation using both Ordinary Least Square (OLS) and Two-stage Least Squares (2SLS). The demand regression results are presented in Table 1.6. First, focusing on the coefficient estimates for variables *Fare* and *ln(Sj/g)*, we find that even though the signs of these coefficients in both OLS and 2SLS regressions are consistent with intuition, there are large differences in the size of the coefficient estimates when compared across the OLS and 2SLS regressions. Even more contrasting, are the OLS versus the 2SLS coefficient estimates on variables *Percent Traditional for Airline* and *Percent Virtual for Airline*. This preliminary evidence suggests that estimates in the OLS regression are biased and inconsistent and thus instruments are needed for these endogenous variables.

To formally confirm that variables *Fare, ln(Sj/g), Percent Traditional for Airline* and *Percent Virtual for Airline* are endogenous, we perform a Hausman exogeneity test. The result of the Hausman test shown in Table 1.6 easily rejects the exogeneity of these four variables at conventional levels of statistical significance. As a check on the validity of instruments used for the 2SLS regression, we estimate first-stage reduced-form regressions for each of the endogenous variables. When *Fare* is the dependent variable in the reduced-form regression, R-squared is 0.32, but when *ln(Sj/g)* is the dependent variable R-squared is 0.56. When *Percent Traditional for Airline* and *Percent Virtual for Airline* are dependent variables, the R-squared values are respectively 0.61 and 0.51. Hence, the following discussion of demand regression results in Table 1.6 is based on 2SLS estimates.

Since coefficient estimates are all statistically significant at conventional levels of statistical significance, the remainder of the discussion focuses on the signs of the coefficient estimates. As expected, the coefficient estimate on *Fare* is negative, implying that higher prices are associated with lower levels of utility. In other words, all else equal, passengers prefer cheaper air travel products.

The coefficient estimate on *Opres_out* is positive. This result is consistent with our priors, and suggests that travelers prefer to fly with airlines, all else equal, that offer services to more destinations from the travelers' origin city. This estimated effect is possibly in part due to the benefits of frequent-flyer programs. Travelers are more likely to hold frequent-flyer membership with the airline they think they are most likely to use in the future, and it is reasonable for a passenger to conjecture that they will most often use the airline that offers service to a relatively large number of destinations from the passenger's origin city. Once the passenger becomes invested in the airline's frequent-flyer program, this helps reinforce the passenger's loyalty to the airline.

Table 1.6 Demand Estimation

Variables	OLS Estimates	OLS Std. Error	2SLS Estimates	2SLS Std. Error
Fare	-0.0004***	2.96E-05	-0.0094***	0.0002
ln(Sj/g)	0.4925***	0.0012	0.0672***	0.0047
Opres_out	0.0114***	0.0001	0.0064***	0.0002
Nonstop	1.1147***	0.0059	1.4223***	0.0119
Inconvenience	-0.9144***	0.0067	-0.8404***	0.0123
Traditional Codeshare	-0.3232***	0.0124	-8.2078***	0.3781
Virtual Codeshare	-0.5009***	0.0132	-7.4341***	0.2327
Percent Traditional for Airline	-0.0023***	0.0002	0.1487***	0.0075
Percent Virtual for Airline	-0.0084***	0.0002	0.1335***	0.0047
Spring	0.1421***	0.0038	0.1400***	0.0076
Summer	0.1065***	0.0038	0.1159***	0.0075
Fall	0.0857***	0.0038	0.0744***	0.0074
Constant	-4.2022***	0.0180	-3.4225***	0.0424
Ticketing carrier fixed effects	YES		YES	
Year fixed effects	YES		YES	
Market Origin fixed effects	YES		YES	
Market Destination fixed effects	YES		YES	
R-squared	0.6142		.	
Durbin-Wu-Hausman chi-sq test:	58663.8***	p = 0.0000		
Robust regression F test:	20168.2***	p = 0.0000		

*** indicates statistical significance at 1%

The coefficient estimate on *Nonstop* is positive, implying that consumers prefer nonstop flights between their origin and destination compared to travel itineraries that require intermediate stops. This is reasonable since passengers should prefer the most convenient travel itinerary from origin to destination. In addition, the coefficient estimate on *Inconvenience* is negative. This intuitively makes sense as well since passengers prefer the most direct route to the destination.

The *Traditional Codeshare* dummy variable has a negative coefficient estimate, implying that a traditional codeshare product makes passengers' utility lower relative to a pure online product. A likely reason is that the flight itinerary for a pure online product is typically very streamlined because an airline can better organize its own flights and schedules to minimize layover time, as well as efficiently organize its own gates at airports. Even though codeshare partners try to streamline flights across carriers to minimize layover times and facilitate smoother connections, the negative coefficient estimate on the *Traditional Codeshare* variable suggests that this process has not achieved parity with pure online products [Gayle (2013)].

The *Virtual Codeshare* dummy variable has a negative coefficient estimate as well. This result suggests that passengers perceive virtual codeshare products as inferior substitutes to pure online products. For the itineraries that include virtual segments, first-class upgrades using accumulated frequent-flyer miles are not usually available [Ito and Lee (2007)]. This could explain why passengers perceive virtual codeshare products as inferior to pure online products.

Note that the coefficient estimates on both *Percent Traditional for Airline* and *Percent Virtual for Airline* are positive, suggesting that consumers tend to choose the airlines that have a higher percentage of their products being codeshared. This result is consistent with the argument that airline codesharing has a demand-increasing effect [Gayle and Brown (2012)]. The rationale for a demand-increasing effect is due to the fact that codeshare partners typically make their frequent-flyer programs reciprocal, thus allowing travelers holding frequent-flyer membership with one partner carrier to accumulate frequent-flyer points when flying with any partner carrier in the alliance. Thus the new opportunities for travelers to accumulate frequent-flyer points across partner carriers can increase demand for the codeshare partners' products.

It is worth noting that the coefficient estimate on *Percent Traditional for Airline* is larger than the coefficient estimate on *Percent Virtual for Airline*, suggesting that traditional codesharing may have a larger impact on increasing demand relative to virtual codesharing. This result makes sense since traditional codesharing requires that partner carriers' route networks are complementary, while virtual codesharing does not. In the situations where partner carriers' route networks are complementary, and therefore require passengers to fly on separate partner carriers' planes to complete a trip, there are greater opportunities for passengers to accumulate frequent-flyer miles from the partner's reciprocal frequent-flyer programs. In other words, frequent-flyer membership with a partner carrier is likely more valuable to customers when partner carriers' route networks are complementary. To the best of our knowledge, this formal evidence suggesting that traditional codesharing may have a larger impact on increasing demand relative to virtual codesharing has not been previously investigated in the literature. So this is a new result, which may also help explain some key results from the dynamic model.

The coefficient on *ln(Sj/g)* is δ, measuring the correlation of consumers' preferences for products offered for sale by the same airline. Our estimate of δ is 0.067. Given that we nest products by airlines and δ is statistically significant, this suggests that passengers' choice behavior shows some amount of brand-loyalty to airlines. However, since the estimate of δ is closer to zero than it is to one, then this brand-loyal behavior is not very strong.

The demand model yields a mean own-price elasticity estimate of -1.62. As pointed out by Oum, Gillen and Noble (1986) and Brander and Zhang (1990), a reasonable range for own-price elasticity in the airline industry is from -1.2 to -2.0. Peters (2006) study of the airline industry yields own-price elasticity estimates ranging from -3.2 to -3.6. Berry and Jia (2010) find own-price elasticity estimates ranging from -1.89 to -2.10 in their year 2006 sample, while Gayle and Wu (2012) find own-price elasticity estimates ranging from -1.65 to -2.39 in their year 2010 sample. Therefore, we are satisfied that the elasticity estimates generated from our model are reasonable and consistent with evidence in the existing literature.

As revealed by equation (8), the demand parameter estimates in Table 1.6 can be combined with the short-run supply-side Nash equilibrium price-setting assumption to compute product markups. Overall, mean price is \$166.35, while the computed mean product markup is \$109.03. We also use the demand estimates along with equations (8) and (9) to compute quarterly market-level variable profits by airline. As we stated previously in the data section of the paper, the original database, before any cleaning, is only a 10% random sample of air travel tickets sold. This implies that the magnitudes of our variable profit estimates are at most roughly 10% of actual variable profits. Variable profits are measured in constant year 1999 dollars. Overall, an airline's mean quarterly market-level variable profit is \$82,775.43, while the median is \$31,492.71.

4.3 Estimation of Dynamic Model

The likelihood function for the dynamic model is given by,

$$L(\theta,\gamma,\lambda) = \prod_{m=1}^{M}\prod_{i=1}^{N}\prod_{t=1}^{T} P\left(\boldsymbol{a}_{mt}|\tilde{Z}_{imt}^{P},\tilde{e}_{imt}^{P},\epsilon_{mt}^{Trad},\epsilon_{mt}^{Virt},\theta\right) f\left(\epsilon_{mt}^{Trad}|Z_{mt},\gamma\right) f\left(\epsilon_{mt}^{Virt}|Z_{mt},\lambda\right) \quad (23)$$

where $\boldsymbol{a}_{mt} = (a_{1mt}, a_{2mt}, \ldots, a_{Nmt})$ is the vector of market participation actions taken by airlines in period t. Note that the likelihood function is comprised of three parts. The first part,

$P(\boldsymbol{a}_{mt}|\tilde{Z}^P_{imt}, \tilde{e}^P_{imt}, \epsilon^{Trad}_{mt}, \epsilon^{Virt}_{mt}, \theta)$ computes the conditional likelihood of observing the logit choice probabilities of airlines being active in markets across the sample during the time span of the data. To obtain the full unconditional likelihood, we multiply the conditional likelihood by the probabilities of observing specific values of ϵ^{Trad}_{mt} and ϵ^{Virt}_{mt}, where $\epsilon^{Trad}_{mt} = Percent\_Trad_{mt} - Z_{mt}\gamma$ and $\epsilon^{Virt}_{mt} = Percent\_Virtual_{mt} - Z_{mt}\lambda$ based on equations (15) and (16). Since we assume that ϵ^{Trad}_{mt} and ϵ^{Virt}_{mt} are normally distributed random variables with zero means and standard deviations σ^{Trad} and σ^{Virt} respectively, then $f(\cdot)$ is the normal probability density function.

While joint estimation of the full set of parameters $(\theta, \gamma, \lambda)$ is desirable due to potential efficiency gains, such joint estimation is extremely computationally demanding in this dynamic model. Fortunately, a convenient feature of the likelihood function above is that each of the three vectors of parameters in $(\theta, \gamma, \lambda)$ is identified by separate parts of the likelihood function. Specifically, $P(\boldsymbol{a}_{mt}|\tilde{Z}^P_{imt}, \tilde{e}^P_{imt}, \epsilon^{Trad}_{mt}, \epsilon^{Virt}_{mt}, \theta)$ is the part that identifies parameters in vector θ, while $f(\epsilon^{Trad}_{mt}|Z_{mt}, \gamma)$ and $f(\epsilon^{Virt}_{mt}|Z_{mt}, \lambda)$ are the parts that identify parameter vectors γ and λ respectively. This implies that parameter vectors γ and λ can be separately estimated in a first step using likelihood functions $\prod_{m=1}^{M}\prod_{t=1}^{T} f(\epsilon^{Trad}_{mt}|Z_{mt}, \gamma)$ and $\prod_{m=1}^{M}\prod_{t=1}^{T} f(\epsilon^{Virt}_{mt}|Z_{mt}, \lambda)$ respectively. Given estimates $\hat{\gamma}$ and $\hat{\lambda}$, we can compute $f(\epsilon^{Trad}_{mt}|Z_{mt}, \hat{\gamma})$ and $f(\epsilon^{Virt}_{mt}|Z_{mt}, \hat{\lambda})$ and use them to construct the relevant parts of $L(\theta, \hat{\gamma}, \hat{\lambda})$ in order to estimate $\hat{\theta}$ in a second step.

Based on the discussion above, we use the following pseudo log likelihood function to estimate parameters in vector θ:

$$
\begin{aligned}
Q(\theta, \boldsymbol{P}, \hat{\gamma}, \hat{\lambda}) = \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{t=1}^{T} \{ & a_{imt} ln[\psi(\tilde{Z}^P_{imt} \times \theta + \tilde{e}^P_{imt})] \\
& + (1 - a_{imt}) ln[\psi(-\tilde{Z}^P_{imt} \times \theta - \tilde{e}^P_{imt})] + ln[f(\epsilon^{Trad}_{mt}|Z_{mt}, \hat{\gamma})] \\
& + ln[f(\epsilon^{Virt}_{mt}|Z_{mt}, \hat{\lambda})]\}
\end{aligned} \tag{24}
$$

where $Q(\theta, \boldsymbol{P}, \hat{\gamma}, \hat{\lambda})$ is called a "pseudo" log likelihood function because airlines' conditional choice probabilities (CCPs) in $\psi(\cdot)$ are arbitrary and do not represent the equilibrium probabilities associated with θ, where θ is the vector of parameters in the fixed and entry cost functions previously specified in equations (13) and (14). Since the focus now is describing how

θ is estimated, in what follows we drop $\hat{\gamma}$ and $\hat{\lambda}$ when discussing "pseudo" log likelihood function $Q(\cdot)$ only for notational convenience.

We begin by implementing the Pseudo Maximum Likelihood (PML) estimation procedure [Aguirregabiria and Ho (2012)]. The PML requires two steps. In step 1, we estimate relevant state transition equations. Appendix A describes transition rules used for state variables. In addition, nonparametric estimates of the choice probabilities $\widehat{P_0}$ are computed in step1. These nonparametric probability estimates, along with state variables and estimated state transition probabilities, are used to compute $\tilde{Z}_{imt}^{\widehat{P_0}}$ and $\tilde{e}_{imt}^{\widehat{P_0}}$ as described in Appendix B. Using $\tilde{Z}_{imt}^{\widehat{P_0}}$ and $\tilde{e}_{imt}^{\widehat{P_0}}$, we are able to construct the pseudo log likelihood function, $Q\left(\theta, \widehat{P_0}\right)$. In step 2 of the PML estimation algorithm, the vector of parameters $\hat{\theta}_{PML}$ is estimated by:

$$\hat{\theta}_{PML} = arg \max_{\theta} Q\left(\theta, \widehat{P_0}\right) \tag{25}$$

This PML algorithm is simple and does not require solving for an equilibrium in the dynamic game, and thus substantially reduces computational burden. However, the two-step pseudo maximum likelihood estimator $\hat{\theta}_{PML}$ can have a large finite sample bias [Aguirregabiria and Mira (2007)]. To achieve consistency of the parameter estimates, we follow Aguirregabiria and Mira (2002, 2007) and use as a starting point the PML parameter estimates along with the non-parametric estimates of the choice probabilities to implement the Nested Pseudo Likelihood (NPL) estimation algorithm. We describe the NPL estimation algorithm in Appendix C.[14]

Results from first-stage estimation of parameter vectors γ and λ

Table 1.7 reports the estimation results for first-stage estimation of parameter vectors γ and λ. The results suggest that more concentrated airline presence at the market endpoints (measured by variable *Lag HHI of Presence*), and longer distance between market endpoints (measured by variable *Nonstop Flight Distance*) seem to incentivize relatively higher levels of traditional codesharing, but lower levels of virtual codesharing. At a minimum we can infer

[14] While the demand model is estimated using all three years in the data set (2005, 2006 and 2007), due to significant computational burden, we find that the dynamic entry/exit model can only feasibly be estimated using, at most, four quarters of the data. We only use data in year 2005 when estimating the dynamic entry/exit model. Even with just four quarters of data, the computer code for the dynamic entry/exit model took more than seven days of continuous running before convergence is achieved.

from these results that airlines' choice of what type of codesharing to employ in a market depends in part on certain market characteristics. Last, results of F-tests shown in the table suggest that all regressors as a group do explain variations in $Percent\_Trad_{mt}$ and $Percent\_Virtual_{mt}$.

Table 1.7 Estimation of Linear Equations for Percent Codeshare Variables

	Dependent Variable: *Percent_Traditional*		Dependent Variable: *Percent_Virtual*	
Variables	Coefficient Estimates (γ)	Standard Error	Coefficient Estimates (λ)	Standard Error
POP	-2.84E-08	2.32E-07	1.37E-07	2.35E-07
Nonstop flight distance	0.0016***	7.68E-05	-0.0012***	7.79E-05
Lag HHI of Presence	0.9831**	0.4001	-3.6714***	0.4056
Constant	-1.5868***	0.4384	2.6997***	0.4444
Origin fixed effects	YES		YES	
Destination fixed effects	YES		YES	
Quarter fixed effects	YES		YES	
R-squared	0.2421		0.2943	
F-test	29.60	Prob>F = 0.000	38.63	Prob>F = 0.000

*** indicates statistical significance at 1%
** indicates statistical significance at 5%
Equations are estimated using ordinary least squares.

4.4 Results from the dynamic model

Table 1.8 reports estimates of parameters in the fixed and entry cost functions from the dynamic model. The quarterly discount factor, β, is fixed at 0.99 (that implies an annual discount factor of 0.96). All the estimated fixed and entry cost parameters are measured in ten thousands of annual 1999 dollars.

First, point estimates of parameters in the fixed cost function are unreasonably small and imprecisely estimated. As such, we cannot draw reliable inferences about the size of fixed cost. Fortunately, based on the objectives of our study we are most interested in parameter estimates in the entry cost function, which is where we now focus the remainder of the discussion.

Based on our Nash equilibrium price-setting game previously discussed, the median quarterly variable profit for an airline in a directional origin-destination market is estimated to be

\$31,492.71. Estimates from Table 1.8 show that the average estimated entry cost is approximately \$30,574, which is approximately 97 percent of variable profit. The decision of market entry is forward-looking, and our estimates suggest that it will take an airline slightly less than one quarter of variable profit to recoup the one-time sunk entry cost investment. Of course, an airline typically needs to use a portion of its variable profit to pay for recurrent fixed expenses that, in part, may be related to its airport operations – e.g. labor cost of ground crew at airport. Therefore, it is likely to take more than one quarter of variable profits to recoup the one-time sunk entry cost investment.

However, it is notable from the estimates that mean entry cost differs by the carrier categories considered. Southwest has the highest mean market entry cost followed by legacy carriers and other low-cost-carriers, \$33,498, \$30,755 and \$27,468 respectively. Furthermore, the pairwise difference between any two of these three mean market entry costs is statistically significant at conventional levels of statistical significance. Even though Southwest has the highest mean market entry cost, estimates from our short-run supply model reveal that it also has a relatively high median quarterly market-level variable profit of \$61,490.78. So based on Southwest's relatively high variable profit, it will only take Southwest a minimum of 0.54 of a quarter (approximately 49 days) of variable profit to recoup it's one-time sunk entry cost investment. In contrast, other low-cost-carriers have the lowest mean market entry cost, but they also have relatively low variable profit, a median \$35,976.57. So on average it takes other low-cost-carriers 0.76 of a quarter (approximately 69 days), which is longer than what it takes Southwest, of variable profits to recoup their one-time sunk entry cost investment.

"Size of Presence at market endpoints" in the entry cost function is variable $Pres_{imt}$ in equation (14). The estimated entry cost coefficient on "Size of Presence at market endpoints" is negative and statistically significant at conventional levels of statistical significance, suggesting that an airline's market entry cost decreases with the size of the airline's presence at the endpoint cities of the market. In other words, larger endpoint city presence makes it easier for the airline to actually start servicing the route. This result is consistent with how the literature believes airline markets work [see Berry (1992); Goolsbee and Syverson (2008); Gayle and Wu (2013) among others].

Table 1.8 Estimates of Parameters in Fixed and Entry Cost Functions

Variables	Parameter Estimates (θ) (In ten thousand $)	Standard Error
Fixed cost (quarterly):		
Mean fixed cost	1.9067E-09	0.0058
Size of Presence at market endpoints	-4.5820E-14	0.0001
Entry costs:		
Mean entry cost for Legacy carriers	3.0755***	0.0277
Mean entry cost for Southwest	3.3498***	0.0815
Mean entry cost for Other LCCs	2.7468***	0.0649
Size of Presence at market endpoints	-0.0072***	0.0004
Traditional Codesharing	-0.0197***	0.0024
Virtual Codesharing	-0.0042**	0.0019
Traditional Codesharing $\times$ Southwest	0.0295***	0.0099
Virtual Codesharing $\times$ Southwest	0.0069	0.0065
Traditional Codesharing $\times$ Other LCCs	0.0090	0.0073
Virtual Codesharing $\times$ Other LCCs	-0.0058	0.0051

*** indicates statistical significance at 1%
** indicates statistical significance at 5%

The coefficient estimates on traditional and virtual codesharing variables are negative and statistically significant. Based on our previous discussion of the interpretation of parameters in the entry cost function (equation (14)), the coefficients on these two codeshare variables essentially capture the influence of codesharing on the market entry cost of potential entrants that are legacy carriers. Therefore, these coefficient estimates suggest that an increase in the extent of codesharing by incumbent carriers in a market reduces the market entry cost of potential entrants that are legacy carriers.

Recall that our descriptive statistics in Table 1.3 show that: (1) the vast majority of codeshare products are provided by legacy carriers; and (2) almost all of each legacy carrier's codeshare products are codeshared with other legacy carriers. Therefore, the econometric evidence in Table 1.8 suggesting that more codesharing in a market makes it less costly for potential entrant legacy carriers to enter the market may in part be driven by the Chen and Ross (2000) argument, which is that incumbents may offer to share their facility (in our context, predominantly airplane seats owned by legacy carriers) with some potential entrants (apparently other legacy carriers) in order to discourage the potential entrant from entering on a larger, and more competitive, scale by exclusively using its own plane on the full route. In other words, entry may be encouraged, as reflected by the lower entry cost, in a way that limits the scale of entry.

A key result is that the coefficient estimate on the interaction variable between traditional codesharing and Southwest is positive and statistically significant, while the coefficient estimate on the interaction variable between virtual codesharing and Southwest is not statistically significant. These coefficient estimates suggest that traditional codesharing between incumbent carriers raises Southwest's entry cost to the relevant market, relative to the fall in entry cost of potential entrant legacy carriers, but virtual codesharing does not differentially affect Southwest' market entry cost relative to potential entrant legacy carriers. In other words, more traditional codesharing between incumbent carriers in a market puts Southwest at a relative disadvantage to enter the market compared to potential entrant legacy carriers.

The coefficient estimates on the interactions between *Other low-cost-carriers* and codeshare variables are not statistically significant at conventional levels of statistical significance. In other words, in terms of dollar amount changes, neither type of codesharing differentially affect *Other low-cost-carriers* market entry cost, relative to the fall in entry cost of potential entrant legacy carriers. We argue above that a possible reason why potential entrant legacy carriers find it less costly to enter markets with more codesharing is due to the fact that the incumbents that codeshare are typically legacy carriers, and legacy carriers typically codeshare with other legacy carriers. So what is the rationale for the econometric result that potential entrants that are other low-cost carriers do not find it any more difficult than potential entrant legacy carriers to enter a market with higher levels of codesharing? Perhaps a reason for this result is that a large set of consumers served by other low-cost carriers does not have significant overlap with the set of consumers served by legacy carriers, and therefore the two carrier types only weakly compete with each other. Brueckner, Lee and Singer (2012) provide evidence that supports this argument. Specifically, they find that incumbent legacy carriers do not cut fares in response to potential competition from other low-cost carriers, but cut fares by 8% in response to potential competition from Southwest.

A useful feature of the structural econometric model is that the model allows us to monetize the extent to which codesharing by market incumbent carriers influences market entry barriers faced by potential entrants. Parameter estimates in the entry cost function suggest that each percentage point increase in traditional codeshare products offered by incumbents in a market raises market entry cost for Southwest by 0.3% ($= \frac{\$295-\$197}{\$33{,}498} \times 100$). In contrast, each percentage point increase in traditional codeshare products offered by incumbents in a market reduces market entry cost by 0.6% ($= \frac{\$197}{\$30{,}755} \times 100$) for potential entrant legacy carriers, and by 0.7% ($= \frac{\$197}{\$27{,}468} \times 100$) for potential entrants that are "other" low-cost carriers.

Summary of key findings and discussion

In summary, based on coefficient estimates in the entry cost function, we can conclude that more traditional codesharing between incumbent carriers in a market puts Southwest at a relative disadvantage to enter the market compared to all other potential entrants (legacy carriers and other low-cost carriers). We interpret this result as suggesting that traditional codesharing has a relative market entry deterrent effect on Southwest. Furthermore, the results suggest that virtual codesharing does not have a market entry deterrent effect.

Codeshare partner carriers typically make their frequent-flyer programs reciprocal. In situations where partner carriers' route networks are complementary, and therefore require passengers to fly on separate partner carriers' planes to complete a trip, there are greater opportunities for passengers to accumulate frequent-flyer miles from the partner's reciprocal frequent-flyer programs. In other words, frequent-flyer membership with a partner carrier is likely more valuable to customers when partner carriers' networks are complementary. This suggests that market incumbents can more effectively increase their loyal customer base with traditional codesharing than they can via virtual codesharing, since traditional codesharing requires travel across complementary partner carriers' networks, while virtual codesharing requires air travel on a single carriers' network. The previously discussed demand results support this argument, since relevant demand coefficient estimates suggest that traditional codesharing is likely more demand-increasing for an airline relative to virtual codesharing.

An increase in incumbents' loyal customer base makes it more difficult for a new entrant to amass a sufficiently large customer base to make entry profitable. Therefore, the empirical result from our entry cost estimates suggesting that traditional codesharing between incumbents is entry deterring, but virtual codesharing is not, is quite reasonable and consistent with the arguments above and supported by our demand-side results on codesharing. Note also that Southwest's relatively higher market entry cost may simply be reflecting the increased difficulty it will face to amass a sufficiently larger customer base in these codeshare markets.

5. Concluding Remarks

The main objective of our paper is to use a structural econometric model to investigate: (1) whether codesharing between airlines in domestic air travel markets, a form of strategic alliance, has a deterrent effect on the entry of potential competitors; (2) whether there is a particular type of codesharing among alliance partners that is most effective at deterring entry; and (3) whether there is a particular type of airline that seems to be more deterred via such type of codesharing between alliance partners. One advantage of using a structural econometric model is that we are able to quantify, in monetary terms, possible market entry barriers associated with codesharing.

We find that more traditional codesharing between incumbent carriers in a market puts Southwest at a relative disadvantage to enter the market compared to all other potential entrants (legacy carriers and other low-cost carriers). Specifically, each percentage point increase in traditional codeshare products offered by incumbents in a market raises market entry cost for Southwest by 0.3%, but reduces market entry cost by 0.6% and 0.7% for legacy and "other" low-cost carriers respectively. Therefore, traditional codesharing by market incumbent carriers has a relative market entry deterrent effect on Southwest. Furthermore, we do not find any evidence that virtual codesharing has a market entry deterrent effect.

We link the market entry deterrent effects inferred from our entry cost estimates to findings from our demand estimates. Estimates from our demand model suggest that incumbents' traditional codesharing has a larger demand-increasing effect for their products compared to virtual codesharing. Since the demand-side evidence is consistent with the argument that traditional codesharing better serves to expand the loyal customer base of market incumbents, then with more traditional codesharing by incumbents, a potential entrant will find it more costly (higher market entry cost) to build its own customer base upon entry, making entry less profitable in these high traditional codeshare markets. We argue that this entry deterrent effect is binding for Southwest but not for others due to evidence that the vast majority of codesharing is done between legacy carriers, and competition between Southwest and legacy carriers is stronger than competition between other low-cost carriers and legacy carriers. For example, Brueckner, Lee and Singer (2012) provide evidence that incumbent legacy carriers do not cut fares in response to potential competition from other low-cost carriers, but cut fares by 8% in response to potential competition from Southwest.

We also find that an airline's market entry cost decreases with the size of the airline's presence at the endpoint cities of the market. This finding is consistent with findings in Aguirregabiria and Ho (2012), and may be due to economies of scale and scope by concentrating most operations in a hub airport.

The focus of our study is on U.S. domestic air travel markets, however future work may investigate whether results similar to ours exist for codesharing in international air travel markets.

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Appendix A - Transition Rules for State Variables

The state variables we observe are: $\{s_{imt}, R^*_{imt}, Pres_{imt}, Percent\_Trad_{mt}, Percent\_Virtual_{mt}\}$. Transition rules for state variables are as follows:

$$s_{im,t+1} = a_{it} \qquad \text{(A1)}$$

$$R^*_{im,t+1} = a_{imt}(\alpha_0^R + \alpha_1^R R^*_{imt} + \zeta^R_{imt}) \qquad \text{(A2)}$$

$$Pres_{im,t+1} = \alpha_0^{Pres} + \alpha_1^{Pres} Pres_{imt} + \zeta^{Pres}_{imt} \qquad \text{(A3)}$$

$$Percent\_Trad_{m,t+1} = \alpha_0^{Percent\_Trad} + \alpha_1^{Percent\_Trad} Percent\_Trad_{mt} + \zeta^{Percent\_Trad}_{mt} \qquad \text{(A4)}$$

$$Percent\_Virtual_{m,t+1} = \alpha_0^{Percent\_Virtual} + \alpha_1^{Percent\_Virtual} Percent\_Virtual_{mt} + \zeta^{Percent\_Virtual}_{mt} \qquad \text{(A5)}$$

where ζ^R_{imt}, ζ^{Pres}_{imt}, $\zeta^{Percent\_Trad}_{mt}$, and $\zeta^{Percent\_Virtual}_{mt}$ are assumed to be normally distributed.

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

$$F_i^\sigma(y_{t+1}|a_{it,}y_t) = \begin{cases} 1\{s_{i,t+1} = 1\} * \mathrm{Pr}_R * \mathrm{Pr}_{Pres} * \mathrm{Pr}_{Percent\_Trad} * \mathrm{Pr}_{Percent\_Vitual} * \mathrm{Pr}_{comp} \\ 1\{s_{i,t+1} = 0\} * \mathrm{Pr}_R{}' * \mathrm{Pr}_{pres} * \mathrm{Pr}_{Percent\_Trad} * \mathrm{Pr}_{Percent\_Vitual} * \mathrm{Pr}_{comp} \end{cases}$$

(A6)

where

$$\mathrm{Pr}_R = F_R(R_{it+1}|R_{it}) * \prod_{j\neq i} F_R(R_{jt+1}|R_{jt}) \qquad \text{(A7)}$$

$$\mathrm{Pr}_{Pres} = F_{Pres}(Pres_{it+1}|Pres_{it}) * \prod_{j\neq i} F_{Pres}(Pres_{jt+1}|Pres_{jt}) \qquad \text{(A8)}$$

$$\mathrm{Pr}_{Percent\_Trad} = F_{Percent\_Trad}(Percent\_Trad_{t+1}|Percent\_Trad_t) \qquad \text{(A9)}$$

$$\mathrm{Pr}_{Percent\_Virtual} = F_{Percent\_Virtual}(Percent\_Virtual_{t+1}|Percent\_Virtual_t) \qquad \text{(A10)}$$

$$\mathrm{Pr}_R{}' = 1\{R_{i,t+1} = 0\} * \prod_{j\neq i} F_R(R_{jt+1}|R_{jt}) \qquad \text{(A11)}$$

$$\mathrm{Pr}_{comp} = \prod_{j\neq i} Pr(s_{jt+1} = \sigma_j(y_{jt}, \varepsilon_{jt})|y_{jt}) \qquad \text{(A12)}$$

Appendix B - Representation of Markov Perfect Equilibrium (MPE) using Conditional Choice Probabilities (CCPs)

Recall that expected one-period profit function, $\Pi_{imt}(a_{it}, y_t)$, is specified as:

$$\Pi_{imt}(a_{it}, y_t) = R^*_{imt} - a_{imt}(FC_i + (1 - s_{imt})EC_i), \tag{B1}$$

where parametric specifications for FC_i and EC_i were previously given in equations (13) and (14). Based on equation (B1):

$$\Pi_{imt}(0, y_t) = R^*_{imt} \tag{B2}$$

and

$$\Pi_{imt}(1, y_t) = R^*_{imt} - FC_i - (1 - s_{imt})EC_i \tag{B3}$$

Let

$$z_{imt}(0, y_t) = \{R^*_{imt}, 0,0,0,0,0,0,0,0,0,0\} \tag{B4}$$

and

$$\begin{aligned} z_{imt}(1, y_t) \quad = \quad \Big\{ & R^*_{imt}, \quad -1, \quad -Pres_{imt}, \\ & -1, \quad -(1 - s_{it})Pres_{imt}, \\ & -(1 - s_{it})Percent\_Trad_{mt}, \\ & -(1 - s_{it})Percent\_Virtual_{mt}, \\ & -(1 - s_{it})Percent\_Trad_{mt} \times Southwest, \\ & -(1 - s_{it})Percent\_Virtual_{mt} \times Southwest, \\ & -(1 - s_{it})Percent\_Trad_{mt} \times Other\_lcc, \\ & -(1 - s_{it})Percent\_Virtual_{mt} \times Other\_lcc \Big\} \end{aligned} \tag{B5}$$

and

$$\theta = \{1, \theta_0^{FC}, \theta_1^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}, \theta_5^{EC}, \theta_6^{EC}, \theta_7^{EC}\} \tag{B6}$$

Therefore, we can re-write:

$$\Pi_{imt}(0, y_t) = z_{imt}(0, y_t) \times \theta \tag{B7}$$

and

$$\Pi_{imt}(1, y_t) = z_{imt}(1, y_t) \times \theta \tag{B8}$$

As discussed in Aguirregabiria and Ho (2012), the MPE can be represented as a vector of conditional choice probabilities (CCPs), **P**. **P** = {$P_i(y)$: *for every firm and state* (i, y)} that solves fixed point problem $\boldsymbol{P} = \psi(\boldsymbol{P}, \theta)$ is a vector of best response mapping:

$$\{\psi\left(\tilde{Z}_i^P(y)\frac{\theta}{\sigma_\varepsilon} + \tilde{e}_i^P(y)\right): for\ every\ firm\ and\ state\ (i, y)\} \tag{B9}$$

where in our study $\psi(\cdot)$ is the *CDF* of the type 1 extreme value distribution, and

$$\tilde{Z}_i^P(y) = Z_i(1, y) - Z_i(0, y) + \beta[F_{i,y}^P(1) - F_{i,y}^P(0)] \times w_{z,i}^P, \tag{B10}$$

$$\tilde{e}_i^P(y) = \beta[F_{i,y}^P(1) - F_{i,y}^P(0)] \times w_{e,i}^P, \tag{B11}$$

$$w_{z,i}^P = (1 - \beta * \overline{F_{i,y}^P})^{-1} \times \{P_i(y) * Z_i(1, y) + [1 - P_i(y)] * Z_i(0, y)\}, \tag{B12}$$

$$w_{e,i}^P = (1 - \beta * \overline{F_{i,y}^P})^{-1} \times [P_i(y) * e_i^P] \tag{B13}$$

and

$$\overline{F_{i,y}^P} = [(P_i(y) \times 1_M') * F_{i,y}^P(1) + \left(\left(1 - P_i(y)\right) \times 1_M'\right) * F_{i,y}^P(0)]. \tag{B14}$$

where $\mathrm{F}_{iy}^{\mathrm{P}}(0)$ and $\mathrm{F}_{iy}^{\mathrm{P}}(1)$ are state transition probability matrices for $a_{it} = 0$ and $a_{it} = 1$ respectively; $w_{z,i}^P$ and $w_{e,i}^P$ 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 γ = 0.5772 is Euler's constant.

Appendix C - Implementing the Nested Pseudo Likelihood (NPL) Estimator

Given the PML estimator, $\hat{\theta}_{PML}$, and the initial nonparametric estimate of CCPs, $\widehat{P_0}$, we construct a new estimator of CCPs, $\widehat{P_1}$,using the best response CCPs equation $\widehat{P_1} = \psi(y, \widehat{P_0}, \hat{\theta}_{PML})$. Then we redo the maximization of the pseudo likelihood function to obtain a new estimate of θ using $\widehat{P_1}$, instead of $\widehat{P_0}$, in the pseudo log likelihood function, that is, we solve $\hat{\theta}_2 = arg \max_{\theta} Q(\theta, \widehat{P_1})$. The process is repeated K times, and the K^{th} estimates of θ and P are obtained by $\hat{\theta}_K = arg \max_{\theta} Q(\theta, \widehat{P_{K-1}})$ and $\widehat{P_K} = \psi(y, \widehat{P_{K-1}}, \hat{\theta}_K)$ respectively. The algorithm is terminated on the K^{th} iteration only if the CCP vector $\widehat{P_K}$ is "close" to $\widehat{P_{K-1}}$ based on a stipulated tolerance level. Based on this algorithm, an NPL fixed point is defined as a pair $(\hat{\theta}_K, \widehat{P_{K-1}})$. Aguirregabiria and Mira (2002, 2007) argue that this NPL estimation algorithm can reduce significantly the finite sample bias of the two-step PML estimator.

Chapter 2 - Firms' Markup, Cost, and Price Changes when Policymakers Permit Collusion: Does Anti-trust Immunity Matter?

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 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. The application process provides carriers with the opportunity to make their case to the relevant authorities that the level of cooperation that antitrust immunity would allow will yield net benefits to consumers. A grant of antitrust immunity 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.

There are numerous instances since the 1990,s 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 antitrust immunity is, on net, beneficial for consumers. However, in recent time the DOJ has argued that antitrust immunity is not necessary for the 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.[15] Furthermore, DOJ points out that granting these airlines antitrust immunity will reduce competition in origin-destination markets between the U.S. and Europe where these carriers compete using nonstop flights.

Despite DOJ's concerns regarding granting antitrust immunity to these airlines, the DOT was convinced that there are sufficient efficiency gains associated with granting the carriers antitrust immunity, 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 antitrust immunity in 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 antitrust immunity on price, markup, and various categories of partner carriers' costs; and (2) investigate the relative effects of implementing an alliance without antitrust immunity versus an alliance with antitrust immunity.

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.[16] 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.

The arguments above describe situations in which an alliance may affect price via influencing the carriers' optimal choice of product markup over marginal cost. So the predicted

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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] 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 (2012); Whalen (2007); Zou, Oum, Yu (2011) among others.

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); 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 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 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.

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 antitrust immunity (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 antitrust immunity 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.

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 markups and quantity sold. With data on which markets each firm is active in 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 an impact on the markup of products offered by the members. For the subsequent grant of ATI to various members, even though we find evidence of increased markup on their products in markets where ATI carrier members each provide substitute products (their overlapping markets), the members' markup in other markets decreased.

Second, implementation of the oneworld alliance appears to increase rather than reduce marginal cost for the members, but the subsequent grant of ATI to various members is associated with reductions in their 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, both implementation of the oneworld alliance and subsequent grant of ATI to various members do not appear to have an impact on partners' sunk market entry cost, but the grant of ATI weakly reduced their recurrent fixed cost.

Last, results from a reduced-form price regression suggest that implementation of the oneworld alliance increased rather than reduced the prices of products offered by the members. More importantly, the subsequent grant of ATI to various members had no effect on price of products offered by ATI carrier members in their overlapping markets, and it led to reductions in their product price in all other markets.

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[17], 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 D1 in Appendix D 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.

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

The oneworld alliance global airline network provides services to more than 800 destinations in over 150 countries.[18] 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.[19]

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 D2 in Appendix D 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,[20] 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.[21] The rationale put forth by the DOT is that this slot remedy will sufficiently lower market entry barriers for potential competitors, and therefore effectively constrain anticompetitive behavior of the antitrust immune carriers. [22]

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

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

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

[21] 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

[22] 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

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.[23] 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[24] 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.[25] 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."[26,27] 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

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

[24] 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.

[25] 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.

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

[27] 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.

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 applicants' employees and shareholders.

In response to the application, DOJ issued a recommendation report on the possible market effects of granting antitrust immunity.[28] 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)

[28] 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.

Traditional Codeshare Type II; and (4) Virtual Codeshare. Table 2.1 provides examples of these categories for an itinerary that uses two segments (i.e. requires one intermediate stop) for the given direction[29] 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 segment(s) of the trip may be different from the classification category on the coming back segment(s) of the trip.

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.

Table 2.1 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

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 2.1 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.

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

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.

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. 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 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 D3 and Table AD in Appendix D 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 2.2 and Table 2.3 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 2.2 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 2.3 List of most frequent destination countries in the "AIT 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		

We define origin presence variables from two different perspectives. The variable *Opres_demand* is a count of the number of different airports that the airline has nonstop flights to, leaving from the origin airport. On the other hand, *Opres_cost* counts the number of airports within the United States that the airline provides nonstop flights from, going to the origin airport. *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.

The variables *Inconvenience_going* and *Inconvenience_coming* are respectively defined as ratios of the miles actually flown on the itinerary to the minimum miles flown in that market for departing and returning trips. As such, the minimum value *Inconvenience_going* or *Inconvenience_coming* can take is 1. Furthermore, an itinerary is less convenient as *Inconvenience_going* or *Inconvenience_coming* increases in value above 1.

Observed product share, S_j, is computed by dividing quantity of product j sold by origin city population, i.e. $S_j = {}^{q_j}/_{POP}$.[30] The population data are obtained from the population estimates of United States Census Bureau.

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 2.4. We use the consumer price index with a base year of 2005 to convert prices into constant year 2005 dollars.

[30] 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 remains positive. The common factor that satisfies these conditions is 183 in the “oneworld Event Sample” and 62 in the “ATI Event Sample”.

Table 2.4 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	6.495	38.496	1	3,210	5.401	38.477	1	3,279
Opres	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
Inconvenience going	1.071	0.131	1	2.346	1.076	0.138	1	2.541
Inconvenience coming	1.072	0.134	1	2.808	1.078	0.142	1	2.789
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 (Sj)	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.

4. Model

4.1 Demand

In the spirit of Peters (2006) and Berry and Jia (2010), we model air travel demand using a nested logit framework. 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. All products may be purchased by *POP* potential consumers. In our nested logit model, we classify products into *G+1* groups, *g = 0, 1,…, G*, where the outside good is the only good in group 0. Groups are defined by ticketing carriers in this study, so products with the same ticketing carrier belong to the same group. The level of utility consumer *c* will obtain from choosing product *j* is as follows:

$$u_{cj} = \mu_j + \delta\zeta_{cg} + (1-\delta)\varepsilon_{cj}^{d}, \tag{1}$$

where μ_j is the mean level of utility across consumers that purchase product *j*, ζ_{cg} is a random component of utility that is common to all products in group g, and ε_{cj}^{d} is consumer *c*'s unobserved utility, specific to product *j*. The parameter δ lies between 0 and 1 and measures the correlation of consumers' utility across products belonging to the same group. As δ approaches 1, the correlation of preferences across products within the same group increases. In contrast, as δ decreases, the correlation of preferences across commonly grouped products decreases. Since products are grouped by ticketing airlines, an estimate of δ reveals the extent to which consumers' preferences are correlated across products offered by the same airline. The reason we choose ticketing airlines as groups is that passengers might prefer to buy flight tickets from particular airlines because of loyalty due to previous experience or membership in the airlines' frequent-flyer program.

The mean level of utility across consumers that purchase product *j* is specified as:

$$\mu_j = x_j\phi^x - \phi^p p_j + \gamma_1 T_{post-Event} + \gamma_2 Event_{Member} + \gamma_3 T_{post-Event} \times Event\_Member + \xi_j , \tag{2}$$

where x_j and p_j are respectively a vector of observed non-price product characteristics and the price of product *j*; $T_{post-Event}$ 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; $Event\_Member$ is a zero-one airline dummy variable that equals 1 when the airline is a direct member of the event being analyzed; and ξ_j represents a composite of a product's characteristics that are observed by consumers and airlines, but unobserved to us the researchers. ϕ^x, ϕ^p, γ_1, γ_2 and γ_3 are parameters to be estimated.

Key parameters of interest in the mean utility function (equation (2)) 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 extent to which mean utility obtained from consuming products offered by event members changes, relative to the change in mean utility from consuming products offered by other airlines. Therefore, γ_3 captures how the event differentially influences mean utility, and consequently demand for event members' products.

The nested logit model assumes that the random terms ζ_{cg} and ε_{cj}^d have distributions such that $\delta\zeta_{cg} + (1-\delta)\varepsilon_{cj}^d$ has the extreme value distribution. The demand, d_j, for product j is simply given by:

$$d_j = s_j(p, x, \xi; \Phi^{\mathrm{d}}) \times POP, \tag{3}$$

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 $s_j(p, x, \xi; \Phi^{\mathrm{d}})$ is the predicted product share function.[31] $\Phi^{\mathrm{d}} = (\phi^p, \phi^x, \gamma, \delta)$ 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

[31] In case of the nested logit model it is well known that the predicted product share function takes the following functional form: $s_j = \frac{\exp(\frac{\mu_j}{1-\delta})}{D_g} \times \frac{D_g^{1-\delta}}{1+\sum_{g=1}^{G} D_g^{1-\delta}}$, where $D_g = \sum_{k \in G_g} \exp[\frac{\mu_k}{1-\delta}]$.

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) and Gayle (2013) 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 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 produces 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:

$$\max_{p_{jmt}} VP_{imt} = \max_{p_{jmt}}\left[\sum_{j\in B_{imt}}(p_{jmt} - mc_{jmt})q_{jmt}\right], \tag{4}$$

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 marginal cost of product *j* in market *m* during period *t*.

Let $f = 1, \dots, F$ index the corresponding operating carriers. If product *j* is a traditional codeshare product, then $mc_{jmt} = c_{jmt}^{i} + w_{jmt}^{f}$, where c_{jmt}^{i} 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_{jmt}^{f} is the price ticketing carrier i pays to operating carrier f for its transportation services on the remaining trip segment(s). If instead product j is a virtual codeshare product, then $mc_{jmt} = w_{jmt}^{f}$, where w_{jmt}^{f} is the price the ticketing carrier pays to operating carrier f for its exclusive transportation services in the provision of product j.[32] Last, if product j is a pure online product, then $mc_{jmt} = c_{jmt}^{i}$. 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_{jmt}^{i} 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_{jmt}^{f} 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 w_{jmt}^{f}, i.e., each operating carrier f solves the following profit maximization problem: $\text{Max}_{w_{jmt}^{f}} \left[\sum_{j \epsilon A_f} (w_{jmt}^{f} - c_{jmt}^{f}) q_{jmt}\right]$, where A_f is the set of products in the market to which carrier f contributes its transportation services, while c_{jmt}^{f} 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_{jmt}^{f} across competing operating carriers yields a positive correlation between w_{jmt}^{f} and c_{jmt}^{f}. Therefore, both c_{jmt}^{i} and w_{jmt}^{f} 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 demand, that is, $q_{jmt} = s_{jmt}(p, x, \xi; \Phi^{\mathrm{d}}) \times POP$. The optimization problem in (4) yields the following set of J first-order conditions – one for each of the J products in the market:

$$s_j + \sum_{k \in B_i} (p_k - mc_k) \frac{\partial s_k}{\partial p_j} = 0 \;\; for\ all\ j = 1, \dots, J. \qquad (5)$$

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

We have dropped the time and market subscripts in equation (5) only to avoid a clutter of notation. Using matrix notation, the system of first-order conditions in equation (5) is represented by:

$$s + (\Omega .* \Delta) \times (p - mc) = 0, \tag{6}$$

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, $.*$ 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.[33] Of course 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 (6), we can obtain a vector of product markups:

$$mkup(x, \xi; \Phi^{\mathrm{d}}) = p - mc = -(\Omega .* \Delta)^{-1} \times s. \tag{7}$$

Using the estimated product-level markups from equation (7), product-level marginal costs are recovered by:

$$\widehat{mc} = p - \widehat{mkup}, \tag{8}$$

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

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[33] Carve-outs are markets in which authorities forbid joint pricing of products by ATI members. We assume that ATI members do not jointly price in carve-out markets, and therefore Ω takes carve-out markets into account.

Finally, with the estimated markups from equation (7), firm-level variable profits can be computed by:

$$VP_{imt} = \sum_{j \in B_{imt}} mkup_{jmt}(x, \xi; \widehat{\Phi^{d}}) q_{jmt}. \tag{9}$$

4.3 Dynamic Entry/Exit model

Specification of dynamic model

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:

$$E_t\left(\sum_{r=0}^{\infty} \beta^r \Pi_{im,t+r}\right), \tag{10}$$

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:

$$\Pi_{imt} = a_{im,t-1} VP_{imt} - a_{imt}\{FC_{imt} + \epsilon_{imt}^{FC} + (1 - s_{imt})[EC_{imt} + \epsilon_{imt}^{EC}]\}, \tag{11}$$

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 and entry costs 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, and $s_{imt} = a_{im,t-1}$. The composite shock $\varepsilon_{imt} = \epsilon_{imt}^{FC} + (1 - s_{imt})\epsilon_{imt}^{EC}$ 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:

$$FC_{imt} = \theta_0^{FC} + \theta_1^{FC} Opres\_cost_{imt} + \theta_2^{FC} T_{post-Event} + \theta_3^{FC} Event\_Member_{imt} + \theta_4^{FC} T_{post-Event} \times Event\_Member_{imt} \quad (12)$$

$$EC_{imt} = \theta_0^{EC} + \theta_1^{EC} Opres\_cost_{imt} + \theta_2^{EC} T_{post-Event} + \theta_3^{EC} Event\_Member_{imt} + \theta_4^{EC} T_{post-Event} \times Event\_Member_{imt} \quad (13)$$

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:

$$\theta = \{\theta_0^{FC}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}\}', \quad (14)$$

where θ_0^{FC} and θ_0^{EC} respectively measure mean fixed and entry costs across airlines, markets and time;[34] 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; 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; θ_4^{FC} and θ_4^{EC} respectively measure the extent to which event members fixed and entry costs change, relative to these cost changes for other airlines, across the pre-post event periods.

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-passenger price the ticketing carrier pays over to an operating carrier for transporting the passenger, while Γ represents a potential lump-sum transfer

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[34] 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 $Opres\_cost_{imt}$.

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

$$R_{imt}^{*} = a_{im,t-1} VP_{imt}. \tag{15}$$

The (x, ξ) in equation (9) 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 (9) and (15) 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:

$$y_{imt} \equiv \{s_{imt}, R_{imt}^{*}, Opres\_cost_{imt}, T_{post-Event}\}. \tag{16}$$

Value Function and Bellman Equation

Let $\sigma \equiv \{\sigma_{im}(y_{imt}, \varepsilon_{imt}), i = 1,2,..,N; m = 1,2,\ldots,M\}$ 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:

$$\begin{aligned} V_i^{\sigma}(y_t, \varepsilon_{it}) = \ & \underset{a_{it}\in\{0,1\}}{\text{Max}} \{\Pi_{it}^{\sigma}(a_{it,} y_t) - \varepsilon_{it} * a_{it} \\ & + \beta \int V_i^{\sigma}(y_{t+1}, \varepsilon_{it+1}) \, dG_i(\varepsilon_{it+1}) F_i^{\sigma}(y_{t+1} | a_{it,} y_t)\}, \end{aligned} \tag{17}$$

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:

$$\sigma_i(y_t,\varepsilon_{it}) = \underset{a_{it}}{arg\max}\{\Pi_{it}^{\sigma}(a_{it,}y_t) - \varepsilon_{it} * a_{it} + \beta\int V_i^{\sigma}(y_{t+1},\varepsilon_{it+1})\,dG_i(\varepsilon_{it+1})F_i^{\sigma}(y_{t+1}|a_{it,}y_t)\}. \tag{18}$$

Transition rules for state variables are described in Appendix E. In Appendix F 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

Our demand estimation strategy is to solve for the set of demand parameter values that equate observed product shares, S_{jmt}, with predicted product shares, $s_{jmt}(p,x,\xi;\Phi^{\mathrm{d}})$, i.e., demand parameter estimates must satisfy:

$$S_{jmt} = s_{jmt}(p,x,\xi;\Phi^{\mathrm{d}}) \tag{19}$$

Given that the functional form for the right-hand-side of equation (19) is based on the nested logit, we have the following well-known estimation equation [see Berry (1994)]:

$$\ln(S_{jmt}) - \ln(S_{0mt}) = x_{jmt}\phi^x - \phi^p p_{jmt} + \delta\ln(S_{jmt|g}) + \gamma_1 T_{post-Event} + \gamma_2 Event\_Member + \gamma_3 T_{post-Event} \times Event\_Member + tkcarrier_j + Quarter_t + Origin_m + Dest_m + \xi_{jmt}, \tag{20}$$

where S_{0mt} is the observed share of the outside good; $S_{jmt|g}$ is the observed product share within group g; and $tkcarrier_j$, $Quarter_t$, $Origin_m$ and $Dest_m$ are fixed effects for ticketing carrier, time period, market origin, and market destination respectively.

We use two-stage-least squares (2SLS) to estimate equation (20) to deal with the endogeneity of p_{jmt} and $S_{jmt|g}$. The endogeneity problem exists because the product price p_{jmt} and within group product share $S_{jmt|g}$ are correlated with the error term ξ_{jmt}. Therefore, an application of valid instruments is necessary. Valid instruments should be correlated with p_{jmt} and $S_{jmt|g}$, but uncorrelated with ξ_{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 competitors' products in the market; (2) 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; (3) the number of other products offered by an airline in a market; (4) the interaction between jet fuel price[35] and itinerary distance for the departing and returning legs of the trip respectively; (5) the sum of the "Inconvenience" variable by ticketing carriers within a market on the departing and returning legs of the trip; (6) the sum of products' number of intermediate stops by ticketing carriers within a market on the departing and returning legs of the trip.

Instrument (1) and (2) measure the degree of market competition facing a product, which affect the size of product markup. A firm typically can achieve a marginally higher markup on a given product the more substitute products it owns in the market, which is the rationale for instrument (3). The rationale for instrument (4) 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. Instruments (5) and (6) may in part explain why passengers choose one airline to some others and thus they are likely correlated with within group share $S_{jmt|g}$.

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 ξ_{jmt}. Furthermore, unlike price and within group product share, the menu of products offered and their associated non-price characteristics are not routinely and easily

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

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.

5.2 Marginal Cost Function Estimation

Our specification of the marginal cost function is as follows:

$$\widehat{mc_{jmt}} = \tau_0 + \tau_1 W_{jmt} + \tau_2 T_{post-Event} + \tau_3 Event_{Members} \ + \ \tau_4 T_{post-Event} \times Event_{Members} + opcarrier_j \ + Quarter_t + Origin_m + Dest_m + \eta_{jmt}, \tag{21}$$

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 (7) and (8)); 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 the dummy variable that equals 1 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. Parameter τ_4, which is the coefficient on interaction variable $T_{post-Event} \times Event\_Members$, measures the extent to which marginal cost of products offered by event members changes across the pre-post event periods, relative to change in marginal cost of products offered 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 passengers per week.[36] 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:

$$Q(\theta,\boldsymbol{P}) = \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\{\begin{matrix} a_{imt}\,ln\left[\psi\left(\tilde{Z}_{imt}^{P}(y)\times\theta+\tilde{e}_{imt}^{P}(y)\right)\right] \\ +(1-a_{imt})\,ln\left[\psi\left(-\tilde{Z}_{imt}^{P}(y)\times\theta-\tilde{e}_{imt}^{P}(y)\right)\right]\end{matrix}\right\}, \qquad (22)$$

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 F), are arbitrary and do not represent the equilibrium probabilities associated with θ in the model.

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

[36] 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).

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 F. 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:

$$\hat{\theta}_{PML} = \arg\max_{\theta} \; Q(\theta, \widehat{\mathbf{P}}_0) \,. \tag{23}$$

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 $\hat{\theta}_{PML}$.

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 will be 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$^{\text{th}}$ 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. Aguirregabiria and Mira (2002, 2007) show that the NPL algorithm reduces the finite sample bias of the two-step PML estimator.

6. Estimation Results

6.1 Results from Demand Estimation

Table 2.5 reports demand estimation results for the “oneworld Event Sample” and “ATI Event Sample” using both ordinary least squares (OLS) and 2SLS. Since it is likely that variables *Fare* and *within group share* are endogenous, we implement a Hausman test to confirm their endogeneity. Based on the results of the Hausmam test shown in Table 2.5, we easily reject that *Fare* and *within group share* are exogenous at conventional levels of statistical significance. Therefore, the following discussion is based on the results from 2SLS.

In Table 2.5, we have a negative coefficient estimate for variable *Fare* in both datasets, implying that price has a negative effect on consumers' utility. This is expected because, assuming all non-price product characteristic are held constant, passengers should prefer itineraries with a cheaper price. We estimate that the coefficient on within group share $ln(S_{jmt|g})$ for both datasets are greater than zero with statistical significance, implying that consumers' choice behavior do display airline-loyalty to some degree. However, due to the coefficient's closer proximity to 0 rather than 1, the degree of airline-loyalty is not strong.

It is estimated that *Opres_demand* has a positive effect on consumers' utility, which is what we expect, since travelers are likely to prefer the products offered by airlines that provide 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 the airline offers nonstop flight to leaving from the travelers' origin airport increases, thus increasing loyalty to the airline.

For both *Nonstop_going* and *Nonstop_coming*, the estimated coefficients are positive, implying passengers prefer itineraries with a nonstop flight to their destination and nonstop flight back to their origin. Moreover, as expected, *Inconvenience_going* and *Inconvenience_coming* have negative effects on consumers' utility in the sense that passengers would choose the itinerary that uses the most convenient routing in terms of travel distance covered.

Table 2.5 Demand Estimation

Variables	"oneworld Event Sample"				"ATI Event Sample"			
	OLS		2SLS		OLS		2SLS	
	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error
Fare	-1.82E-05***	1.90E-06	-0.004***	3.57E-04	-1.19E-05***	1.22E-06	-0.002***	9.24E-05
$\ln(S_{jmt\|g})$	0.462***	0.002	0.109***	0.018	0.419***	0.001	0.211***	0.007
Opres_demand	0.008***	9.70E-05	0.011***	7.90E-04	0.005***	4.40E-05	0.006***	1.91E-04
Nonstop_going	0.711***	0.014	0.705***	0.054	0.830***	0.009	0.817***	0.022
Nonstop_coming	0.674***	0.013	0.449***	0.056	0.828***	0.010	0.825***	0.022
Inconvenience_going	-0.568***	0.021	-0.809***	0.090	-0.444***	0.012	-0.491***	0.037
Inconvenience_coming	-0.501***	0.021	-0.740***	0.092	-0.424***	0.011	-0.522***	0.036
Traditional_I_going	-0.243***	0.007	-0.206***	0.036	-0.203***	0.004	-0.057***	0.015
Traditional_II_going	-0.527***	0.076	1.095	1.115	-0.228***	0.020	-0.151**	0.076
Traditional_I_coming	-0.224***	0.007	-0.095***	0.038	-0.175***	0.003	0.038**	0.017
Traditional_II_coming	-0.444***	0.078	-0.495	0.423	-0.172***	0.019	-0.051	0.071
Virtual_going	-0.642***	0.018	-0.693***	0.080	-0.472***	0.009	-0.387***	0.029
Virtual_coming	-0.604***	0.017	-0.416***	0.085	-0.462***	0.009	-0.121***	0.031
$\mathrm{T}_{\mathrm{post-Event}}$	0.033***	0.005	-0.489***	0.055	0.006**	0.003	-0.022***	0.009
Event_Member	1.355***	0.138	0.903***	0.311	0.783***	0.256	1.504**	0.778
$\mathrm{T}_{\mathrm{post-Event}} \times$ Event_Member	-0.056***	0.010	0.070*	0.040	-0.062***	0.007	-0.048***	0.019
Spring (Summer)	0.066***	0.004	-0.036**	0.019	-0.059***	0.002	0.040***	0.008
Constant	-7.290***	0.217	4.578**	2.122	-8.457***	0.278	-5.903***	0.906
Tkcarriers fixed effects	YES		YES		YES		YES	
Market Origin fixed effects	YES		YES		YES		YES	
Market Destination fixed effects	YES		YES		YES		YES	
R-squared	0.7179		-		0.7733		-	
Durbin-Wu-Hausman chi-sq test	8027.75		(p = 0.0000)		17348.2		(p = 0.0000)	
Robust regression F test	4335.83		(p = 0.0000)		9924.88		(p = 0.0000)	

*** statistically significant at 1% level
** statistically significant at 5% level
* statistically significant at 10% level

The coefficients on the codeshare dummy variables provide a comparison with respect to pure online products. Most of these coefficients are shown to be negative in both datasets, implying that consumers less prefer codeshare itineraries to pure online itineraries. Pure online products are viewed to be of higher quality than codeshare products in the sense that an airline can better organize its own flights to streamline connection schedules and arrange gates to reduce layover time. 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. Ito and Lee (2007) argue that passengers perceive virtual codeshare product as an inferior substitute to an otherwise equivalent pure online product since the frequent-flyer programs often do not allow upgrade of a virtual codeshare ticket to first class.

For the "oneworld Event Sample", coefficient estimate on $T_{post-Event} \times Event\_Member$ is positive and statistically significant at 10%. This suggests that formation of the oneworld alliance raises demand for the alliance members. Relatively more passengers would like to fly with oneworld alliance members in the post-alliance period, perhaps because consumers expect to enjoy more privileges and thus the alliance increases the value to consumers of holding FFP membership with a oneworld airline. However, in the "ATI Event Sample", the coefficient estimate on $T_{post-Event} \times Event\_Member$ is negative and statistically significant. This result suggests that the subsequent grant of ATI decreases demand for the ATI members.

The mean of own-price elasticities that the demand model yields are 3.85 in the "oneworld Event Sample" and 2.77 in "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.

6.2 Recovered Marginal Costs, Markups and Computed Variable Profits

Information with regards to marginal costs, prices, markups, and variable profits may reveal more about market competitiveness. Based on equation (7), combined with demand parameter estimates shown in Table 2.5, product markups can be computed and then marginal costs consequently recovered by subtracting markups from prices.

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 \$283.35 and \$453.65 respectively. Recall that all monetary variables in both datasets are measured with respect to year 2005 constant dollars. 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 48.79% in the "oneworld Event Sample" and 56.95% in the "ATI Event Sample".

We implement a counterfactual experiment in which the markups are re-calculated based on the assumption that oneworld ATI was not approved, i.e., members cannot cooperatively price their products in a given market. The counterfactual experiment focuses on the markets where ATI carrier members each provide substitute products, i.e., markets in which their service 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 0.14% lower if cooperative pricing among the members were forbidden. Such small changes in markups make us believe that the approval of oneworld ATI has not resulted in significant competitive harm.

The quarterly market-level variable profits of each airline can be computed using equation (9). 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 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 2.6 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.

Table 2.6 Markup Estimation

Variable	"oneworld Event Sample" Coefficient Estimates	"oneworld Event Sample" Std. Error	"ATI Event Sample" Coefficient Estimates	"ATI Event Sample" Std. Error
Opres_demand	0.064***	0.002	0.021***	3.33E-04
Nonstop_going	4.453***	0.469	2.702***	0.160
Nonstop_coming	4.384***	0.456	1.877***	0.125
Inconvenience_going	-0.735***	0.400	-0.901***	0.309
Inconvenience_coming	0.122	0.401	-0.909***	0.298
Close_comp_going	-0.021	0.014	0.002	0.005
Close_comp_coming	-0.022	0.014	-0.017***	0.006
Traditional_1_going	-0.652***	0.082	-0.008	0.048
Traditional_2_going	-1.863***	0.627	-0.082	0.107
Traditional_1_coming	-0.406***	0.079	0.012	0.051
Traditional_2_coming	-0.869	0.591	0.117	0.109
Virtual_going	-3.130***	0.230	-0.827***	0.066
Virtual_coming	-3.033***	0.228	-0.600***	0.061
$\mathrm{T}_{\mathrm{post-Event}}$	0.744***	0.055	-0.052	0.047
Event_Member	-2.395*	1.347	0.900***	0.372
$\mathrm{T}_{\mathrm{post-Event}} \times$ Event_Member	-0.305	0.267	-0.111*	0.064
Market_Overlap_ATI_tkcarriers	-	-	0.208***	0.061
$\mathrm{T}_{\mathrm{post-Event}} \times$ Event_Member $\times$ Market_Overlap_ATI_tkcarriers	-	-	0.357***	0.083
Constant	282.059***	1.632	447.672***	2.092
Ticketing carriers fixed effects	YES		YES	
Season effect	YES		YES	
Market Origin fixed effect	YES		YES	
Market Destination fixed effect	YES		YES	
R-squared	0.1715		0.1915	

*** statistically significant at 1%
** statistically significant at 5%
* statistically significant at 10%

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 coefficients on the inconvenience variables have statistically significant effect on markup, the effect is negative as expected. These results largely suggest that airlines are more likely to charge lower markups when itineraries use less convenient routing for passengers in terms of miles flown in excess of the possible minimum flight miles needed.

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 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.

Examining the effect of codeshare on markups, we notice that the coefficients of these variables in Table 2.6 are mostly negative and statistically significant. Overall, these results suggest that airlines charge lower markups for codeshare products compared to pure online products. Consumers less prefer both traditional and virtual codeshare products to pure online products, and thus airlines are more likely to lower markups on codeshare products.

The interaction variable, $T_{post-Event} \times Event\_Member$, has no effect on markups 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 provide substitute products, i.e., markets in which ATI members' service overlap. The interaction term $T_{post-Event} \times Event\_Member \times Market\_Overlap\_ATI\_tkcarriers$ has a positive coefficient, implying that granting oneworld ATI increased the market power of the oneworld members that received ATI only in the overlapping markets. However, the negative coefficient estimate on the two-way interaction variable $T_{post-Event} \times Event\_Member$ suggests that the grant of ATI may have resulted in ATI members lowering markup on their products in markets where their service do not overlap.

Table 2.7 provides the estimation results for the marginal cost regression based on equation (21). The variable *Opres_cost* has a positive coefficient estimate in both samples, while the coefficient estimate of *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 an airline's marginal cost increases initially with increases in its origin airport presence, but eventually declines with further increases in the airline's 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 result. The evidence we find suggesting the presence of economy of passenger-traffic density is consistent with findings in Brueckner and Spiller (1994).

Table 2.7 Marginal Cost Estimation

	"oneworld Event Sample"		"ATI Event Sample"	
Variables	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error
Opres_cost	2.861***	0.414	3.668***	0.229
Opres_cost_square	-0.003	0.003	-0.014***	0.002
Nonstop_going	61.636***	14.137	26.500***	9.808
Nonstop_coming	13.234	13.589	28.297***	10.323
Distance_going	0.060***	0.013	0.039***	0.007
Distance_coming	0.082***	0.013	0.027***	0.007
traditional_I_going	5.184	14.457	40.585***	8.911
traditional_II_going	667.304**	329.922	24.603	44.232
traditional_I_coming	39.728***	13.795	86.664***	8.687
traditional_II_coming	173.730	157.308	35.111	41.631
virtual_going	-6.622	22.201	-1.188	14.670
virtual_coming	66.884***	22.909	103.898***	14.844
$T_{\text{post-Event}}$	-154.198***	6.023	14.622***	4.446
Event_Members	9.684	93.932	13.550	42.057
$T_{\text{post-Event}} \times \text{Event\_Members}$	23.417**	11.051	-20.836***	8.362
Constant	1617.711***	511.732	413.714***	166.725
Operating carrier group fixed effects	YES		YES	
Season effect	YES		YES	
Market Origin fixed effect	YES		YES	
Market Destination fixed effect	YES		YES	
R-squared	0.2356		0.2786	

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 when the itinerary is nonstop, 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 distance variables are positive and statistically significant. The results 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 seems 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 to make transfers smoother. The evidence apparently suggests that there also exists some costly coordination between operating and ticketing carriers when offering virtual codeshare products.

The coefficient estimate on $T_{post-Event} \times Event\_Members$ is positive and statistically significant in the "oneworld Event Sample", but negative and statistically significant in the "ATI Event Sample". This sign pattern of these coefficient estimates suggests that oneworld alliance members were not able to achieve marginal cost efficiency gains by implementing the alliance without ATI, but upon the subsequent grant of ATI, these ATI members were able to achieve marginal cost efficiency gains. 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.

6.4 Results from a Reduced-form Price Regression

Based on standard oligopoly theory, a product's price in equilibrium is simply the sum of marginal cost and markup. Details on how markup is determined depend on details of the specific oligopoly model under consideration. Therefore, equilibrium price changes should be driven by changes in marginal cost, changes in markup, or both.

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. So results produced by a reduced-form price regression can serve to help put in context results from a structural model. However, unlike a structural model, a reduced-form price regression cannot separately identify changes in markup versus changes in marginal cost. By estimating both a structural model and a reduced-form price regression, we are able to exploit the advantages of both empirical approaches to better understand the estimated market effects.

Table 2.8 presents the estimation results of a reduced-form price regression. The signs and magnitude of coefficient estimates on *Opres_cost* and *Opres_cost_square* variables in both dataset are similar to those in the marginal cost regression, so the fare effects of the size of an airline's presence at the origin airport seem to be primarily driven by its airport presence effects on marginal cost. The estimated price effects suggest that an airline's price initially increases as the size of its presence at the origin airport increases, but further increases in its origin airport presence are associated with decreases in its price. As we previously discussed, 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 marginal cost to fall, which apparently is sufficient to drive fares down.

Most of the nonstop variables are associated with higher fares. Results from the markup and marginal cost regressions both suggest that nonstop products are associated with higher markup and higher marginal cost, which are consistent with the estimated reduced-form fare effects of the nonstop variables.

The inconvenience variables are associated with lower price. These results are consistent with our previous findings that a more inconvenient travel itinerary, in terms of distance flown in excess of the minimum distance necessary, is associated with lower passenger utility (demand result), and lower markup. As expected, the estimated coefficients on the distance variables suggest that longer itinerary distances are associated with higher product price. This makes sense since we found itinerary distance is positively related to marginal cost.

Table 2.8 Reduced-form Price Equation Estimation

	"oneworld Event Sample"		"ATI Event Sample"	
Variables	Coefficient Estimates	Std. Error	Coefficient Estimates	Std. Error
Opres_cost	3.000***	0.414	3.656***	0.229
Opres_cost_square	-0.003	0.003	-0.014***	0.002
Nonstop_going	61.337***	15.657	19.061**	10.959
Nonstop_coming	4.003	14.982	25.430**	11.425
Inconvenience_going	-89.439***	32.413	-95.140***	17.941
Inconvenience_coming	-125.244***	31.848	-50.261***	17.364
Distance_going	0.059***	0.019	0.048***	0.011
Distance_coming	0.090***	0.019	0.026***	0.010
Close_comp_going	-0.288	0.897	-0.358	0.322
Close_comp_coming	-0.939	0.920	-0.086	0.322
Traditional_I_going	6.147	14.467	39.869***	8.951
Traditional_II_going	671.243**	330.151	-24.451	44.221
Traditional_I_coming	40.112***	13.799	87.085***	8.736
Traditional_II_coming	172.011	157.179	35.421	41.630
Virtual_going	-8.749	22.235	-1.541	14.678
Virtual_coming	62.820***	22.959	103.613***	14.850
$T_{post-Event}$	-152.212***	6.052	15.421***	4.440
Event_Members	12.551	89.778	16.408	43.989
$T_{post-Event} \times$ Event_Members	24.447**	11.039	-29.427***	10.689
Market_Overlap_ATI_carriers	-	-	-10.454**	4.616
$T_{post-Event} \times$ Event_Members $\times$ Market_Overlap_ATI_carriers	-	-	13.136	10.523
Constant	2051.691***	511.1769	959.160***	167.695
Operating carrier group fixed effects	YES		YES	
Year fixed effect	YES		YES	
Season fixed effect	YES		YES	
Market Origin fixed effect	YES		YES	
Market Destination fixed effect	YES		YES	
R-squared	0.2364		0.2785	

Equations estimated using ordinary least squares.
*** statistically significant at 1%
** statistically significant at 5%
* statistically significant at 10%

The variables, *Close_comp_going* and *Close_comp_coming* measure for the given product under consideration, 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. The higher the measure of each of these variables for a given product, the more competition this product faces in the market. There is no evidence in the reduced-form price regression that these variables influence price.

Overall, it appears that codeshare itineraries are associated with higher price relative to pure online itineraries. Recall that we found that codeshare itineraries are associated with lower markup but higher marginal cost. So the estimated reduced-form price effect of codeshare is more reflective of how codesharing influences marginal cost rather than markup.

Focusing on the interaction variable, $T_{post-Event} \times Event\_Members$, we find that implementation of the alliance is associated with a relative increase in prices being charged by alliance members. In the "ATI Event Sample, we include the dummy variable $Market\_Overlap\_ATI\_carriers$, which equal to 1 for markets in which there exists substitute products that are both ticketed and operated by ATI carrier members, i.e., markets in which the ATI members' service overlap. The coefficient estimate on the three-way interaction variable, $T_{post-Event} \times Event\_Members \times Market\_Overlap\_ATI\_carriers$, is not statistically significant, simply implying no effect of granting ATI on fares of products provided by its members in their overlapping markets. However, the negative coefficient estimate on the two-way interaction variable, $T_{post-Event} \times Event\_Members$, indicates that the grant of ATI to oneworld members appear to be associated with a relative decline in price being charged by these oneworld ATI members in markets where their service do not overlap. Therefore, it seems that granting Antitrust Immunity brought benefits to consumers in terms of lower fares.

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. Additionally, even though markup went up in ATI members' overlapping markets, price in these markets was not affected. In other markets, price even went down.

6.5 Result from the Dynamic Model

Table 2.9 and Table 2.10 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 estimates of parameters in the fixed cost function for the "oneworld Event Sample" are unreasonably small and not precisely estimated. As such, we cannot draw reliable inferences about size of fixed cost in the "oneworld Event Sample". However, based on the objectives of our study we are most interested in parameter estimates for the fixed cost and entry cost functions in the "ATI Event Sample".

Table 2.9 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	1.71E-07	0.0305	5.60E-06
$Opres\_cost_{imt}$	-5.78E-11	4.31E-05	-1.34E-06
$T_{post-Alliance}$	-1.62E-07	0.0489	-3.32E-06
$Alliance\ Member$	-1.41E-07	0.0529	-2.66E-06
$T^{alliance}$ × Alliance	1.44E-07	0.0897	1.60E-06
Entry Cost Function			
Mean entry cost across all carriers	4.2200***	0.0431	97.9504
$Opres\_cost_{imt}$	-0.0078***	2.91E-04	-26.7740
$T^{alliance}$	0.0413	0.0754	0.5484
$Alliance$	-0.7109***	0.0727	-9.7786
$T^{alliance}$ × Alliance	-0.1004	0.1271	-0.7896

*** indicates statistical significance at the 1% level.

Table 2.10 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	0.6560***	0.0308	21.2921
$Opres\_cost_{imt}$	-0.0038***	2.04E-04	-18.6726
T^{ATI}	0.0028	0.0345	0.0816
ATI	0.1369***	0.0472	2.8996
$T^{ATI} \times$ ATI	-0.1398*	0.0820	-1.7038
Entry Cost Function			
Mean entry cost across all carriers	3.4562***	0.0389	88.9242
$Opres\_cost_{imt}$	-0.0040***	2.92e-04	-13.6984
T^{ATI}	0.6787***	0.0559	12.1415
ATI	-0.3144***	0.0666	-4.7233
$T^{ATI} \times$ ATI	0.0496	0.1287	0.3855

*** indicates statistical significance at the 1% level.
* indicates statistical significance at the 10% level.

According to the coefficient estimate of mean fixed cost in "ATI Event Sample", the mean fixed cost across all carriers is $6,560. Based on our Nash equilibrium price-setting game previously discussed, the overall mean quarterly variable profits in a directional origin-destination market are estimated to be $31,752.06. Therefore, mean fixed costs account for 20.66% of the variable profits in the "ATI Event Sample".

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 negative and statistically significant fixed cost coefficient estimate on $Opres\_cost_{imt}$ in the "ATI Event Sample" suggests that an airlines recurrent fixed cost is lower the larger is its presence at the origin airport of the market. This result may in part reflect relatively favorable access to airport facilities (gates, check-in counters, etc.) that an airline enjoys at its hub airports. In addition, an airline's larger airport presence may result in it using airport facilities more intensely and efficiently.

The fixed cost coefficient estimate on variable T^{ATI} in Table 2.10 measures the extent to which non-ATI airlines' fixed costs change over the pre and post-ATI periods. This coefficient estimate is not statistically significant, suggesting that fixed cost for the carriers that are not oneworld ATI members is not different in the post- ATI period than in the pre-ATI period.

ATI is a dummy variable equal to 1 if the carrier is a oneworld ATI member. The positive fixed cost coefficient estimate on this variable suggests that fixed cost for oneworld ATI members is persistently higher than the mean fixed cost of other airlines. The fixed cost coefficient estimate on the interaction variable, $T^{ATI} \times ATI$, measures the fixed cost effect of granting ATI on ATI members' fixed cost. This fixed cost coefficient estimate is negative and statistically significant at the 10% level, suggesting that granting oneworld members ATI reduced these airlines quarterly fixed cost in the origin-destination markets they serve. As such, there is some evidence, even though it is statistically weak, of fixed cost efficiency gains associated with the grant of immunity.

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 $42,200 in the "oneworld Event Sample" and $34,562 in the "ATI Event Sample". Based on our overall mean variable profit estimates from the Nash price-setting game, it will take at least 2 quarters of variable profits to recoup their one-time sunk entry cost investment.

The entry cost function coefficient on $Opres\_cost_{imt}$ in Table 2.9 and Table 2.10 are both negative and statistically significant, suggesting that an airline's entry cost to a market declines the larger 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 (2013) among others].

The $T^{alliance}$ and T^{ATI} dummy variables in the entry cost functions measure how the market entry cost of non-alliance/ATI member airlines changes between the pre and post alliance/ATI periods. Coefficient estimates on these time dummy variables suggest that non-alliance airlines' market entry cost did not change between the pre and post-alliance periods, while the entry cost of non-ATI airlines increased by $6,787 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 results show that the coefficients on both $T^{alliance} \times Alliance$ and $T^{ATI} \times ATI$'s are not statistically significant. The evidence therefore suggests that the implementation of oneworld alliance in 1999 and the grant of oneworld ATI in 2010 had no statistically discernable impact on their members' market entry costs.

In summary, both the implementation of the oneworld alliance and the subsequent grant of ATI to various members do not appear to have an impact on partners' sunk market entry costs, but the grant of ATI weakly reduced their recurrent fixed cost.

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 an impact on markup of products offered by the alliance members, while the subsequent grant of ATI to various members increased markup on their products in markets where ATI members each provide substitute products (their overlap markets), but decreased their markup in other markets. Furthermore, we find that forming oneworld alliance did not create cost efficiency in terms of marginal cost, but granting oneworld ATI reduced its members' marginal costs. 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. In markets where their service do overlap, the evidence suggest that increases in markup associated with the grant of ATI are sufficient to offset reductions in marginal cost such that prices remain unchanged. 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 do not provide evidence to counter alliance carriers' argument that ATI is required to achieve benefits to consumers and alliance carriers. Specifically, both implementation of oneworld alliance and the subsequent grant of ATI did not seem to impact alliance partners' sunk market entry cost, but weakly decreased their recurrent fixed cost.

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

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Appendix D - Additional Chapter 2 Tables

Table D.1 Oneworld Alliance Members

Members	Code	Year
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 D.2 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 D.2 Continue

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*[3]	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	

Table D.3 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	Mal év 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

Appendix E - Transition Rules for State Variables

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:

$$s_{im,t+1} = a_{it} \tag{E1}$$

$$R^*_{im,t+1} = a_{imt}(\alpha_0^R + \alpha_1^R R^*_{imt} + \zeta^R_{imt}) \tag{E2}$$

$$Opres\_cost_{im,t+1} = \alpha_0^{Opres\_cost} + \alpha_1^{Opres\_cost} Opres\_cost_{imt} + \zeta_{imt}^{Opres\_cost} \tag{E3}$$

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

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

$$F_i^\sigma\left(y_{t+1}\middle|a_{it,}y_t\right) = \begin{cases} 1\{s_{i,t+1} = 1\} * \mathrm{Pr}_R * \mathrm{Pr}_{Opres\_cost} * Pr\left(T_t^{Alliance/ATI} = 1\middle|y_t\right) * \mathrm{Pr}_{comp} \\ 1\{s_{i,t+1} = 0\} * \mathrm{Pr}_R{}' * \mathrm{Pr}_{Opres\_cost} * Pr\left(T_t^{Alliance/ATI} = 1\middle|y_t\right) * \mathrm{Pr}_{comp} \end{cases} \tag{E4}$$

where

$$\mathrm{Pr}_R = F_R\left(R^*_{i,t+1}\middle|R^*_{it}\right) * \prod_{j\neq i} F_R\left(R^*_{jt+1}\middle|R^*_{jt}\right) \tag{E5}$$

$$\mathrm{Pr}_{Opres\_cost} =$$
$$F_{Opres\_cost}(Opres\_cost_{it+1}|Opres\_cost_{it}) * \prod_{j\neq i} F_{Opres\_cost}\left(Opres\_cost_{jt+1}\middle|Opres\_cost_{jt}\right) \tag{E6}$$

$$\mathrm{Pr}_R{}' = 1\{R^*_{it+1} = 0\} * \prod_{j\neq i} F_R\left(R^*_{jt+1}\middle|R^*_{jt}\right) \tag{E7}$$

$$Pr(T_t^{Alliance/ATI} = 1|y_t) = \Phi(\alpha_0^T + \alpha_1^T s_{it} + \alpha_2^T R^*_{it} + \alpha_3^T Opres\_cost_{it}) \tag{E8}$$

$$\mathrm{Pr}_{comp} = \prod_{j\neq i} Pr\left(s_{jt+1} = \sigma_j\left(y_{jt}, \varepsilon_{jt}\right)\middle|y_{jt}\right) \tag{E9}$$

Appendix F - 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:

$$\Pi_{imt}(a_{it}, y_t) = R^*_{imt} - a_{imt}(FC_i + (1 - s_{imt})EC_i) \quad \text{(F1)}$$

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:

$$\{\psi\left(\tilde{Z}^P_i(y)\frac{\theta}{\sigma_\varepsilon} + \tilde{e}^P_i(y)\right): for\ every\ firm\ and\ state\ (i, y)\} \quad \text{(F2)}$$

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

$$\tilde{Z}^P_i(y) = Z_i(1, y) - Z_i(0, y) + \beta[F^P_{i,y}(1) - F^P_{i,y}(0)] \times w^P_{z,i} \quad \text{(F3)}$$

$$\tilde{e}^P_i(y) = \beta[F^P_{i,y}(1) - F^P_{i,y}(0)] \times w^P_{e,i} \quad \text{(F4)}$$

$$w^P_{z,i} = (1 - \beta * \overline{F^P_{i,y}})^{-1} \times \{P_i(y) * Z_i(1, y) + [1 - P_i(y)] * Z_i(0, y)\} \quad \text{(F5)}$$

$$w^P_{e,i} = (1 - \beta * \overline{F^P_{i,y}})^{-1} \times [P_i(y) * e^P_i] \quad \text{(F6)}$$

and

$$\overline{F^P_{i,y}} = [P_i(y) \times 1'_M) * F^P_{i,y}(1) + \left(\left(1 - P_i(y)\right) \times 1'_M\right) * F^P_{i,y}(0)] \quad \text{(F7)}$$

$$\overline{F^P_{i,y}} = [P_i(y) \times 1'_M) * F^P_{i,y}(1) + \left(\left(1 - P_i(y)\right) \times 1'_M\right) * F^P_{i,y}(0)] \quad \text{(F8)}$$

$w^P_{z,i}$ 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^P_i is a function vector equal to $e^P_i = \gamma - ln\left(P_i(y)\right)$, where γ = 0.5772 is Euler's constant.