

Entry Deterrence and Strategic Alliances: Evidence from a Dynamic Structural Econometric Model

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Abstract

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 paper examines the market entry deterrent impact of codesharing, a form of strategic alliance, between incumbent carriers in 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. We quantify the extent to which market incumbents' codesharing influences market entry cost of potential entrants.

Keywords: Entry Deterrence; Strategic Alliances; Dynamic Entry/Exit Model; Airline Competition

JEL Classification codes: L13, L93

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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 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,

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).

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. As we subsequently show in the data description section of the paper, in the case of U.S. domestic air travel markets, which is the focus of our study, the vast majority of codesharing is done by legacy carriers and between legacy carriers.

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 presence of an alliance

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.

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 (2011) empirically test for the presence of entry-deterrence motives behind codesharing alliances, and find that an incumbent is approximately 20% more likely than average to codeshare when facing the threat of entry by low-cost carriers. However, Goetz and Shapiro (2011) 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

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.

LCC in U.S domestic air travel markets, is certainly among the most formidable LCCs in these markets. 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 (2011) 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 specify and estimate a static differentiated products Bertrand-Nash game, which incorporates both demand and supply sides of the static model. In particular, we first estimate a discrete choice model of air travel demand. Second, for the supply side, we assume that prices are set according to a static Bertrand-Nash equilibrium with multiproduct firms. The static Bertrand-Nash 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 in 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 in the current period. The dynamic entry/exit game allows us to estimate fixed and entry costs by exploiting 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 codesharing 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 LCC. 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 differentially deter market entry of: (1) other legacy carriers; (2) Southwest Airlines; (3) other LCC; 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. 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 carriers 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 same as 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 code-shared 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% 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.

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).

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 reports a list of the cities and the relevant airport groupings we use based on common metropolitan areas.

Table 1
Cities, 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 Continued
Cities, 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 Spr, 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 data 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 are dropped from the data.⁷ Also, we eliminate the 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 airports of a market from different perspectives. The variable *Opres_out* is a count of the number of different cities that the airline has nonstop flights to, leaving from the origin airport. On the other hand, *Opres_in* counts the number of different cities that the airline provides nonstop flights from, going into the origin airport 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 airport.

Opres_out is intended to help 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, the *Opres_in* and *Dpres_out* may better explain an airline's

⁷ Berry (1992) Aguirregabiria and Ho (2012) among others use 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.

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 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 2. The variable *Fare* is measured in constant year 1999 dollars. We use the consumer price index to deflate *Fare*.

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 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: ^aThe variable Fare is measured in constant year 1999 dollars. We use the consumer price index to deflate Fare.

Table 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 3 show that, among all airlines in the dataset, only 10 airlines are involved in codeshare products and 7 of these airlines are the ones we classify as legacy carriers. The fifth column in Table 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 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 3
List of Airlines in the Dataset,
by Product type they offer to Consumers

Airlines Involved in Pure online Products		Airlines that offer Codeshare Products to consumers			
Airlines Name	Code	Airlines Name	Code	Percent of codeshare products in the sample	Percent of each carrier's codeshare products codeshared with legacy carriers
American Airlines Inc.	AA	Legacy Carriers			
Aloha Air Cargo	AQ	American Airlines Inc.	AA	13.47	98.87
Alaska Airlines Inc.	AS	Alaska Airlines Inc.	AS	7.87	100
JetBlue Airways	B6	Continental Air Lines Inc.	CO	5.76	100
Continental Air Lines Inc.	CO	Delta Air Lines Inc.	DL	4.76	99.88
Independence Air	DH	Northwest Airlines Inc.	NW	10.03	100
Delta Air Lines Inc.	DL	United Air Lines Inc.	UA	28.75	100
Frontier Airlines Inc.	F9	US Airways Inc.	US	12.56	99.82
AirTran Airways	FL	Sub-total		83.20	
Allegiant Air	G4	Low Cost Carriers			
America West Airlines Inc.	HP	Southwest Airlines Co.	WN	9.28	0
Spirit Air Lines	NK	ATA Airlines	TZ	7.45	0
Northwest Airlines Inc.	NW	Frontier Airlines Inc.	F9	0.07	91.67
Skybus Airlines, Inc.	SX	Sub-total		16.80	
Sun Country Airlines	SY	Total		100	
ATA Airlines	TZ				
United Air Lines Inc.	UA				
US Airways Inc.	US				
Southwest Airlines Co.	WN				
ExpressJet Airlines Inc.	XE				
Midwest Airlines	YX				

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 4 summarizes our data according to the three types of products. Of the 434,329 observations/products in our sample, 4 percent are codeshared products. As expected, the overwhelming majority of passengers (approximately 98 percent) in our sample travel on pure online itineraries. A point worth noting from data in Table 4 is that among codeshared products, the number of traditional code-shared 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 4
Classification of Cooperative Agreement in Data Set

Classification	Example	Observations		Passengers	
		Frequency	Percent	Frequency	Percent
Pure online	AA/AA → AA/AA UA/UA →	416,537	95.90	64,150,292	98.75
Traditional	UA/UA → US/UA	8,847	2.04	254,065	0.39
Virtual	NW/CO → NW/CO	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 static 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 the airline transports at least 130 passengers in this

market during the quarter.⁹ Each airlines' 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 become 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 fixed and entry costs from the dynamic model. Table 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 costs than fixed cost.

Table 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

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).

3. Model

3.1 Demand

The demand model is a simple nested logit demand model. There are *POP* potential consumers, who may either buy one of J air travel products, $j = 1, \dots, J$, 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:

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

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:

$$\mu_j = x_j \phi^x - \phi^p p_j + \xi_j \quad (2)$$

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:

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

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

$$q_j = s_j(p, x, \xi; \Phi^d) \times POP \quad (4)$$

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

3.2 Supply

We assume that prices are set according to a static Bertrand-Nash equilibrium with multiproduct airlines. Let $i=1, \dots, N$ index airlines and B_i be a subset of the J products that are offered for sale by airline i . The variable profit of airline i in market m during period t is:

$$VP_{imt} = \sum_{j \in B_{imt}} (p_{jmt} - mc_{jmt}) q_{jmt} \quad (5)$$

where 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 marginal cost incurred from offering product j .

The static Bertrand-Nash assumption implies the following set of J first-order conditions – one for each of the J products:

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

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:

$$(\Omega.*\Delta) \times (p - mc) + s = 0 \quad (7)$$

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 airline ownership structure of the products, $.*$ is the operator for element-by-element matrix multiplication, and Δ is a $J \times J$ matrix of own and cross-price effects.

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

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

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

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

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. 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 previously discussed static differentiated products Bertrand Nash game; $a_{im,t-1}$ is a zero-one indicator that equals 1 only if airline i 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:

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

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 operate 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 operate 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), $\varepsilon_{imt} = \epsilon_{imt}^{FC} + (1 - a_{im,t-1})\epsilon_{imt}^{EC}$. 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:

$$FC_{imt} = \theta_0^{FC} + \theta_1^{FC} Pres_{imt} \quad (13)$$

$$\begin{aligned} EC_{imt} = & \theta_0^{EC} + \theta_1^{EC} Pres_{imt} \\ & + \theta_2^{EC} Percent_Trad_{mt} \\ & + \theta_3^{EC} Percent_Virtual_{mt} \\ & + \theta_4^{EC} Percent_Trad_{mt} \times Southwest \\ & + \theta_5^{EC} Percent_Virtual_{mt} \times Southwest \\ & + \theta_6^{EC} Percent_Trad_{mt} \times Other_lcc \\ & + \theta_7^{EC} Percent_Virtual_{mt} \times Other_lcc \end{aligned} \quad (14)$$

where $Pres_{imt}$ is the mean of size-of-presence variables $Opres_in$ and $Dpres_out$ for airline i at the endpoint cities of market m ; ¹⁰ $Percent_Trad_{mt}$ 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.

¹⁰ 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 airport of the market, while variable $Dpres_out$ counts the number of distinct cities that the airline has nonstop flights to, leaving from the destination airport.

$Percent_Trad_{mt}$ 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 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 begin providing its own service in the market (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:

$$Percent_Trad_{mt} = Z_{mt}\gamma + \epsilon_{mt}^{Trad} \quad (15)$$

$$Percent_Virtual_{mt} = Z_{mt}\lambda + \epsilon_{mt}^{Virt} \quad (16)$$

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 airports, where an airline's size of airport presence is measured by the previously defined variables, $Opres_in$ and $Dpres_out$; ¹¹ (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:

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

where θ_0^{FC} measures mean (across airlines, markets and time) fixed cost; θ_1^{FC} measures

¹¹ $Opres_in$ is a variable that counts the number of different cities that the airline provides nonstop flights from, going into the origin airport of the market, while variable $Dpres_out$ counts the number of distinct cities that the airline has nonstop flights to, leaving from the destination airport.

the effect that size of an airline's airport presence has on fixed cost; 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 airport 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 firm-specific component of fixed cost and entry cost for two reasons. First, estimation of the dynamic model is very computationally 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 Bertrand-Nash static model, firm-level variable profit is: $VP_{imt}(x, \xi; \Phi^d) = \sum_{j \in B_{imt}} mkup_{jmt}(x, \xi; \Phi^d) * q_{jmt}$. Let

$$R_{imt}^* = a_{im,t-1} VP_{imt} \quad (18)$$

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:

$$y_{imt} \equiv \{s_{imt}, R_{imt}^*, Pres_{imt}, Percent_Trad_{mt}, Percent_Virtual_{mt}, \epsilon_{mt}^{Trad}, \epsilon_{mt}^{Virt}\}. \quad (19)$$

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

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

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:

$$\begin{aligned} & \sigma_i(y_t, \varepsilon_{it}) \\ &= \text{argmax}_{a_{it}} \{ \Pi_{it}^\sigma(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ &+ \beta \int V_i^\sigma(y_{t+1}, \varepsilon_{it+1}) dG_i(\varepsilon_{it+1}) F_i^\sigma(y_{t+1} | a_{it}, y_t) \} \end{aligned} \quad (21)$$

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 $\mathbf{P} = \psi(\mathbf{P}, \theta)$, where $\mathbf{P} = \{P_i(\mathbf{y}): \text{for every firm and state } (i, \mathbf{y})\}$. $\mathbf{P} = \psi(\mathbf{P}, \theta)$ 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)]:

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

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

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 price¹² 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.

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

¹² The jet fuel price we use is U.S. Gulf Kerosene-Type Jet Fuel Spot Price FOB from U.S. Energy Information Administration.

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 airports 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 6. First, focusing on the coefficient estimates for variables *Fare* and $\ln(S_{j|g})$, 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 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 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 airport. 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 airport. Once the passenger becomes invested in the airline's frequent-flyer program, this helps reinforce the passenger's loyalty to the airline.

Table 6
Demand Estimation

Variables	OLS		2SLS	
	Estimates	Std. Error	Estimates	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.

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 $\ln(S_j/g)$ 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 seems 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 (2012b) 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 6 can be combined with the static Bertrand-Nash assumption to compute product markups. Overall, mean price is \$166.35, while 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% 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,

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

where $\mathbf{a}_{mt} = (a_{1mt}, a_{2mt}, \dots, a_{Nmt})$ 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, $P(\mathbf{a}_{mt} | \tilde{Z}_{imt}^P, \tilde{\epsilon}_{imt}^P, \epsilon_{mt}^{Trad}, \epsilon_{mt}^{Virt}, \theta)$ 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_{mt}^{Trad} and ϵ_{mt}^{Virt} , where $\epsilon_{mt}^{Trad} = Percent_Trad_{mt} - Z_{mt}\gamma$ and $\epsilon_{mt}^{Virt} = Percent_Virtual_{mt} - Z_{mt}\lambda$ based on equations (15) and (16). Since we assume that ϵ_{mt}^{Trad} and ϵ_{mt}^{Virt} 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, $P(\mathbf{a}_{mt} | \tilde{Z}_{imt}^P, \tilde{\epsilon}_{imt}^P, \epsilon_{mt}^{Trad}, \epsilon_{mt}^{Virt}, \theta)$ is the part that identifies parameters in vector θ , while $f(\epsilon_{mt}^{Trad} | Z_{mt}, \gamma)$ and $f(\epsilon_{mt}^{Virt} | Z_{mt}, \lambda)$ 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 $\prod_{m=1}^M \prod_{t=1}^T f(\epsilon_{mt}^{Trad} | Z_{mt}, \gamma)$ and $\prod_{m=1}^M \prod_{t=1}^T f(\epsilon_{mt}^{Virt} | Z_{mt}, \lambda)$ respectively. Given estimates $\hat{\gamma}$ and $\hat{\lambda}$ we can compute $f(\epsilon_{mt}^{Trad} | Z_{mt}, \hat{\gamma})$ and $f(\epsilon_{mt}^{Virt} | Z_{mt}, \hat{\lambda})$ and used 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 :

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

where $Q(\theta, \mathbf{P}, \hat{\gamma}, \hat{\lambda})$ 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, $Q(\theta, \widehat{P}_0)$. In step 2 of the PML estimation algorithm, the vector of parameters $\hat{\theta}_{PML}$ is estimated by:

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

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 ensure 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.¹³

¹³ While the demand model is estimated using all three years in the data set (2005, 2006 and 2007), due to

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

Table 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 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 7
Estimation of Linear Equations
for Percent Codeshare Variables

Variables	Dependent Variable: <i>Percent_Traditional</i>		Dependent Variable: <i>Percent_Virtual</i>	
	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.

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.

4.4 Results from the dynamic model

Table 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 static Bertrand-Nash model previously discussed, median quarterly variable profit for an airline in a directional origin-destination market is estimated to be \$31,492.71. Estimates from Table 8 show that 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 static model reveal that it also has a relatively high median quarterly market-level variable profit of \$61,490.78. So based on Southwest 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 its 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 more than a quarter (approximately 118 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 airports of the market. In other words, larger endpoint airport 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 (2012a) among others].

Table 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 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 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 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 carrier 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. We use a

structural econometric model in order to investigate these issues. 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, 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, 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 airports 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.

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:

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

$$R_{im,t+1}^* = a_{imt}(\alpha_0^R + \alpha_1^R R_{imt}^* + \zeta_{imt}^R) \quad (A2)$$

$$Pres_{im,t+1} = \alpha_0^{Pres} + \alpha_1^{Pres} Pres_{imt} + \zeta_{imt}^{Pres} \quad (A3)$$

$$Percent_Trad_{m,t+1} = \alpha_0^{Percent_Trad} + \alpha_1^{Percent_Trad} Percent_Trad_{mt} + \zeta_{mt}^{Percent_Trad} \quad (A4)$$

$$Percent_Virtual_{m,t+1} = \alpha_0^{Percent_Virtual} + \alpha_1^{Percent_Virtual} Percent_Virtual_{mt} + \zeta_{mt}^{Percent_Virtual} \quad (A5)$$

where ζ_{imt}^R , ζ_{imt}^{Pres} , $\zeta_{mt}^{Percent_Trad}$, and $\zeta_{mt}^{Percent_Virtual}$ are assumed to be normally distributed.

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

$$F_i^\sigma(y_{t+1}|a_{it}, y_t) = \begin{cases} 1\{s_{i,t+1} = 1\} * Pr_R * Pr_{Pres} * Pr_{Percent_Trad} * Pr_{Percent_Virtual} * Pr_{comp} \\ 1\{s_{i,t+1} = 0\} * Pr_R' * Pr_{pres} * Pr_{Percent_Trad} * Pr_{Percent_Virtual} * Pr_{comp} \end{cases} \quad (A6)$$

where

$$Pr_R = F_R(R_{it+1}|R_{it}) * \prod_{j \neq i} F_R(R_{jt+1}|R_{jt}) \quad (A7)$$

$$Pr_{Pres} = F_{Pres}(Pres_{it+1}|Pres_{it}) * \prod_{j \neq i} F_{Pres}(Pres_{jt+1}|Pres_{jt}) \quad (A8)$$

$$Pr_{Percent_Trad} = F_{Percent_Trad}(Percent_Trad_{t+1}|Percent_Trad_t) \quad (A9)$$

$$Pr_{Percent_Virtual} = F_{Percent_Virtual}(Percent_Virtual_{t+1}|Percent_Virtual_t) \quad (A10)$$

$$Pr_R' = 1\{R_{i,t+1} = 0\} * \prod_{j \neq i} F_R(R_{jt+1}|R_{jt}) \quad (A11)$$

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

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:

$$\Pi_{imt}(a_{it}, y_t) = R_{imt}^* - a_{imt}(FC_i + (1 - s_{imt})EC_i), \quad (\text{B1})$$

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

$$\Pi_{imt}(0, y_t) = R_{imt}^* \quad (\text{B2})$$

and

$$\Pi_{imt}(1, y_t) = R_{imt}^* - FC_i - (1 - s_{imt})EC_i \quad (\text{B3})$$

Let

$$z_{imt}(0, y_t) = \{R_{imt}^*, 0, 0, 0, 0, 0, 0, 0, 0, 0\} \quad (\text{B4})$$

and

$$\begin{aligned} z_{imt}(1, y_t) &= \left\{ R_{imt}^*, \quad -1, \quad -Pres_{imt}, \right. \\ &\quad -1, \quad -(1 - s_{it})Pres_{imt}, \\ &\quad -(1 - s_{it})Percent_Trad_{mt}, \\ &\quad -(1 - s_{it})Percent_Virtual_{mt}, \\ &\quad -(1 - s_{it})Percent_Trad_{mt} \times Southwest, \\ &\quad -(1 - s_{it})Percent_Virtual_{mt} \times Southwest, \\ &\quad -(1 - s_{it})Percent_Trad_{mt} \times Other_lcc, \\ &\quad \left. -(1 - s_{it})Percent_Virtual_{mt} \times Other_lcc \right\} \end{aligned} \quad (\text{B5})$$

and

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

Therefore, we can re-write:

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

and

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

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

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

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

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

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

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

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

and

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

where $F_{i,y}^P(0)$ and $F_{i,y}^P(1)$ 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 $e_i^P = \gamma - \ln(P_i(y))$ where $\gamma = 0.577215665$ 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.

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