ESSAYS ON THE COST EFFECTS OF AIRLINE MERGERS AND ALLIANCES

by

HUUBINH B. LE

B.S., Georgia State University, 2007

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2014

Abstract

My dissertation is comprised of two essays in the field of industrial organization with an emphasis on the airline industry. In particular, I investigate how airline mergers and alliances affect the components of total cost. By using a methodology that does not require the researcher to have cost data, I am able to infer marginal costs, fixed costs and sunk costs changes associated with mergers and alliances.

My first essay examines two recent airline mergers—Delta/Northwest and United/Continental. Most post-merger analysis in airlines disproportionately focuses on assessing price rather than cost changes. Perhaps one reason is that reliable price data are more readily available. Despite the difficulty of obtaining cost data, researchers have sought to empirically assess whether cost efficiency gains associated with a merger outweigh the increased market power of the merged firm. The results from my analysis suggest that both mergers are associated with marginal and fixed costs savings, but higher market entry costs. The magnitude of the cost effects differed across the mergers. Moreover, I find that the market power effects of these mergers were negligible.

My second essay investigates the cost effects of the codesharing alliance between Delta, Northwest and Continental Airlines. Codesharing is one of the most popular forms of airline cooperation that allows an airline to market and sell seats on its partners' flights as though it owns those flights. Studies have found that airline alliances have very little to no effect on total cost. Rather than analyzing cost as a whole, I study whether a disaggregate analysis on cost is more appropriate. I find evidence that forming an alliance helps generate more passenger traffic for the alliance partners thereby reducing the partner carriers' marginal cost. Even though the literature has found that the total cost effects to be small, an alliance can have a considerable impact on some components of cost.

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Approved by:

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Philip G. Gayle

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Dedication

To my Mom and Dad.

Essay 1 - Measuring Merger Cost Effects: Evidence from a Dynamic Structural Econometric Model

1.1 Introduction

As suggested in Whinston (2007, pp. 2435), most papers that conduct a retrospective empirical analysis of mergers focus on assessing price rather than cost changes associated with mergers.[1] Perhaps a reason for the disproportionate focus on price rather than cost is that reliable price data are more readily available. Despite the difficulty in obtaining cost data, researchers have sought to empirically assess whether cost efficiency gains associated with a merger outweigh the increased market power of the merged firm.[2] For example, Kim and Singal (1993) use pre-post merger relative changes in price and industry concentration to infer whether cost efficiency gains from a set of mergers outweigh increased market power of the merged firms. The idea is that if the merger causes both price and industry concentration to increase, then it can be inferred that market power increases outweigh cost efficiency gains. Even when price and cost data are not available, researchers have relied heavily on theory and market share data to empirically assess whether cost efficiency gains of a merger outweigh market power increases of the merged firm [Gugler and Siebert (2007)]. In this case the theoretical prediction relied on is that if the merged firm's market share increases relative to the pre-merger joint market share of the firms that merge, then it can be inferred that cost efficiency gains outweigh market power increases [see Gugler and Siebert (2007)].

It is clear from the literature that researchers are interested in measuring cost efficiency gains associated with mergers. Furthermore, merger cost efficiency gains may not just be restricted to marginal cost, even though this is the type of cost efficiency gain that most quickly puts downward pressure on short-run pricing. For example, a merger may eliminate duplication of some service departments of a firm, such as marketing and other administrative areas, which in turn is more likely to lower recurrent fixed cost rather than marginal cost. In addition,

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[1] Examples of such merger analyses in the airline industry include: Werden, Joskow, and Johnson (1989); Borenstein (1990); Brown (2010); Luo (2011); Brueckner, Lee, and Singer (2012); Huschelrath, and Muller (2012).

[2] See Williamson (1968) and Farrell and Shapiro (1990) for theoretical treatments of the opposing effects of efficiency gains and increased market power that may result from a merger.

complementary characteristics/expertise across firms that merge may lower the merged firm's cost of entry into new markets. Lower recurrent fixed and sunk entry costs may allow the merged firm to enter new markets in the medium or long-run that the unmerged firms would not have individually entered without the merger [Benkard, Bodoh-Creed, and Lazarev (2010)].[3] New entry potentially reduces price. So in the medium or long-run, recurrent fixed and sunk market entry cost efficiency gains could result in lower prices and higher welfare. We are unaware of papers in the literature that explicitly separate merger cost effects into these three main categories of cost – (1) marginal cost; (2) recurrent fixed cost; and (3) sunk market entry cost.

The main objective of our paper is to estimate marginal, recurrent fixed and sunk entry cost effects associated with two recent airline mergers – Delta/Northwest (DL/NW) and United/Continental (UA/CO) mergers – using a methodology that does not require the researcher to have cost data. Before describing our methodology, it is useful to briefly discuss previous related work.

Werden, Joskow and Johnson (1989) investigated the price effects of two airline mergers: (1) Northwest (NW) and Republic (RC) airlines; and (2) Trans World Airline (TWA) and Ozark Airlines (OZ). Both mergers occurred in fall 1986. The authors find that the TWA-OZ merger caused a slight overall increase in fares in city pairs out of their major hub in St. Louis (1.5 percent). However, the merger between Northwest and Republic appears to have caused a more significant increase in fares. Overall fares went up by 5.6 percent on city pairs out of their major hub in Minneapolis-St. Paul.

Borenstein (1990) also examines market effects of the NW/RC and TWA/OZ airline mergers. He finds that the TWA/OZ merger had no systematic impact on these carriers price on routes originating at their St. Louis HUB since their price changes on these routes averaged almost exactly the same as the industry average price changes. In contrast, NW/RC merger seems to increase their price on routes out of their main hub in Minneapolis. Borenstein finds that both mergers are associated with increases in the merged firms' market share on routes originating from their main hub.

---

[3] Benkard, Bodoh-Creed, and Lazarev (2010), study the potential medium and long-run dynamic effects of three airline mergers. They focus on predicting the "potential" medium and long-run effects of mergers on industry structure, rather than explicitly measuring the "actual" effects of mergers on firms' cost structure.

Kim and Singal (1993) examine price changes associated with 27 airline mergers during 1985 – 1988. The authors compute price changes of merging firms on sample routes (or treated routes) and compare them to price changes on control routes that do not have the merging firms. Using this same difference-in-differences methodology used for computing relative fare changes, the authors compute relative changes in industry concentration (relative changes in Herfindahl-Hirschman Index (HHI)). The authors infer that market power effects outweigh cost efficiency gains if a positive relationship between relative price changes and industry concentration is found. Alternatively, the authors infer that cost efficiency gains outweigh market power effects if a negative relationship between relative price changes and industry concentration is found. The authors find that for the full sample, cost efficiency gains are dominated by the exercise of market power because the relationship between relative price changes and relative changes in industry concentration is positive and statistically significant.

Peters (2006) investigates five mergers that occur in the 1980s. He first uses pre-merger data to estimate a model derived from the assumption that airlines set prices according to a static Bertand-Nash game. The estimated model is then used to simulate predicted post-merger prices. He compares the simulation prediction of post-merger prices with observed post-merger prices and investigates the sources of deviations between these two sets of prices. He finds that there are significant differences between the average observed price changes and the average predicted price changes. He argues that these differences are mainly due to supply-side effects that may include changes in marginal costs, implying that mergers do influence marginal cost.

It is also useful to briefly describe findings of merger analyses in other industries. Gugler and Siebert (2007) find that mergers in the semiconductor industry raise the market share of participating firms. They argue on theoretical grounds that this is sufficient evidence to suggest that cost efficiency gains dominate market power effects for mergers in this industry.

Dranove and Lindrooth (2003) use actual cost data to empirically investigate whether hospital consolidation leads to cost savings. The authors, with cost data in hand, estimated a translog cost function at the hospital level over pre-post consolidation periods. The authors rely on a difference-in-differences identification methodology. Cost function estimates reveal that consolidations into systems (i.e. common ownership but operations and financial reporting remain separate for the entities that consolidated, therefore limited corporation post-

consolidation) does not generate cost savings, even after 4 years. However, mergers in which hospitals consolidate financial reporting and licenses generate saving of approximately 14%.

Harrison (2011) examines cost savings due to scale economies associated with hospital mergers. Using actual cost data, she non-parametrically estimate costs for each individual reporting entity before and after the merger. Her findings suggest that economies of scale exist for the merging hospitals and that they take advantage of these cost savings immediately following a merger. The findings also indicate that cost savings are higher one year after the merger than in subsequent years.

In the set of papers cited above we can see that some researchers were able to use actual cost data to measure merger efficiencies, while others relied on theoretical predictions to exploit more readily available data on price and/or market share to infer whether merger cost efficiency gains outweigh increases in market power. One of the key distinctions between our paper and previous work that we are aware of is that, without the need for actual cost data, we use a methodology that allows for separate identification of marginal; recurrent fixed; and sunk entry cost effects associated with a merger. The following is a brief summary description of our methodology.

We begin by specifying and estimating a static differentiated products Bertrand-Nash game. The static model incorporates both demand and short-run supply. We first estimate a discrete choice model of air travel demand. For the short-run supply aspect of the model, we assume that prices are set according to a static differentiated products Bertrand-Nash equilibrium with multiproduct firms. The static Bertrand-Nash assumption allows us to derive product-specific markups and recover product-level marginal cost. With marginal cost estimates in hand, along with data on variables that should shift marginal cost, we then specify and estimate a marginal cost function. For a given merger of interest, we specify the marginal cost function in a way that allows all firms' (both non-merging firms and firms that merge) marginal cost to change in the post-merger period relative to the pre-merger period. Consistent with a difference-in-differences methodology, we identify marginal cost effects of a merger by comparing the pre-post merger change in merging firms' marginal cost relative to the change in non-merging firms' marginal cost.

With the product-specific markups in hand, we are able to compute firm-level variable profits. Estimates of firm-level variable profits are subsequently used in a dynamic entry/exit

game, which is the long-run part of our model used for identifying recurrent fixed and sunk entry cost. In the dynamic entry/exit game, each airline chooses markets in which to be active during specific time periods in order to maximize its expected discounted stream of profit, where per-period profit comprises variable profit less per-period fixed cost and a one-time entry cost if the airline is not currently serving the market but plans to do so next period. The dynamic entry/exit game allows us to estimate fixed and entry costs by exploiting estimates of variable profits previously computed from the static Bertrand-Nash game along with observed data on airlines' decisions to enter and exit certain markets. For a given merger of interest, we allow all firms' (both non-merging and the firms that merge) fixed and entry cost functions to change in the post-merger period relative to the pre-merger period. Consistent with a difference-in-differences methodology, we identify fixed and entry cost effects of a merger by comparing the pre-post merger change in merging firms' fixed and entry cost functions relative to the change in non-merging firms' fixed and entry cost functions.

Our empirical results reveal that for the merging firms: (1) Marginal cost efficiency gains are associated with both DL/NW and UA/CO mergers; (2) Fixed cost efficiency gains are associated with both DL/NW and UA/CO mergers; (3) Both mergers however are associated with increased market entry costs; and (4) The magnitudes of these effects differ across the two mergers. The magnitude of marginal cost savings associated with the DL/NW merger is smaller than that of the UA/CO merger. In contrast, the magnitude of fixed cost savings associated with the DL/NW merger is greater than that of the UA/CO merger. The magnitude of the increase in market entry costs associated with the UA/CO merger is greater than that of the DL/NW merger. In the case of non-merging airlines, we find that their recurrent fixed costs are unchanged throughout the entire evaluation periods for both mergers. However, non-merging airlines' market entry costs increase after the DL/NW merger, but decrease after the UA/CO merger.

We also estimate a regression in which a variable of product markups generated from the structural model is regressed on several determinants of markup. Results from this product markup regression reveal that both mergers led to only small increases in markups, suggesting that market power effects of these mergers were negligible.

Results from our structural model are consistent with results from a reduced-form price regression we estimate. The reduced-form price regression reveals evidence that each merger is associated with price decreases, which suggests the marginal cost efficiencies outweigh market

power increases. However, the reduced-form price regression is not able to separately measure the magnitudes of marginal cost efficiencies and markup increases associated with the mergers, hence the need for our structural model analysis.

The rest of the paper is organized as follows: The next section presents some details of the two mergers. Section 1.3 describes the working sample. Sections 1.4 and 1.5 present the static and dynamic models, respectively. Section 1.6 describes the estimation procedure of the static model. A brief discussion of those estimation results follows in section 1.7. Section 1.8 describes the estimation method for the dynamic model, as well as discussions of those results. Section 1.9 provides additional discussion of some results and section 1.10 concludes.

1.2 Details of the DL/NW and UA/CO mergers

Delta and Northwest announced their plan to merge on April 14, 2008. At the time, it would create the largest U.S. commercial airline measured by available seat miles. Delta's headquarters and primary hub are based in Atlanta, Georgia while Northwest was headquartered in Eagan, Minnesota and has a primary hub in Minneapolis, Minnesota. At the time, Delta and Northwest were the third and fifth largest airlines in the United States, respectively.

On October 29, 2008, the United States Department of Justice (DoJ) approved the merger after a six months investigation. The DoJ's approval release statement suggests that the two airlines networks overlapped in some origin-destination markets, which normally triggers antitrust concerns with a proposed merger. However, the DoJ did not challenge the merger in these markets because the DoJ is satisfied that either: (1) sufficient competition from other airlines was present; or (2) cost efficiency gains would be sufficient to mitigate anti-competitive effects. The DoJ stated the following in its approval release statement:[4]

"The two airlines currently compete with a number of other legacy and low cost airlines in the provision of scheduled air passenger service on the vast majority of nonstop and connecting routes where they compete with each other. In addition, the merger likely will result ***in efficiencies such as cost savings*** *in airport operations, information technology, supply chain economics, and fleet optimization that will benefit consumers."*

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[4] Department of Justice. "Statement of the Department of Justice's Antitrust Division on Its Decision to Close Its Investigation of the Merger of Delta Air Lines Inc. and Northwest Airlines Corporation." 19 October 2008. <http://www.justice.gov/atr/public/press_releases/2008/238849.htm>

From the perspective of the merging airlines' executives, they believe that Delta and Northwest are a good fit on many levels. They assert that the combination will benefit customers, employees, shareholders, and the communities they serve. Moreover, it will help create a more resilient airline for long-term success and financial stability. In terms of possible efficiency gains from the merger, they anticipate that by 2012, major revenue and cost synergies in excess of $1 billion a year will be achieved.[5] Approximately $700-$800 million of benefits is anticipated to come from combining and improving the airlines' complementary network structure, where effective fleet optimization will account for more than half of those network benefits. Cost synergies are anticipated to come from the combining of sales agreements, vendor contracts, and more efficient operation of airport facilities. They will also streamline overhead structures, redundant facilities, and technology integration. While the airlines anticipate that much of these costs savings will be offset by higher wages and benefits for employees of the combined carrier, they estimate these gains to be in the $300-$400 million range.

Approximately two years following the DL/NW merger, on May 3, 2010 United (UA) and Continental (CO) made public their plan to merge. Even though the formal announcement did not take place until two years later, United and Continental merger negotiations were underway at the time of the DL/NW merger. The unification of distinct cultures and groups of workers who were represented by different unions slowed progress of the merger. Nonetheless, the merger was approved by the DoJ on August 27, 2010 creating the largest U.S. passenger airline based on capacity, as measured by year 2009 available seat miles, surpassing DL/NW.

Although it only took three months for the DoJ to approve the UA/CO merger—much shorter than the DL/NW approval— there was a major concern. The number of overlapping routes between United's hub airports and Continental's hub at Newark Liberty Airport was large. Continental had a high share of service at this hub, and new entry into markets connected to this hub was difficult because of the limited number of available slots. Therefore, Continental and United had to agree to give up some take-off and landing slots at Newark Liberty Airport to

[5] See seeking Alpha. "Delta Air Lines, Northwest Airlines Merger Call Transcript." 16 April 2008. <http://seekingalpha.com/article/72537-delta-air-lines-northwest-airlines-merger-call-transcript>

Southwest Airlines in order to gain DoJ's approval.[6] Continental would lease 18 pairs of take-off and landing slots during peak and off-peak travel times to Southwest. Although the number is relatively small, Southwest did not have any presence there previously and it only had limited service at neighboring La Guardia Airport. The slot-transfer agreement therefore was enough to ease DoJ's anticompetitive concerns.

Unlike the Delta and Northwest executives, United and Continental did not provide numerical projections of the possible efficiency gains from the merger. They believe, however that UA and CO are compatible partners in many ways. For example, both have similar fleets and operate in different geographic markets that complement each other. Flying mainly Boeing aircrafts helps reduce costs associated with multiple orders. Operating in distinct geographical markets enables them to link and expand their networks as United's strength is mainly in the western part of the United States while Continental has a larger presence in the east coast.[7] In sum, efficiency gains are anticipated from both mergers. However, by providing numerical projections, Delta and Northwest seem to be more confident in achieving of those gains compare to United and Continental.

1.3 Data Construction, Descriptive Statistics and Definitions

The dataset comes from the Origin and Destination Survey (DB1BMarket) collected by the Bureau of Transportation Statistics. It is quarterly data that constitute a 10 percent sample of airline tickets from reporting carriers. Each observation is a flight itinerary that includes information such as the identity of the airline, airfare, number of passengers that purchase the specific itinerary, market miles flown on the trip itinerary, origin and destination airports, as well as intermediate airport stops. Unfortunately, the DB1B data do not contain passenger-specific information, or information on ticket restrictions such as advance-purchase and length-of-stay requirements.

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[6] See Department of Justice. "United Airlines and Continental Airlines Transfer Assets to Southwest Airlines in Response to Department of Justice's Antitrust Concerns." 27 August 2010. http://www.justice.gov/opa/pr/2010/August/10-at-974.html

[7] Alukos, Basili. "How Long Has a Continental-United Merger Been in the Works?" Seeking Alpha. 30 April 2010. <http://seekingalpha.com/article/202056-how-long-has-a-continental-united-merger-been-in-the-works>

We use data that span from the first quarter of 2005 to the third quarter of 2011. The raw dataset contains millions of observations each quarter. For example, there are 9,681,258 observations in the third quarter of 2011. We define and construct our estimation sample in the following manner:

i. *City selection*: Following Aguirregabiria and Ho (2012) among others, we focus on air travel between the 64 largest US cities based on the Census Bureau's Population Estimates Program (PEP) which produces estimates of the population for the United States. We use data from the category "Cities and Towns". We group cities that belong to the same metropolitan areas and share the same airport. Table 1.1 provides a list of the cities, corresponding airport groupings and population estimate in 2009.[8] Our sample has a total of 55 metropolitan areas ("cities") and 63 airports.

ii. *Market definition*: A market is defined as directional origin-destination-time period combination. Directional means that Dallas to Atlanta is a different market than Atlanta to Dallas.

iii. *Product definition*: A product is defined as an itinerary-operating carrier combination. For example, a direct flight from Dallas to Atlanta operated by American Airline.

iv. *Airlines*: There are three types of carriers in the data—ticketing carrier, operating carrier, and reporting carrier. The ticketing carrier is the airline that issues the flight reservation or ticket to consumers. The operating carrier is the airline that engages directly in the operation of the aircraft, i.e., the airline that actually transports the passengers. The reporting carrier submits the ticket information to the Office of Airline Information. We focus on products that use a single operating carrier for all segments of the trip itinerary and designate the operating carrier as the "owner" of the product. Table 1.2 lists the names and associated code of the 41 carriers in our sample.

v. *Itinerary selection*: We drop all itineraries with market fares less than $50 or greater than $2,000. Eliminating fares that are too low helps avoid discounted fares that may

[8] Population estimates of each year were used even though only year 2009 estimates are reported.

be due to passengers using their frequent-flyer miles to offset the full price of the trip. We also drop all itineraries with the following characteristics: (1) outside the 48 mainland US states; (2) one-way tickets; and (3) more than two intermediate stops.

vi. *Price and quantity*: An observation in the data may contain more than one passenger buying the same product at different fares. Thus, the dataset has many repeated products due to passengers paying different fares. We construct the price and quantity variables by averaging the market fare and aggregating number of passengers by defined products respectively. During a given time period, a product appears only once in the collapsed data. Last, a product survives deletion from our sample if it is purchased by at least 9 consumers during a quarter, which helps in eliminating products that are not part of the regular offerings by an airline.

vii. *Observed Product Shares*: From the collapsed dataset, *Observed Product Shares* (subsequently denoted by upper case $\boldsymbol{S}_j$) are constructed by dividing quantity of product j purchased (subsequently denoted by q_j) by the market size (subsequently denoted by *POP*). As in Berry, Carnall and Spiller (2006) and Berry and Jia (2010), we use the geometric mean of a market's origin city population and destination city population as a measure of the market size.[9]

viii. *Origin and destination presence*: We create two variables that capture the magnitudes of an airline's "presence" at the market endpoint cities. The *Origin presence* variable is calculated by aggregating the number of destinations that an airline connects with the origin city using non-stop flights. Similarly, the *Destination presence* variable is calculated by aggregating the total number of destinations that an airline connects with the destination city using non-stop flights. The greater the number of different cities that an airline provides service to using non-stop flights from a given airport, the greater the "presence" the airline has at that airport.

ix. *Creation of other variables*: *Interstop* is a variable that captures one measure of travel itinerary convenience, and is measured by the number of intermediate stops in a product's itinerary. *Inconvenience* is another variable that captures the relative

[9] Since we find that many products have extremely small product shares based on the definition of market size used, we scaled up all product shares in the data set by a common factor. The common factor used is the largest integer such that the outside good share ($\boldsymbol{S}_0 = 1 - \sum_{j=1}^{J} \boldsymbol{S}_j$) in each market remains positive. In our data set this common factor is 35. It turns out that estimation results are qualitatively similar with or without using this scaling factor.

convenience to the consumer of a product's flight itinerary. It is calculated by dividing the itinerary distance flown from the origin to destination by the nonstop flight distance between the origin and destination. If a product uses a nonstop itinerary, its *Inconvenience* measure takes the minimum value, which is 1.

Table 1.3 shows summary statistics of variables used in estimation. The average market fare is approximately $166. Origin and destination presence variables measure an airline's scale of operation at an airport. On average, airlines service approximately 29 different cities from the relevant market's origin and destination cities respectively. The average distance flown across all products is about 1,500 miles.

Table 1.1 Cities Airports and Population

City, State	Airports	2009 Population	City, State	Airports	2009 Population
New York City, NY and Newark, NJ	LGA, JFK, EWR	8,912,538	Las Vegas, NV	LAS	567,641
Los, Angeles, CA	LAX, BUR	3,831,868	Louisville, KY	SDF	566,503
Chicago, IL	ORD, MDW	2,851,268	Portland, OR	PDX	566,143
Dallas, Arlington, Fort Worth and Plano, TX	DAL, DFW	2,680,817	Oklahoma City, OK	OKC	560,333
Houston, TX	HOU, IAH, EFD	2,257,926	Tucson, AZ	TUS	543,910
Phoenix-Tempe-Mesa, AZ	PHX	2,239,335	Atlanta, GA	ATL	540,922
Philadelphia, PA	PHL	1,547,297	Albuquerque, NM	ABQ	529,219
San Antonio, TX	SAT	1,373,668	Kansas City, MO	MCI	482,299
San Diego, CA	SAN	1,306,300	Sacramento, CA	SMF	466,676
San Jose, CA	SJC	964,695	Long Beach, CA	LGB	462,604
Denver-Aurora, CO	DEN	933,693	Omaha, NE	OMA	454,731
Detroit, MI	DTW	910,921	Miami, FL	MIA	433,136
San Francisco, CA	SFO	815,358	Cleveland, OH	CLE	431,369
Jacksonville, FL	JAX	813,518	Oakland, CA	OAK	409,189
Indianapolis, IN	IND	807,584	Colorado Spr., CO	COS	399,827
Austin, TX	AUS	786,386	Tula, OK	TUL	389,625
Columbus, OH	CMH	769,332	Wichita, KS	ICT	372,186
Charlotte, NC	CLT	704,422	St. Louis, MO	STL	356,587
Memphis, TN	MEM	676,640	New Orleans, LA	MSY	354,850
Minneapolis-St. Paul, MN	MSP	666,631	Tampa, FL	TPA	343,890
Boston, MA	BOS	645,169	Santa Ana, CA	SNA	340,338
Baltimore, MD	BWI	637,418	Cincinnati, OH	CVG	333,012
Raleigh-Durham, NC	RDU	634,783	Pittsburg, PA	PIT	311,647
El Paso, TX	ELP	620,456	Lexington, KY	LEX	296,545
Seattle, WA	SEA	616,627	Buffalo, NY	BUF	270,240
Nashville, TN	BNA	605,473	Norfolk, VA	ORF	233,333
Milwaukee, WI	MKE	605,013	Ontario, CA	ONT	171,603
Washington, DC	DCA, IAD	599,657			

Table 1.2 List of Airlines in Sample

Airline Code	Airline Name	Airline Code	Airline Name
16	PSA Airlines	L3	Lynx Aviation
17	Piedmont Airlines	NK	Spirit
3C	Regions Air	NW	Northwest[4]
3M	Gulfstream	OO	SkyWest
9E	Pinnacle	QX	Horizon Air
9L	Colgan Air	RP	Chautauqua
AA	American[1]	RW	Republic
AL	Skyway	S5	Shuttle America Corp.
AQ	Aloha Air Cargo	SX	Skybus
AS	Alaska	SY	Sun Country
AX	Trans States	TZ	ATA
B6	JetBlue	U5	USA 3000
C5	Commutair	UA	United[5]
C8	Chicago Express	US	US Airways[6]
CO	Continental[2]	VX	Virgin America
CP	Compass	WN	Southwest
DH	Independence Air	XE	ExpressJet
DL	Delta[3]	YV	Mesa[7]
F9	Frontier	YX	Midwest
FL	AirTran		
G4	Allegiant Air		
G7	GoJet		

[1] American (AA) + American Eagle (MQ) + Executive (OW)
[2] Continental (CO) + Expressjet (RU)
[3] Delta (DL) + Comair (OH) + Atlantic Southwest (EV)
[4] Northwest (NW) + Mesaba (XJ)
[5] United (UA) + Air Wisconsin (ZW)
[6] US Airways (US) + America West (HP)
[7] Mesa (YV) + Freedom (F8)

Table 1.3 Descriptive Statistics

Time period span of data: 2005:Q1 to 2011:Q3				
Variable	Mean	Std. Dev.	Min	Max
Price[a]	165.89	50.67	38.51	1,522
Quantity	213.85	604.05	9	11,643
Inconvenience	1.14	0.22	1	3.09
Interstop	0.79	0.45	0	2
Origin presence	29.06	25.86	0	177
Destination presence	28.92	25.60	0	176
Itinerary distance flown (miles)[b]	1,544	720.96	36	4,099
Nonstop flight distance (miles)	1,377	667.41	36	2,724
Observed Product Shares ($\boldsymbol{S}_j$)	0.0090	0.026	5.39e-5	0.97
Number of Products	647,167			
Number of markets[c]	75,774			

[a] Inflation-adjusted.
[b] In DB1B database this variables is reported as "Market miles flown".
[c] Recall that a market is defined as a origin-destination-time period combination.

We estimate the static parts of our model (demand and marginal cost equations) on the full sample of data (2005:Q1 to 2011:Q3) since estimating these parts of the model are not computationally intensive. However, due to significant computational intensity required to estimate the dynamic part of the model, we had to treat each merger separately when examining fixed and entry cost effects, which allows us to use more manageable pre-post merger periods data subsamples for each merger. In case of the DL/NW merger, we use 2007:Q1 and 2007:Q2 for the pre-merger period data, and 2011:Q1 and 2011Q:2 for the post-merger period data. In case of the UA/CO merger, we use 2009:Q1 and 2009:Q2 for the pre-merger period data, and 2011:Q1 and 2011:Q2 for the post-merger period data.

Similar to Aguirregabiria and Ho (2012), we use a number of passengers' threshold to determine whether or not an airline is actively servicing an origin-destination market. 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.[10] Table 1.4 indicates that in the post-merger period, UA/CO has entered into 65 new markets—markets where neither operated before merging. Likewise, the table shows that DL/NW has entered into as many as 123 new markets—markets where neither operated before they merged. Perhaps these markets are the high cost-to-enter markets where if it were not for the merger, they would not have entered.

Table 1.4 Number of Unique Markets Entered and Exited Post-merger

	United/Continental	Delta/Northwest
Number of Entries	65	123
Number of Exits	187	267

Reduced-form Price Regression

To help motivate the need for our subsequent structural model, we start by examining how each merger affects price via a reduced-form price regression. Identification of the merger price effects in the reduced-form price regression relies on a difference-in-differences methodology. This identification strategy is in keeping with how many studies, some of which we discussed in the introduction, conduct retrospective analyses of mergers.

[10] The 130 passenger threshold we use for a directional market is equivalent to the 260 for non-directional market used by Aguirregabiria and Ho (2012).

Table 1.5 shows estimation results from a simple reduced-form price equation. T_t^{dn} and T_t^{cu} are zero-one time period dummy variables that take the value 1 only in the post-merger period for each merger respectively. T_t^{dn} is for the DL/NW merger, while T_t^{cu} is for the UA/CO merger. DN_{jmt} is a zero-one airline-product dummy variable that equals 1 for all products that are associated with either Delta or Northwest. Similarly, CU_{jmt} is a zero-one airline-product dummy variable that equals 1 for all products that are associated with either Continental or United. The coefficients on the interaction variables, $T_t^{dn} \times DN_{jmt}$ and $T_t^{cu} \times CU_{jmt}$, therefore measure how DL/NW and UA/CO's prices change over the respective pre and post-merger periods, while the coefficients on T_t^{dn} and T_t^{cu} measure how non-merging airlines' price change over the respective pre-post merger periods.

Table 1.5 Estimation Results for Reduced-form Price Regression

647,167 observations: 2005-Q1 to 2011-Q3		
Variable	Coefficient Estimate	Robust Standard Errors
T_t^{dn}	-0.2181	0.3340
$T_t^{dn} \times DN_{jmt}$	-7.2244***	0.3130
T_t^{cu}	1.1342***	0.2975
$T_t^{cu} \times CU_{jmt}$	-14.6719 ***	0.5417
Itinerary distance flown (miles)	0.0357***	0.0001
Interstop	-0.1187	0.1554
Origin presence	0.4998***	0.0086
$(\text{Origin presence})^2$	-0.0003***	0.00008
Dest. Presence	0.5335***	0.00871
$(\text{Dest. presence})^2$	-0.0005***	0.00007
Constant	113.1979***	1.2036
Operating carrier effects	YES	
Origin city effects	YES	
Destination city effects	YES	
Quarter and Year effects	YES	

*** Statistical significance at the 1% level. The equation is estimated using ordinary least squares.

The coefficient estimate on T_t^{dn} is not statistically significant at conventional levels of statistical significance, suggesting that non-merging airlines' price, on average, did not change over the pre-post DL/NW merger periods. However, the negative and statistically significant coefficient estimate on $T_t^{dn} \times DN_{jmt}$ indicates that the prices of products offered by Delta and

Northwest, on average, declined by $7.22 (a 4% decline from pre-merger mean price level) over the pre-post DL/NW merger periods.

The coefficient estimate on T_t^{cu} is positive and statistically significant, and suggests that non-merging airline prices increase, on average, by $1.13 (a 0.7% increase over pre-merger mean price level) over the pre-post UA/CO merger periods. In contrast to non-merging airlines, the negative and statistically significant coefficient estimate on $T_t^{cu} \times CU_{jmt}$ suggests that the prices of products offered by United and Continental declined, on average, by $14.67 (a 8% decline from pre-merger mean price level) over the pre-post UA/CO merger periods.

The reduced-form evidence suggests that both mergers are associated with lowering the merging firms' prices. However, the UA/CO merger seems to be associated with a larger decline in prices, both in terms of dollars and percentage, compared to the DL/NW merger. Since the mergers are associated with falling prices, we can infer that marginal cost savings outweigh market power increases associated with the mergers. However, a structural model is needed to disentangle and separately measure the magnitudes of marginal cost savings and markup increases (a measure of market power) associated with the mergers.

All other control variables in the reduced-form price regression have the expected sign. Itinerary distance positively affect price, likely via its influence on marginal cost. Prices are lower for products with intermediate stops, perhaps because passengers prefer nonstop products. The size of an airlines' presence at the endpoint airports of a market is initially positively related to price, but becomes negatively related to price as size of airport presence increases beyond a certain threshold. This relationship between price and size of airport presence could in part be driven by economies of passenger-traffic density, i.e., lowering of marginal cost as airlines channel large number of passengers though their major hub airports.

1.4 Model

Demand

We model air travel demand using a discrete choice framework. A passenger c chooses among a set of $J_{mt} + 1$ alternatives in market m during period t, that is, the passenger either chooses one of the J_{mt} differentiated air travel products in the market or the outside option/good $(j = 0)$. The outside option includes other modes of transportation besides air travel. Products

are organized into $G + 1$ mutually exclusive groups, $g = 0,1, \dots, G$ where the outside good is the only member of group 0. A group is a set of products offered by an airline within a market.

Potential passenger c solves the following utility maximization problem:

$$\underset{j \epsilon \{0,1,\dots J_{mt}\}}{Max} \{U_{cjmt} = \mu_{jmt} + \delta \varsigma_{cgmt} + (1 - \delta)\varepsilon_{cjmt}^{d}\}, \quad (1)$$

where U_{cjmt} is passenger c's indirect utility from choosing product j; μ_{jmt} is the mean level of utility across passengers that choose product j; ς_{cgmt} is a random component of utility common across all products within the same group; and ε_{cjmt}^{d} is an independently and identically distributed (across products, consumers, markets and time) random error term assumed to have type 1 extreme value distribution. The parameter δ lies between 0 and 1 and measures the correlation of consumer utility across products belonging to the same group/airline. The correlation of preferences increases as δ approaches 1. In the case where δ is 0, the model collapses to the standard logit model where products compete symmetrically.

The mean utility, μ_{jmt}, is specified as:

$$\mu_{jmt} = x_{jmt}\phi^{x} + \phi^{p} p_{jmt} + \eta_{j} + \upsilon_{t} + origin_{m} + dest_{m} + \xi_{jmt}, \quad (2)$$

where x_{jmt} is a vector of observed non-price product characteristics. The variables in x_{jmt} were briefly defined in the previous section, they include: (1) the number of intermediate stops in a product (*Interstop*); (2) an alternate measure of itinerary convenience (*Inconvenience*); and (3) a measure of the size of an airline's presence at the origin city (*Origin presence*). The vector of parameters, ϕ^{x}, measures passengers' marginal utilities associated with the measured non-price product characteristics. The price is p_{jmt}, and associated parameter, ϕ^{p}, captures the marginal utility of price. Airline fixed effects, η_{j}, are captured by airline dummy variables. Time period effects, υ_{t}, are captured by quarter and year dummy variables. $origin_{m}$ and $dest_{m}$ are origin and destination city fixed effects. ξ_{jmt} is the unobserved (by researchers) component of product characteristics that affect consumer utility. For notational convenience, we drop the market and time subscripts in some subsequent equations.

The demand for product j is given by:

$$d_{j} = POP \times s_{j}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^{p}, \phi^{x}, \delta), \quad (3)$$

where POP is the geometric mean between the origin city population and destination city population, which is our measure of market size; and $s_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^p, \phi^x, \delta)$ is the predicted share function that has functional form based on the nested logit model.[11] $\mathbf{x}$, $\mathbf{p}$, and $\boldsymbol{\xi}$ are vectors of observed non-price product characteristics, price, and the unobserved vector of product characteristics, respectively. ϕ^p, ϕ^x, and δ are demand parameters to be estimated.

Variable Profit, Product Markups and Product Marginal Costs

Each airline i offers a set of B_i products for sale. Thus, airline i has the variable profit function:

$$VP_i = \sum_{j \epsilon B_i} (p_j - c_j) q_j, \qquad (4)$$

where p_j, c_j, and q_j are the respective price, marginal cost, and the quantity of product j sold by airline i. In equilibrium, the amount of product j an airline sells equals to the demand, that is, $q_j = d_j = POP \times s_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^p, \phi^x, \delta)$.

We assume that airlines set prices according to a static Nash-Bertrand game. Therefore, the Nash-Bertrand equilibrium is characterized by the following system of J first-order equations:

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

Using matrix notation, the system of first-order conditions in equation (5) is represented by:

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

where s, p, and mc are $J \times 1$ vectors of predicted product shares, product prices, and marginal costs respectively, Ω is $J \times J$ matrix of appropriately positioned zeros and ones that describes airlines' ownership structure of the J products, $.*$ is the operator for element-by-element matrix

[11] The nested logit model has the following well-known predicted product share function: $s_j = \frac{exp\left(\frac{\mu_j}{1-\delta}\right)}{D_g} \times \frac{D_g^{1-\delta}}{\left[1 + \sum_{g=1}^{G} D_g^{1-\delta}\right]}$, where $D_g = \sum_{j \epsilon G_g} exp\left(\frac{\mu_j}{1-\delta}\right)$ and G_g is the set of products belonging to group g.

multiplication, and Δ is a $J \times J$ matrix of first-order derivatives of product market shares with respect to prices, where element $\Delta_{jk} = \frac{\partial s_k}{\partial p_j}$.

The structure of matrix Ω effectively determines groups of products in a market that are jointly priced. Therefore, the structure of Ω is different in pre-merger periods compared to post-merger periods. In pre-merger periods Ω reflects the fact that separately owned airlines non-cooperatively price their products, however in post-merger periods we appropriately update the structure of Ω to reflect the fact that products offered by the airlines that merged are jointly priced.[12]

Re-arranging equation (6), we can obtain a vector of product markups:

$$\boldsymbol{Mkup}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^{\mathrm{d}}}\right) = p - mc = -(\Omega.* \Delta)^{-1} \times s. \tag{7}$$

where $\widehat{\Phi^{\mathrm{d}}} = (\widehat{\phi^p}, \widehat{\phi^x}, \hat{\delta})$ is the vector of demand parameter estimates. Let $markup_j(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d})$ be an element in $\boldsymbol{Mkup}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^{\mathrm{d}}}\right)$. Note that $markup_j(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d})$ is a product markup function which depends exclusively on demand-side variables and parameter estimates.

With computed product markups in hand, product marginal costs can be recovered by:

$$\hat{c}_{jmt} = p_{jmt} - markup_{jmt}(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}) \tag{8}$$

In addition, an airlines' variable profit in a market can be computed by:

$$VP_{imt} = \sum_{j \epsilon B_{imt}} markup_{jmt}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}\right) * q_{jmt} \tag{9}$$

1.5 Dynamic Entry/Exit Game

In every period (quarter), each airline decides which market(s) to be active in to maximize its expected intertemporal profits. Let airlines be indexed by i, markets by m, and period by t. An airline's expected discounted stream of profit in market m is given by:

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

[12] See Nevo (2000) for details on how matrix Ω differs pre-merger versus post-merger.

where $\Pi_{im,t+r}$ is the per-period profit of the airline in market m and $\beta \in (0,1)$ is the time discount factor. Each airline's per-period profit is specified as the difference between variable profit and the sum of fixed and one-time market entry costs:

$$\Pi_{imt} = R^*_{imt} - a_{imt}\{FC_{imt} + \epsilon^{FC}_{imt} + (1 - s_{imt})[EC_{imt} + \epsilon^{EC}_{imt}]\}, \quad (11)$$

where $R^*_{imt} = s_{imt}VP_{imt}$ is the variable profit of airline i in market m during period t. The value VP_{imt} is computed from the static Nash-Bertrand game described previously. s_{imt} is a zero-one indicator variable that equals to 1 if airline i had decided in period $t-1$ to be active in market m during period t. a_{imt} is also a zero-one indicator variable, but unlike s_{imt}, a_{imt} equals to 1 if airline i decides in period t to be active in $t+1$. Therefore, by definition $s_{imt} = a_{im,t-1}$.

After deciding to be active in a market, we assume that it takes time (one period) for airline i to actually begin operating in market m - time-to-build assumption. This time-to-build assumption implies that if $a_{imt} = 1$ and $s_{imt} = 0$, then airline i pays fixed and entry costs in period t even though flight operations do not actually begin until $t+1$. Note that in period t, a_{imt} is a decision variable, while s_{imt} is a state variable. So we use different letters (a_{imt} versus s_{imt}) to make the distinction between an airline's decision versus a state variable.

FC_{imt} and EC_{imt} are the deterministic portions of fixed and entry costs functions respectively and are common knowledge for all airlines. ϵ^{FC}_{imt} and ϵ^{EC}_{imt} represent private information shocks to fixed and entry costs respectively. The composite shock $\varepsilon_{imt} = \epsilon^{FC}_{imt} + (1 - s_{imt})\epsilon^{EC}_{imt}$ is assumed to be independent and identically distributed (i.i.d) over airlines, markets, and time period based on a specific probability distribution function, which we assume is the type 1 extreme value distribution.

We specify the deterministic portions of fixed and entry cost functions as follows:

$$\begin{aligned} FC_{imt} = {} & \theta^{FC}_0 + \theta^{FC}_1 Pres_{imt} + \theta^{FC}_2 Post_Merger_Period_t + \\ & \theta^{FC}_3 A_Merging_Firm_{imt} + \\ & \theta^{FC}_4 Post_Merger_Period_t \times A_Merging_Firm_{imt}, \end{aligned} \quad (12)$$

$$\begin{aligned} EC_{imt} = {} & \theta^{EC}_0 + \theta^{EC}_1 Pres_{imt} + \theta^{EC}_2 Post_Merger_Period_t + \\ & \theta^{EC}_3 A_Merging_Firm_{imt} + \\ & \theta^{EC}_4 Post_Merger_Period_t \times A_Merging_Firm_{imt}, \end{aligned} \quad (13)$$

$Pres_{imt}$ is a measure of an airline's presence at the endpoint airports of origin-destination market m, which we define as the mean number of destinations the airline serves from the market's endpoint airports using nonstop flights. $Post_Merger_Period_t$ is a zero-one time-period dummy variable that takes the value 1 only during the post-merger period for the relevant merger being studied. $A_Merging_Firm_{imt}$ is a zero-one airline dummy variable that takes the value 1 if the airline is one of the airlines that is a part of the relevant merger being studied. The structural parameters to be estimated are:

$$\{\theta_0^{FC}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}\}'$$

θ_0^{FC} and θ_0^{EC} measure the mean fixed and entry costs across airlines, markets and time, respectively. θ_1^{FC} and θ_1^{EC} capture the effects of the size of airport presence on fixed and entry costs. θ_2^{FC} and θ_2^{EC} capture how fixed and entry costs change for all other airlines except the merging parties across the pre and post-merger periods. θ_3^{FC} and θ_3^{EC} measure any persistent systematic difference in mean fixed and entry costs of the merging airlines relative to other airlines. The coefficients of interest are θ_4^{FC} and θ_4^{EC} which identify changes in fixed and entry costs resulting from the relevant merger being studied, that is, these parameters capture the possible fixed and entry cost efficiency gains associated with a merger.

Reducing the Dimensionality of the State Space

Recall that the variable profit function is defined as:

$$R_{imt}^* = a_{im,t-1} VP_{imt}, \tag{14}$$

where

$$VP_{imt}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}\right) = \sum_{j \in B_{imt}} \left\{ markup_{jmt}(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}) * q_{jmt} \right\}. \tag{15}$$

Note that variable profits are functions of state variables $(\mathbf{x}, \boldsymbol{\xi})$. Aguirregabiria and Ho (2012) suggest that these state variables can be aggregated into a single state variable, R_{imt}^* rather than treating $(\mathbf{x}, \boldsymbol{\xi})$ as separate state variables. In other words, we can treat $R_{imt}^*(\cdot)$ as a firm-specific state variable rather than treating $\mathbf{x}$ and $\boldsymbol{\xi}$ as separate state variables, which serves to significantly reduce the dimensionality of the state space. The vector of payoff-relevant state variables is the following:

$$y_{imt} = \{s_{imt}, R^*_{imt}, Pres_{imt}, Post_Merger_Period_t\} \quad (16)$$

Each airline has the same vector of state variables, which it takes into account when making decisions. Decision-making of each airline also depends on the strategies and actions of other airlines via R^*_{imt}. Recall that 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. Thus, our dynamic entry-exit model does implicitly take into account this strategic interaction among competitors.

Markov Perfect Equilibrium (MPE)

For notational convenience, we drop the market subscript. Let $\sigma \equiv \{\sigma_i(y_{it}, \varepsilon_{it})\}$ be the vector of strategies for each airline where $y_{it} = \{s_{it}, R^*_{it}, Pres_{it}, Post_Merger_Period_t\}$ is a vector of common knowledge state variables and ε_{it} is assumed to be i.i.d. In a Markov Perfect Equilibrium each airline behaves according to its best response strategy, which maximizes its own value function given the state and strategies of other airlines.

Let $V_i^\sigma(y_t, \varepsilon_{it})$ be the value function for airline i. This value function is the unique solution to the following Bellman equation:

$$V_i^\sigma(y_t, \varepsilon_{it}) = \underset{a_{it} \epsilon \{0,1\}}{Max} \left\{ \begin{array}{c} \Pi_{it}^\sigma(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ +\beta \int V_i^\sigma(y_{t+1}, \varepsilon_{i,t+1}) dG_i(\varepsilon_{i,t+1}) F_i^\sigma(y_{t+1}|y_t, a_{it}) \end{array} \right\}. \quad (17)$$

$\Pi_{it}^\sigma(a_{it}, y_t)$ is the expected per-period profit function and $F_i^\sigma(y_{t+1}|y_t, a_{it})$ is the expected transition of state variables. We describe how state variables transition in Appendix A. The profile of strategies in σ is a MPE if, for every airline *i* and every state (y_t, ε_{it}), we have:

$$\sigma_i(y_t, \varepsilon_{it}) = \underset{a_{it} \epsilon \{0,1\}}{argmax} \left\{ \begin{array}{c} \Pi_{it}^\sigma(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ +\beta \int V_i^\sigma(y_{t+1}, \varepsilon_{i,t+1}) dG_i(\varepsilon_{i,t+1}) F_i^\sigma(y_{t+1}|y_t, a_{it}) \end{array} \right\}. \quad (18)$$

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 $\mathbf{P} = \Psi(\theta, \mathbf{P})$, where $\mathbf{P} = \{P_i(\mathbf{y})\text{: for every firm and state } (i, \boldsymbol{y})\}$. $\mathbf{P} = \Psi(\theta, \mathbf{P})$ is a vector of best response probability mapping, where $\Psi(\cdot)$ is the *CDF* of the type 1 extreme value distribution.

1.6 Demand and Marginal Cost Estimation

Our strategy for estimating the demand parameters (ϕ^p, ϕ^x, δ) is such that the observed market shares, $\mathbf{S}_{jmt}$, are equal to the market shares predicted by the model s_{jmt}. As shown in Berry (1994), in the case of the nested logit model, such an estimation strategy implies the following linear equation to be estimated:

$$\ln(\mathbf{S}_{jmt}) - \ln(\mathbf{S}_{0mt}) = x_{jmt}\phi^x + \phi^p p_{jmt} + \delta \ln(\mathbf{S}_{jmt/g}) + \eta_j + \upsilon_t + origin_m + dest_m + \xi_{jmt}, \quad (19)$$

where $\boldsymbol{S}_{0mt}$ is the observed share of the outside good and $\boldsymbol{S}_{jmt/g}$ is the observed within group share of product j. Equation (19) can be estimated by Two Stage Least Squares (2SLS) given that the equation is linear, and p_{jmt} and $\ln(\mathbf{S}_{jmt/g})$ are endogenous.

We use the following linear specification for the marginal cost function:

$$\hat{c}_{jmt} = \tau_0 + \tau_1 W_{jmt} + \tau_2 T_t^{dn} + \tau_3 T_t^{dn} \times DN_{jmt} + \tau_4 T_t^{cu} + \tau_5 T_t^{cu} \times CU_{jmt} + \psi_j + \lambda_t + origin_m + dest_m + \varepsilon_{jmt}^{mc}, \quad (20)$$

where $\hat{c}_{jmt}$ represents product-level marginal cost estimates that were recovered using equation (8). W_{jmt} is a vector of observed marginal cost-shifting variables and τ_1 is the associated vector of parameters to be estimated. Recall that T_t^{dn} is a zero-one time-period dummy variable that equals 1 during time periods after the DL/NW merger. DN_{jmt} is a zero-one airline-product dummy variable that equals 1 for all products that are associated with either Delta or Northwest. τ_2 is a parameter that measures, on average, how marginal cost changes over the pre-post DL/NW merger periods for products that are not associated with Delta or Northwest. However, τ_3 is a parameter that measures, on average, how marginal cost changes over the pre-post DL/NW merger periods for Delta and Northwest products. Therefore, τ_3 measures the possible marginal cost efficiencies associated with the DL/NW merger.

T_t^{cu} is a zero-one time-period dummy variable that equals 1 during time periods after the UA/CO merger. CU_{jmt} is a zero-one airline-product dummy variable that equals 1 for all products associated with either United or Continental. τ_4 is a parameter that measures, on average, how marginal cost changes over the pre-post UA/CO merger periods for products that are not associated with United or Continental. However, τ_5 is a parameter that measures, on

average, how marginal cost changes over the pre-post UA/CO merger periods for United and Continental products. Therefore, τ_5 measures the possible marginal cost efficiencies associated with the UA/CO merger.

ψ_j is an airline-specific component of marginal cost captured by airline dummy variables. λ_t captures time-varying effects on marginal cost that are unobserved by us the researchers. These unobserved time-varying effects are measured using quarter and year dummy variables. $origin_m$ and $dest_m$ are sets of origin and destination city dummy variables respectively. Finally, ε_{jmt}^{mc} is an unobserved random component of marginal cost. Equation (20) is estimated via ordinary least squares (OLS).

Instruments

It is likely that in the demand equation, equation (19), the product price (p_{jmt}) and the within group share ($\mathbf{S}_{jmt/g}$) are correlated with unobserved product characteristics, ξ_{jmt}. For example, an airline may have a very effective advertising campaign to promote its brand. Even though this activity is unobservable to the researcher, it is observable to the consumers and to the airline and therefore may affect how that airline sets prices for its products.

To estimate equation (19) consistently, we need a set of variables (instruments) that are uncorrelated with the demand residual but correlated with price and within group share. The instruments that we use are: (1) itinerary distance; (2) interaction of jet fuel price with itinerary distance; (3) interaction of jet fuel price with operating carrier dummies; (4) an airline's market mean itinerary inconvenience measure; (5) an airline's market sum itinerary inconvenience measure; (6) mean number of intermediate stops across products offered by an airline in a market.

As discussed in Gayle (2007 and 2012), instruments (1)-(3) are motivated by the fact that a product's price is influenced by the marginal cost of providing the product. The intuition for instrument (1) is that flying distance covered by an air travel product is likely to be correlated with the marginal cost of providing the product. The intuition for instruments (2) and (3) is that airlines' marginal costs are likely to change differently when there are shocks to jet fuel price.[13] This differential effect across airlines is due to the fact that airlines differ in the intensity with

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[13] Jet fuel price data are drawn from the U.S. Energy Information Administration.

which they use jet fuel because: (i) they differ in their mix of aircrafts; and (ii) they differ in their route network structures, and therefore itinerary flight distances may differ across airlines.[14] Furthermore, instruments (1) to (3) should be valid since itinerary distance and fuel price shocks are each unlikely to be correlated with ξ_{jmt}.

Instruments (4)-(6) are used for within group product share. Instruments (4) and (5) respectively measure the average and sum of itinerary inconvenience associated with products offered by an airline in a market. Recall that itinerary inconvenience is a flight distance-based measure we previously defined in the data section. In addition, recall that for the nested logit demand model we group products by airline. Since passengers may prefer the set of products offered by an airline in a market because these products offer relatively more convenient travel itineraries, then it is likely that within group share is correlated with instruments (4) and (5). Similarly, instrument (6) is likely to be correlated with within group share because passengers may prefer a set of products offered by a particular airline to other airlines' products owing to differences in number of intermediate stops associated with the products. The validity of instruments (4) – (6) rely on the reasonable, and often used, assumption that non-price product characteristics are medium to long-run decision variables, and therefore are pre-determined in the short-run, which implies that these non-price characteristics are uncorrelated with ξ_{jmt}.

1.7 Estimation Results for Demand, Markup and Marginal Cost

Demand Results

Table 1.6 presents ordinary least squares (OLS) and two-stage least squares (2SLS) estimates of the nested logit demand model. Recall that p_{jmt} and $\ln(\mathbf{S}_{jmt/g})$ are likely to be endogenous, which is not taken in account by OLS estimates. The coefficient estimate on price in the OLS regression is unusually small and statistically insignificant. Although the OLS and 2SLS coefficient estimates on $\ln(\mathbf{S}_{jmt/g})$ lie between zero and one as required by utility maximization theory, they are very different in size. We perform Hausman tests, reported in the last row of Table 1.6, to assess the endogeneity of these variables. The results of these endogeneity tests show that we can reject the hypothesis that p_j and $\ln(\mathbf{S}_{\mathrm{j/g}})$ are exogenous. Therefore, instruments are needed. As a check on how well the instruments can explain

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[14] See Villas-Boas (2007) for similarly motivated types of instruments.

variations in the endogenous variables, we regress each endogenous variable against the instruments using OLS. R^2 measures for the regressions of price against instruments and within group product share against instruments are 0.20 and 0.49 respectively, which suggest that the instruments can explain variations in the endogenous variables.

Based on the clear need to instrument for price and within group product shares, we now turn to the 2SLS estimation results for discussion. The coefficient on price now has the correct sign (negative) and its magnitude has increased. The magnitude of the coefficient on the within group product share becomes smaller and approaches zero rather than one. This suggests that although consumers do exhibit some loyalty to respective airlines, their loyalty is not as strong. Nonetheless, both coefficients are statistically significant at conventional levels.

Consistent with what we expect, the coefficient on the *Interstop* variable is negative, which indicates that consumer's utility decreases as the number of intermediate stop(s) increases. The *Inconvenience* variable is the ratio of itinerary distance to nonstop distance between the origin and destination city. The intuition is that two itineraries can have the same number of intermediate stop(s), but depending on differences across the two itineraries in where the intermediate stop(s) is(are) relative to the origin and destination cities, the two itineraries may yield different levels of travel convenience for the passenger (Gayle 2007). Therefore, this variable captures aspects of the itinerary inconvenience that the variable *Interstop* does not. As expected, the coefficient associated with the *Inconvenience* variable is negative and statistically significant, suggesting that, among itineraries with equivalent number of intermediate stop(s), passengers prefer itineraries with intermediate stop(s) that best minimize travel distances.

The positive coefficient on the *Origin presence* variable suggests that all else equal, passengers' utilities are higher when an airline offers nonstop service to more cities from the passengers' local airport. In other words, consumers are more likely to choose air travel products offered by the airline that serves the larger number of destinations via nonstop flight from the consumer's origin city's airport. This result can be interpreted as capturing a "hub-size" effect on air travel demand. Positive marginal utility associated with "hub-size" may indicate that consumers are possibly reaping the benefits from these airlines in the form of better services such as convenient departure times, gate locations or benefits from participating in frequent flyer programs.

The coefficients on the dummy variables for different seasons suggest that air travel demand display seasonal variations. Specifically, air travel demand seems to be highest in Spring and Summer, which accords with our expectation.

Our demand model yields a mean own-price elasticity estimate of -1.89. Oum, Gillen and Noble (1986), and Brander and Zhang (1990) argue that a reasonable range for own price elasticity in the airline industry is from -1.2 to -2.0. Berry and Jia (2010) find own-price elasticity estimates ranging from -1.89 to -2.10 in their 2006 sample, while Peters (2006) study of the airline industry produces own-price elasticity estimates ranging from -3.2 to -3.6. Although our elasticity estimate is on the lower range, we believe that it is reasonable and accords with evidence in the existing literature.

Table 1.6 Demand Estimation Results

647,167 observations: 2005-Q1 to 2011-Q3				
	OLS		2SLS	
Variable	Estimates	Std. Error	Estimates	Std. Error
Price	-2.96e-5	(2.75e-5)	-0.0110***	(0.0001)
$\ln(S_{j/g})$	0.4990***	(0.0011)	0.0843***	(0.0023)
Interstop	-0.9528***	(0.0034)	-1.2536***	(0.0045)
Inconvenience	-0.9927***	(0.0063)	-1.1236***	(0.0076)
Origin presence	0.0147***	(0.0001)	0.0117***	(0.0001)
Spring	0.1451***	(0.0034)	0.1648***	(0.0041)
Summer	0.1294***	(0.0034)	0.1546***	(0.0041)
Fall	0.1037***	(0.0036)	0.1059***	(0.0043)
Constant	-4.6684***	(0.0284)	-2.6787***	(0.0361)
Operating carrier effects	YES		YES	
Origin airport effects	YES		YES	
Destination airport effects	YES		YES	
Year effects	YES		YES	
R^2	0.5768		0.3927	
Wu-Hausman:	28950.4***	F(2; 647,002)	Prob_Value = 0.0000	
Durbin-Wu-Hausman:	53158.4***	$\chi^2(2)$	Prob_Value = 0.0000	

*** Statistical significance at the 1% level.

Computed Variable Profits and Recovered Marginal Costs

All monetary variables in this study are measured in constant year 1999 dollars. The overall mean price and product markup are $165.90 and $92.82, respectively. We find that airlines are able to raise their price above marginal cost by a mean 60.80%. Mean product-level marginal cost is $73.08. The mean number of miles flown on an itinerary in the sample is

1,544.25 miles (see summary statistics for "Market miles flown" variable in Table 3). Therefore, our model predicts a marginal cost per mile of 4.7 cents.

Quarterly market-level variable profits by airline are computed using equation (9) along with the demand parameter estimates. It is useful at this point to put in context the magnitudes of quarterly market-level variable profit estimates. Recall that the original database, before any cleaning, is only a 10% sample of air travel tickets sold. This implies that the magnitudes of variable profit estimates are at most roughly 10% of actual variable profits. Mean quarterly market-level variable profit for an airline in the sample is $84,188.81, while the median is $33,451.05.

Product markup function estimation results

Table 1.7 reports estimation results for a regression in which a variable of product markups generated from the structural model is regressed on several determinants of markup, including the relevant dummy variables needed to investigate how product markup change with implementation of each respective merger. The variables of interest are $T_t^{dn} \times DN_{jmt}$ and $T_t^{cu} \times CU_{jmt}$. Their coefficients indicate whether product markups are any different over the relevant pre-post merger periods for each merger.

As expected, the positive coefficient estimate on the $T_t^{dn} \times DN_{jmt}$ variable suggests that the DL/NW merger is associated with higher markup for the products offered by the newly merged DL/NW airline. However, the economic magnitude of the coefficient is small. Markup for products offered by DL/NW only increases by an average 65 cents following the merger, which corresponds to a 0.70% increase over these airlines' pre-merger mean markup. While the coefficient estimate on $T_t^{cu} \times CU_{jmt}$ is also positive, it is statistically insignificant suggesting that markups for UA/CO products are not different over the pre-post merger periods.

Other control variables in the markup regression include: (i) size of an airline's presence at the origin airport, measured by the *Origin presence* variable; and (ii) the number of intermediate stops required by a flight itinerary, measured by the *Interstop* variable. As expected, *Origin presence* has a positive effect on product markup, which is consistent with the argument in the literature that airlines are able to charge a premium at their hub airport [Berry (1990); Berry, Carnall and Spiller (2006); Borenstein (1989)]. An increase in the number of intermediate stops in a product reduces markup. This result is also expected because passengers

usually prefer nonstop flights to their destinations, as confirmed by our demand equation estimation results.

In summary, both mergers increase markup but the economic magnitude is negligible. Since product markup measures market power, these results suggest that the mergers, on average, did not reduce the level of competition in the industry.

Table 1.7 Estimation Results for Product Markup Regressed on Several of its Determinants

647,167 observations: 2005-Q1 to 2011-Q3		
Variable	Coefficient Estimate	Robust Standard Errors
T_t^{dn}	-0.2260***	0.0576
$T_t^{dn} \times DN_{jmt}$	0.6506***	0.0514
T_t^{cu}	0.1650***	0.0517
$T_t^{cu} \times CU_{jmt}$	0.0258	0.0483
Origin presence	0.0606***	0.0004
Interstop	-1.3308***	0.0682
Constant	89.6996***	0.0660
Operating carrier effects	YES	
Origin city effects	YES	
Destination city effects	YES	
Quarter and Year effects	YES	

*** Statistically significant at the 1% level, while * statistically significant at the 10% level. Model is estimated using ordinary least squares.

Marginal cost function estimation results

Table 1.8 presents OLS estimates of the marginal cost equation. The coefficient on *Itinerary distance flown* (from origin to destination) has the expected positive sign and is statistically significant. All else equal, marginal cost increases by $3.77 with each 100 miles increment in distance flown.

The sign pattern of the coefficients on the airport presence variables suggest that marginal cost initially increases in airport presence, then eventually declines with further increases in airport presence. The coefficients on the airport presence variables can be interpreted as capturing the effect of "hub-size" on marginal cost. In other words, coefficients on the "hub-size" variables indicate that airlines will not be able to achieve marginal cost efficiencies until they reach a certain scale of operation. Therefore, we believe these variables indirectly capture economies of passenger-traffic densities that airlines can enjoy by channeling a relatively large volume of passengers through these endpoint airports.

Brueckner and Spiller (1994), in an earlier study, find robust direct evidence of economies of passenger-traffic densities. They use a structural econometric model to show that marginal cost per passenger on a route falls as airlines channel high volumes of passengers on segments of the route.

Relative to the DL/NW pre-merger time period, there is no evidence that marginal costs for non-DL/NW products change in the post-merger period. However, the DL/NW merger is associated with a decline of $7.5 in the marginal cost of DL/NW products. These inferences are drawn from the coefficients on T_t^{dn} and $T_t^{dn} \times DN_{jmt}$ respectively. Therefore, the results suggest that there are marginal cost efficiencies associated with the DL/NW merger.

Table 1.8 Marginal Cost Estimation Results

647,167 observations: 2005-Q1 to 2011-Q3		
Variable	Coefficient Estimate	Robust Standard Errors
Itinerary distance flown (miles)	0.0377***	0.0001
Origin presence	0.4549***	0.0087
(Origin presence)^2	-0.0004***	0.0001
Dest. presence	0.4849***	0.0088
(Dest. presence)^2	-0.0006***	0.0001
T_t^{dn}	0.0949	0.3398
$T_t^{dn} \times DN_{jmt}$	-7.5935***	0.3180
T_t^{cu}	1.0132***	0.3013
$T_t^{cu} \times CU_{jmt}$	-14.6084***	0.5389
Constant	23.0705***	1.2079
Operating carrier effects	YES	
Origin city effects	YES	
Destination city effects	YES	
Quarter and Year effects	YES	

*** Statistically significant at the 1% level.

There is strong evidence that the UA/CO merger lowers marginal cost even more than the DL/NW merger. Marginal cost of non-UA/CO products seem to be higher comparing UA/CO pre-merger and post-merger time periods. However, the marginal cost of United/Continental products seems to decline substantially (approximately $13.60=($1.01-$14.61)) when comparing the pre-merger and post-merger periods.

In summary, there are marginal cost efficiencies associated with both mergers, but the magnitude of the marginal cost decrease associated with the UA/CO merger is greater than that

associated with the DL/NW merger. These marginal cost efficiency gains closely reflect the reduced-form price effects of the mergers reported in Table 5.

1.8 Estimation of Dynamic Model

Consider the following pseudo log likelihood function:

$$Q(\theta, \mathbf{P}) = \sum_{m=1}^{M} \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ \begin{array}{c} a_{imt} \ln \Psi\left(\tilde{Z}_{imt}^{\mathbf{P}} \boldsymbol{\theta} + \tilde{e}_{imt}^{\mathbf{P}}\right) \\ + (1 - a_{imt}) \ln \Psi\left(-\tilde{Z}_{imt}^{\mathbf{P}} \boldsymbol{\theta} - \tilde{e}_{imt}^{\mathbf{P}}\right) \end{array} \right\}, \quad (21)$$

where $Q(\theta, \mathbf{P})$ is called the "pseudo" log likelihood function because players' conditional choice probabilities (CCPs) in $\mathbf{P}$ are arbitrary and do not represent the equilibrium probabilities associated with θ implied by the model. We begin by implementing a two-step pseudo maximum likelihood estimator (PML). The first step involves estimating the relevant state transition equations and obtaining nonparametric estimates of the choice probabilities, $\widehat{\mathbf{P}}_0$. Estimating the state transition equations allow us to construct the state transition matrices, $\mathbf{F}_{iy}^{\mathbf{P}}(1)$ and $\mathbf{F}_{iy}^{\mathbf{P}}(0)$.[15] Nonparametric estimates of choice probabilities allow us to construct consistent estimates of $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$. $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$ are components of expected profit, which we define in Appendix B. With $\mathbf{F}_{iy}^{\mathbf{P}}(1)$, $\mathbf{F}_{iy}^{\mathbf{P}}(0)$, $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$ in hand, we can construct the pseudo log likelihood function, $Q\left(\theta, \widehat{\mathbf{P}}_0\right)$.

In the second step, we estimate the vector of parameters by solving the following problem:

$$\hat{\theta}_{PML} = \arg\max_{\theta} \; Q\left(\theta, \widehat{\mathbf{P}}_0\right), \quad (22)$$

where $\hat{\theta}_{PML}$ is the two-step pseudo maximum likelihood estimator (PML). The computation in the second step is simple as it only involves estimation of a standard discrete choice model. The main advantage of the two-step estimator is its computational simplicity because it does not require solving for an equilibrium in the dynamic game, which greatly

[15] To facilitate construction of the transition matrices, continuous state variables are discretized. The two continuous state variables are, variable profit (R_{imt}^{*}), and size of an airline's presence at endpoint airports of a market ($Pres_{imt}$). R_{imt}^{*} is discretized using intervals based on the 20th, 40th , 60th and 80th percentiles of the continuous variable, while $Pres_{imt}$ is discretized based on the 25th, 50th and 75th percentiles of the continuous variable.

reduces the computational burden. However, as discussed in Aguirregabiria and Mira (2007), the two-step PML estimator may be subjected to finite sample bias. To deal with such potential bias, we follow Aguirregabiria and Mira (2007) and implement a recursive K-step extension of the two-step PML estimator, which they refer to as the Nested Pseudo Likelihood (NPL) estimator.[16] In Appendix C we provide more discussion on implementing the NPL estimator.

Fixed and Entry Cost Estimation Results

Tables 1.9 and 1.10 present our recurrent fixed and sunk market entry cost estimation results for the two mergers. We begin by discussing recurrent fixed cost results for both mergers and then turn to discussing sunk market entry cost results. First, the parameters that measure mean fixed cost as well as coefficients on the size of an airline's airport presence—measured by the mean number of destinations that an airline connects from the market's endpoint airports using non-stop flight—are unreasonably small and not precisely estimated. We expected these coefficients to be positive, reflecting that mean fixed cost is positive and increasing in the size of an airline's operations at the market endpoint airports. The reason for this expected result is that, the larger the size of an airline's operations at an airport, the more gates and ground crew the airline will need for operations, which imply higher fixed expenses.

[16] While the demand model is estimated using all years in the data set (2005Q1-2011Q3), due to significant computational burden, we find that the dynamic entry/exit model can only feasibly be estimated using, at most, four quarters of the data. Even with just four quarters of data, the computer code for the dynamic entry/exit model took more than two weeks of continuous running before convergence is achieved.

Table 1.9 Recurrent Fixed and Sunk Market Entry Cost Functions Parameter Estimates for the Sample used to Evaluate the United/Continental Merger

Pre-merger period - 2009:Q1-Q2: Post-merger period - 2011:Q1-Q2			
	Theta (in $10,000)	Standard Error	T-stat
Fixed Cost Function			
Mean Fixed Cost	7.52e-12	0.0051	1.49e-9
$Presence_{imt}$	5.34e-13	9.49e-5	5.63e-09
CU_{imt}	-0.6479***	0.0584	-11.08
T_t^{cu}	2.23e-11	0.0055	4.06e-09
$T_t^{cu} \times CU_{imt}$	-1.8462***	0.1656	-11.15
Entry Cost Function			
Mean Entry Cost	3.1129***	0.0361	86.29
$Presence_{imt}$	-0.0113***	0.0004	-29.14
CU_{imt}	0.9994***	0.0742	13.46
T_t^{cu}	-0.2762***	0.0458	-6.03
$T_t^{cu} \times CU_{imt}$	3.0569***	0.2089	14.63

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

Table 1.10 Recurrent Fixed and Sunk Market Entry Cost Functions Parameter Estimates for the Sample used to Evaluate the Delta/Northwest Merger

Pre-merger period - 2007:Q1-Q2: Post-merger period - 2011:Q1-Q2			
	Theta (in $10,000)	Standard Error	T-stat
Fixed Cost Function			
Mean Fixed Cost	8.51e-05	0.0278	0.0031
$Presence_{imt}$	-5.86e-07	0.0003	-0.0019
DN_{imt}	-0.5478***	0.0538	-10.19
T_t^{dn}	-6.77e-07	0.0318	-2.13e-05
$T_t^{dn} \times DN_{imt}$	-2.7602***	0.2055	-13.43
Entry Cost Function			
Mean Entry Cost	3.0993***	0.0409	75.83
$Presence_{imt}$	-0.0119***	0.0004	-27.72
DN_{imt}	0.5802***	0.0679	8.54
T_t^{dn}	0.2138**	0.0541	3.95
$T_t^{dn} \times DN_{imt}$	2.7363***	0.2248	12.17

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

The fixed cost function coefficient estimates on dummy variable CU_{imt} in Table 1.9 and dummy variable DN_{imt} in Table 1.10 are both negative and statistically significant at conventional levels of statistical significance. The negative coefficient on CU_{imt} suggests that over the pre- and post-merger sample periods used for evaluating the UA/CO merger, United and Continental Airlines have lower mean fixed cost relative to the mean fixed cost across other airlines. The coefficient estimate suggests that, for a typical origin-destination market during the

relevant sample period, the mean quarterly fixed cost of Continental and United Airlines is approximately \$6,479 lower than the mean quarterly fixed cost across other airlines. Similarly, the negative coefficient on DN_{imt} suggests that over the pre- and post-merger sample periods used for evaluating the DL/NW merger, Delta and Northwest Airlines have lower mean quarterly fixed cost relative to the mean quarterly fixed cost across other airlines. The coefficient estimate suggests that, for a typical origin-destination market during the relevant sample period, the mean quarterly fixed cost of Delta and Northwest Airlines is approximately \$5,478 lower than the mean quarterly fixed cost across other airlines.

The fixed cost function coefficient on variable T_t^{cu} in Table 1.9 and variable T_t^{dn} in Table 1.10 measure the extent to which non-merging airlines' fixed cost change between the respective pre- and post-merger periods under consideration. The coefficients on T_t^{cu} and T_t^{dn} are not statistically different from zero in both cases, suggesting that non-merging airlines' fixed cost did not change between the respective pre- and post-merger periods under consideration.

The fixed cost function coefficients on the interaction variables $T_t^{cu} \times CU_{imt}$ and $T_t^{dn} \times DN_{imt}$ in Tables 1.9 and 1.10 respectively, measure if the merging airlines cost change is different relative to other airlines between the respective pre- and post-merger periods. Therefore, these coefficients capture possible merger efficiencies with respect to fixed costs. The coefficients on both interaction terms are negative and statistically significant, suggesting that both airline mergers have fixed cost savings associated with it. The coefficient estimates suggest that the UA/CO and DL/NW mergers reduce these airlines quarterly fixed cost by an average \$18,462 and \$27,602 respectively in the typical origin-destination market served by these carriers. Therefore, the fixed cost efficiency gains from the DL/NW merger are greater in magnitude compare to the UA/CO merger.

We now turn to discussing the results on market entry costs. All the variables that enter the entry cost function are the same as the variables in the fixed cost function. The coefficient estimates in the entry cost functions in Tables 1.9 and 1.10 are all statistically significant at the one percent level. The one-time mean cost to enter a market is approximately \$31,000 on average across all airlines in both samples. Based on the static model estimates previously discussed, the median quarterly variable profit an airline earns in an origin-destination market is approximately \$33,450. Therefore, our models suggest that the size of the mean entry cost takes up almost the entire (92.68%) one-period median variable profit.

The entry cost function coefficient on the size of market endpoint airport presence across Tables 1.9 and 1.10 are both negative as expected. In other words, greater endpoint airport presence seems to lower the airlines' entry cost to begin actually serving the market. This result is consistent with much of the airline literature that discusses the determinants of market entry [for example see Berry (1992) and Goolsbee and Syverson (2008)].

The entry cost coefficient estimates on dummy variable CU_{imt} in Table 1.9 and dummy variable DN_{imt} in Table 1.10 are both positive. The positive coefficient on CU_{imt} suggests that over the pre- and post-merger sample periods used for evaluating the UA/CO merger, United and Continental Airlines have higher mean entry cost relative to the mean entry cost across other airlines. The coefficient estimate suggests that, for a typical origin-destination market during the relevant sample period, the mean entry cost of Continental and United Airlines is approximately $9,994 higher than the mean entry cost across other airlines. Similarly, the positive coefficient on DN_{imt} suggests that over the pre- and post-merger sample periods used for evaluating the DL/NW merger, Delta and Northwest Airlines have higher mean entry cost relative to the mean entry cost across other airlines. The coefficient estimate suggests that, for a typical origin-destination market during the relevant sample period, the mean entry cost of Delta and Northwest Airlines is approximately $5,802 higher than the mean entry cost across other airlines.

The entry cost function coefficient on variable T_t^{cu} in Table 1.9 and variable T_t^{dn} in Table 1.10 measure the extent to which non-merging airlines' market entry cost change between the respective pre- and post-merger periods under consideration. The negative coefficient on T_t^{cu} suggests that non-merging airlines' market entry cost fell between the pre- and post-merger sample periods used to evaluate the UA/CO merger. On the contrary, the positive coefficient on T_t^{dn} suggests that non-merging airlines' market entry cost increase between the pre- and post-merger sample periods used to evaluate the DL/NW merger. All else equal, non-merging airlines' market entry costs increase about $2,138 after DL and NW merged, however non-merging airlines' market entry cost fall about $2,762 after UA and CO merged.

Although we have found evidence of fixed cost savings, we are also interested in knowing whether those mergers lower the merging firms' market entry costs. Interestingly, the entry cost function coefficients on the interaction variables $T_t^{cu} \times CU_{imt}$ and $T_t^{dn} \times DN_{imt}$ in Tables 1.9 and 1.10 respectively, suggest that the merging airlines' market entry costs rise as a result of the mergers. The DL/NW merger increases DL and NW market entry costs by

approximately $27,363, while the UA/CO merger is associated with a larger increase in UA and CO market entry costs, approximately $30,569.

In summary, we find evidence that fixed cost efficiency gains are associated with both mergers. The DL/NW merger experiences a greater magnitude of reduction in fixed costs compare to the merger between United and Continental. Market entry costs for the merging airlines however increased as a result of the mergers. The UA/CO merger is associated with a larger increase in the merging airlines' market entry cost as compared to the increase in the merging airlines' entry cost associated with the DW/NW merger. In the case of non-merging airlines, we find that their fixed costs are unchanged throughout the entire evaluation periods for both mergers. However, non-merging airlines' market entry cost increase after the DL/NW merger, but decrease after the UA/CO merger.

1.9 Discussion

Since merging airlines are likely to be more efficient with the use of their aircraft fleets, and handling of their airport operations, it is not surprising to find evidence of fixed costs savings, as we do, associated with the mergers. However, we thought that the merging airlines' market entry cost would also decline, rather than increase as the estimates suggest. So the increase in the market entry cost of the merging airlines' is a bit surprising. One possible explanation for this may be related to the fixed cost efficiency gains that we found. The argument is as follows. With lower recurrent fixed cost, the merged airlines can now profitably operate in markets that are more costly to enter compared to the type of markets that they typically enter prior to the merger. In other words, without the merger-specific fixed-cost efficiencies, entry into these markets may not have been possible otherwise. In this case, the merging firms' new market entry choice behavior in the post-merger period reveals the higher entry cost markets that the merged firm is now entering. This argument is consistent with data in Table 1.4, which indicate that in the post-merger period, UA/CO has entered into 65 new markets—markets where neither operated before merging. Likewise, the table shows that DL/NW has entered into as many as 123 new markets—markets where neither operated before they merged. Perhaps these markets are the high cost-to-enter markets where if it were not for the merger, they would not have entered.

An interesting result that merits further discussion is that non-merging airlines' market entry cost increases following the DL/NW merger, but declines following the UA/CO. In other words, rivals to the newly merged DL/NW airlines find it more difficult in the post-merger period to enter markets and possibly compete with the newly merged airline. On the other hand, rivals to the newly merged UA/CO airline find it easier in the post-merger period to enter markets and possibly compete with the newly merged airline. One implication of this result is that initial increases in market concentration due to the DL/NW merger might persist longer compared to initial increases in market concentration due to the UA/CO merger.

1.10 Concluding Remarks

Researchers have long been interested in measuring possible cost efficiency gains associated with mergers. We are unaware of papers in the literature that explicitly separate merger cost effects into these three main categories of cost: (1) marginal cost; (2) recurrent fixed cost; and (3) sunk entry cost. Therefore, the main objective and contribution of our paper is to empirically estimate marginal, recurrent fixed and sunk entry cost effects associated with two recent airline mergers – Delta/Northwest and United/Continental mergers – using a methodology that does not require the researcher to have cost data.

Our empirical results reveal that for the merging airlines: (1) Marginal cost efficiency gains are associated with both DL/NW and UA/CO mergers; (2) Fixed cost efficiency gains are associated with both DL/NW and UA/CO mergers; (3) Both mergers however are associated with increased market entry costs; and (4) The magnitudes of these effects differ across the two mergers. The magnitude of marginal cost savings associated with the DL/NW merger is smaller than that of the UA/CO merger. In contrast, the magnitude of fixed cost savings associated with the DL/NW merger is greater than that of the UA/CO merger. The magnitude of the increase in market entry costs associated with the UA/CO merger is greater than that of the DL/NW merger. In the case of non-merging airlines, we find that their fixed costs are unchanged throughout the entire evaluation periods for both mergers. However, non-merging airlines' market entry costs increase after the DL/NW merger, but decrease after the UA/CO merger. One implication of this last result is that initial increases in market concentration due to the DL/NW merger might persist longer compared to initial increases in market concentration due to the UA/CO merger.

We also estimate a regression in which a variable of product markups generated from the structural model is regressed on several determinants of markup. Results from this product markup regression reveal that both mergers led to only small increases in markups, suggesting that market power effects of these mergers were negligible.

Results from our structural model are consistent with results from a reduced-form price regression we estimate. The reduced-form price regression reveals evidence that each merger is associated with price decreases, which suggests that marginal cost efficiencies outweigh market power increases. However, the reduced-form price regression is not able to separately measure the magnitudes of marginal cost efficiencies and markup increases associated with the mergers, hence the need for our structural model analysis.

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Essay 2 - Airline Alliances and their Effects on Costs

2.1 Introduction

The prevalence of airline alliances among domestic carriers following passage of the Airline Deregulation Act in 1978 leads one to wonder the extent to which these alliances generate cost efficiency gains for the partner carriers. Investigating the cost effects associated with an alliance is of particular interest since it is the traditional legacy carriers with hub-and-spoke route networks that typically form alliances, and these carriers face increasingly stiff competition from low-cost-carriers. The most common form of airline cooperation is a codesharing agreement that allows a carrier to put its designator code on its partners' flights. For example, DL001 is flight 001 operated by Delta. The word operated here means that Delta is the airline that transports the passenger. If Delta has a codesharing agreement with Northwest, this flight can also be marketed and sold by Northwest under the code and flight number NW002 even though Northwest is not the operator of the flight. Thus, a single flight can be ticketed and sold my multiple carriers even though the operator of the flight may be different from the one that sold the ticket.

The literature on codeshare alliances is extensive. Many facets have been examined such as their effects on airfares, passenger traffic, and social welfare [Brueckner and Whalen (2000); Brueckner (2001 and 2003); Bamberger, Carlton and Neumann (2004); Ito and Lee (2007); Gayle (2007, 2008 and 2013); among others].[17] Nonetheless, perhaps due to the difficulty of obtaining cost data at the route-level, few studies have looked into how airline alliances might influence costs. Furthermore, even the few studies that did find that alliances have very little impact on costs. For example, Goh and Yong (2006) estimate a translog cost function using firm-level data of 10 US airlines from 1994-2001 and find that the economic magnitude of the effect on cost is small. A one percent increase in the number of alliance partners reduces total costs by only 0.029 percent. In another study by Gagnepain and Marin (2010), they find that although being a member of an alliance on average lowers prices compared to airlines outside the alliance, there are no significant effects of the alliance on airlines' operating costs. Also, Chen (2000) uses the American Productivity Centre (APC) model to empirically investigate the

[17] Important early contributions to this literature include: Oum and Park (1997); Park (1997); Park and Zhang (1998); and Park and Zhang (2000).

profitability of airlines that are members of an international alliance. The author decomposes changes in airlines' profitability into changes in their productivity and cost recovery, and finds that in terms of their ability to recover cost, no airline exhibited any significant improvement regardless of their involvement with other airlines or the size of their partner airlines.

These studies examine cost as a whole (total cost), and even though they find that total cost seems to matter little as a motivating factor for airlines forming alliances, we think that perhaps there are differential changes in various components of costs that may mask cost effects if the analysis only focuses on total cost. More importantly, a disaggregate cost analysis is very useful since changes in marginal cost, recurrent fixed cost, and sunk market entry cost are likely to affect equilibrium market outcomes differentially over different time horizons. For example, theory tells us that a change in marginal cost will be reflected in price more quickly than changes in recurrent fixed or sunk market entry cost. However, changes in recurrent fixed cost and sunk market entry cost are more likely to change the medium to long-run market structure configuration. So a great deal of economic outcomes associated with an alliance could potentially be overlooked if analyses only focus on total cost when analyzing the cost effects of an alliance.

But what is the rationale for positing that an alliance may influence various components of partner airlines' cost, and why might these cost components be differentially affected? Figure 1 is used to help lay out the arguments why an alliance may influence the three types of costs we stated above.

Figure 2.1 illustrates two separate hub-and-spoke (HS) route networks operated by Airline 1 and Airline 2 respectively. Airline 1 has a hub airport in city H1 and serves spoke cities A, B and C via this hub. Airline 2 has a hub airport in city H2 and serves spoke cities X, Y and Z via this hub. Furthermore, suppose these two airlines are initially non-allied and each only provides service to their spoke cities via their respective hubs, H1 and H2.

As suggested above, a codeshare alliance effectively allows a carrier to sell tickets for seats on its partners' plane as if the carrier selling the seats owned these seats. Suppose Airline 1 and Airline 2 form a codeshare alliance, which incentivizes Airline 1 to begin operating a flight between its own hub H1 and Airline 2's hub H2. The dashed line in Figure 1 represents this new nonstop flight service by Airline 1 between cities H1 and H2. Note that the codeshare alliance allows Airline 1 to use this single new nonstop flight to leverage the expansive reach of Airline

2’s route network. In other words, by codesharing with Airline 2, Airline 1 can offer service to customers in its spoke cities A, B, and C to destinations X, Y and Z, where these customers will ride on Airline 1’s plane(s) up to city H2, then change over to Airline 2’s plane to get to their final destination. So the codeshare alliance effectively allows Airline 1 to enter several new origin-destination markets more cheaply by leveraging its partners’ network, rather than having to use its own planes exclusively to enter these markets. Therefore, this example illustrates that an alliance can decrease partner airlines’ market entry costs.

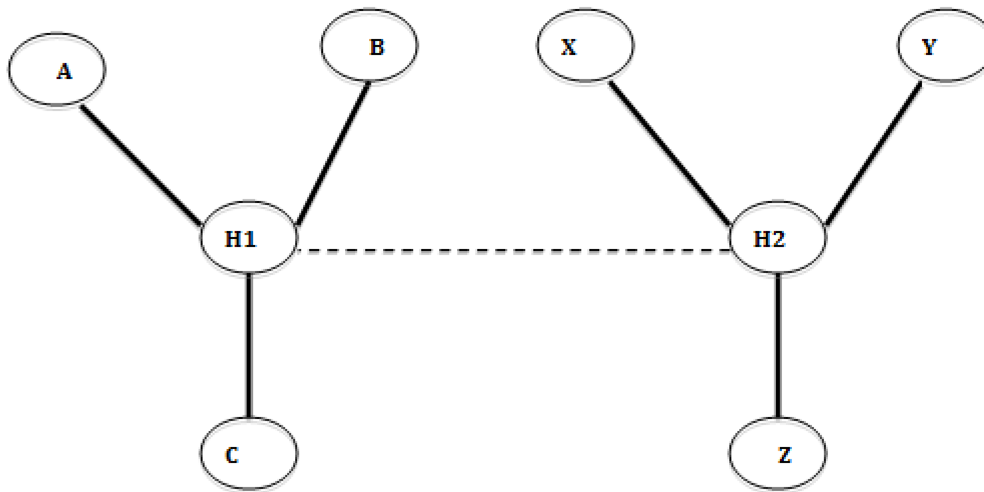

Figure 2.1 Two Separate Hub-and-Spoke Route Networks

By channeling passengers from different origins, who have a common destination, through the carrier’s intermediate-stop hub airport, these passengers can be put on a single plane in the last segment(s) of the trip to their destination. Therefore, the HS network enables carriers to better fill their planes with passengers. It is well documented in the literature that the HS route network structure enables carriers to exploit economies of passenger-traffic density, i.e., the marginal cost of transporting a passenger on a route is lower, the more passengers that the airline transports on segments of the route [Brueckner and Spiller (1994); and Keeler and Formby (1994)].

Our example in Figure 1 can be used to illustrate that a codeshare alliance further enables partner carriers to exploit economies of passenger-traffic density. The additional passenger-traffic that is coming from Airline 1’s spoke cities A, B, and C that will now travel on Airline 2’s network for a segment of the trip to get to cities X, Y, and Z, will allow Airline 2 to better exploit economies of passenger-traffic density. That is, Airline 2’s marginal cost of transporting a

passenger on its network is lower because of the higher volume of passengers it now transports due to the alliance. Likewise, due to typical reciprocity of codeshare alliances, Airline 1 will also enjoy lower marginal cost on its network due to the additional passengers it will transport that originate in cities X, Y, and Z and traveling to destination cities A, B, and C by flying on both partners' planes to complete the trip.

Accommodating a higher volume of passengers may require partner carriers to acquire more airport gates and a larger airport staff to handle more intensive airport operations. Therefore, it is possible that partners' recurrent fixed cost could increase as a result of the alliance. On the other hand, it has been argued in the literature that since alliance partners often share their airport facilities (lounges, gates, check-in counters etc.), ground and flight personnel, this could result in more efficient use of airport facilities and staff, which could effectively yield recurrent fixed cost savings [Park (1997)]. The arguments therefore suggest that partner carriers' recurrent fixed cost may either rise or fall due to the alliance.

In summary, an alliance can cause partner carriers' sunk market entry cost and marginal cost to fall, but recurrent fixed cost may either fall or rise. If an alliance causes recurrent fixed cost to rise, while other components of cost fall, then an aggregated cost analysis may not capture the economically important ways that an alliance influences various cost components. Unfortunately, a challenge we face in studying these different types of cost effects that may be associated with an alliance is that cost data at the route-level are not readily available.

Therefore, the main objective of our study is to estimate marginal, recurrent fixed, and sunk market entry costs effects associated with an airline alliance using a structural econometric model that does not require the researcher to have cost data. Our study offers two crucial distinguishing features from others in the literature. First, our methodology does not require having actual cost data to draw inference on changes in cost associated with an alliance. Second, our methodology separately identifies changes in economically relevant components of cost associated with an alliance.

The short-run parts of our model allow us to draw inference on how economies of passenger-traffic density – measured indirectly by the size of an airline's presence at the market endpoint cities – might affect marginal cost of transporting a passenger. Medium to long-run parts of our model are used to draw inference on changes in partner carriers' recurrent fixed and sunk market entry costs associated with the alliance relative to non-alliance carriers. We apply

our model to the Delta/Northwest/Continental (DNC hereafter) domestic alliance formed in 2003. Below is a brief summary of the methodology we use.

We begin by specifying and estimating short-run demand and supply of air travel. Consumer demand is estimated via a discrete choice model. For the short-run supply-side of the model, we assume that firms set prices according to a differentiated products Nash equilibrium in prices. This assumption allows us to derive product-specific markups and recover product-level marginal cost. With implied marginal cost estimates in hand, we specify and estimate marginal cost as a function of various regressors. These regressors include time period and alliance-specific dummy variables that allow us to compare how the marginal cost of products offered by Delta, Northwest and Continental changed across the DNC pre-post alliance periods relative to the marginal cost of products offered by other carriers. Furthermore, to indirectly capture the role economies of passenger-traffic density might play, we allow changes in marginal cost to depend on the size of carriers' presence at the endpoint airports of an origin-destination market.

Product-specific markups from the Nash price-setting game part of the model enables us to compute firm-level variable profits in a market, which we use in the dynamic part of the model to examine the effects of the alliance on recurring fixed and sunk market entry costs. The dynamic part of our model is an entry/exit game in which each airline chooses markets in which to be active during specific time periods in order to maximize its expected discounted stream of per-period profit. Per-period profit is comprised of variable profit less per-period fixed cost and a one-time entry cost if the airline is not currently serving the market but plans to do so next period. The dynamic entry/exit game allows us to estimate fixed and entry costs by exploiting estimates of variable profits previously computed from the Nash price-setting game along with observed data on airlines' decisions to enter and exit certain markets. We allow all firms' (both alliance and non-alliance firms) fixed and entry costs to change in the DNC post-alliance period relative to the pre-alliance period. Consistent with a difference-in-differences identification strategy, we identify fixed and entry cost effects of the alliance by comparing pre-post alliance periods' changes in Delta, Northwest and Continental fixed and entry costs relative to changes in other airlines' fixed and entry costs over these pre-post alliance periods.

Our empirical results suggest that implementation of the DNC alliance resulted in: (1) A decrease in marginal costs for the alliance partners in markets where the airlines have a large presence at their market endpoints; (2) A reduction in sunk market entry costs for the alliance

partners; and (3) The alliance however is associated with higher recurrent fixed costs for the partners. The absolute magnitude of the increase in fixed cost is higher than that of the decrease in entry cost. Interestingly, other firms' recurrent fixed cost remain unchanged, while their market entry cost decreases over the DNC pre-post alliance periods.

The rest of the paper is organized as follows: The next section presents some background information on the alliance. Section 2.3 describes the data sample. Sections 2.4 and 2.5 present the short-run demand and supply, as well as the dynamic parts of the model, respectively. Section 2.6 describes the estimation procedure of the short-run part of the model. A brief discussion of those estimation results follows in section 2.7. Section 2.8 describes the estimation method for the dynamic part of the model, and results from this estimation are discussed in section 2.9. Section 2.10 concludes.

2.2 Background Information on the DL/NW/CO alliance

On August 23, 2002 three hub-and-spoke route network carriers, Delta, Northwest, and Continental, submit their alliance proposal to the Department of Transportation (DoT) for review. This proposal requests a comprehensive alliance that involves codesharing, reciprocal frequent-flyer programs and reciprocal access to airport lounges. Despite the claim by the airlines that the alliance will benefit consumers in the form of improved services and the expansion of on-line services into new markets, the DoT had serious concerns about the potential anticompetitive effects.[18]

The two major aspects of concerns are: (1) substantially high combined market share of the three airlines; and (2) the large number of markets in which their service overlap. First, at the time of the proposed alliance, the three airlines have a combined market share of 35 percent—18 percent for Northwest and Continental combined, and 17 percent for Delta—measured by domestic revenue passenger miles. Therefore, the high combined market share of the three carriers is significant when compared to the 23 percent market share of the United/US Airways alliance that was in operation at the time. Second, the three airlines' services overlapped in 3,214 markets, accounting for approximately 58 million annual passengers. This number of

[18] US Department of Transportation, 2003. "Termination of Review Under 49 U.S.C. 41720 of Delta/Northwest/Continental Agreements." (http://www.gpo.gov/fdsys/pkg/FR-2003-01-23/pdf/03-1528.pdf)

overlapping markets is substantial when compared to the United/US Airways alliance, which only had 543 overlapping markets and 15.1 million annual passengers.

As a result of these facts, regulators were not convinced that the alliance will have many positive effects on consumers nor on the airlines in the form of cost savings. Instead, the alliance can potentially create barriers to entry based on their significantly high combined market share.

In the DoT's initial review of the proposed alliance, it remarked that the alliance would:

"Create neither substantial operating efficiencies nor substantial cost reductions for the three airlines" and *"at many cities the alliance's impact on the prospects of entry by competing airlines would be substantially equivalent to the impact that a single airline's dominance would have at that city."*

In order to mitigate these concerns, the DoT outlined several conditions that should be met before the airlines could implement their alliance. These conditions are meant to limit potential collusion, size of market presence, joint marketing efforts that could prevent competition from other carriers, "hoarding" of airport facilities, and "crowding-out" of other airlines from computer reservation system displays. [19] A separate review by the Department of Justice (DoJ) was also conducted, and it came to the conclusion that the alliance "could result in lower fares and better service for passengers".[20] However, alliance partners cannot codeshare on each other's flights wherever they offer competing nonstop service.

In the end the airlines agreed to modifications that satisfied regulators and the alliance was allowed to go through. The airlines began their codeshare alliance in June, 2003.

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[19] US Department of Transportation, 2003. "Review Under 49 U.S.C. 41720 of Delta/Northwest/Continental Agreements." (http://www.gpo.gov/fdsys/pkg/FR-2003-03-06/pdf/03-5450.pdf)

[20] US Department of Justice, 2003. "Department of Justice Approves Northwest/Continental/Delta Marketing Alliance with Condition." (http://www.justice.gov/atr/public/press_releases/2003/200645.pdf)

2.3 Definitions, Data Construction and Descriptive Statistics

Definitions

A *market* is directional and defined as a combination of origin and destination cities. For example, air travel from Los Angeles to New York is considered a different market than air travel from New York to Los Angeles. Defining a market this way allows us to capture heterogeneity in demographics across origin cities.

An *itinerary* specifies the origin, destination, and intermediate-stop(s) cities of the trip. For example, a passenger wanting to travel from Los Angeles to New York may have the option to consider two distinct travel itineraries: (1) a nonstop flight from Los Angeles to New York; or (2) an itinerary that requires one intermediate stop in St. Louis, i.e., Los Angeles to St. Louis, then St. Louis to New York.

Each flight on an itinerary has a *ticketing carrier* and an *operating carrier*. The ticketing carrier is the airline that sells the ticket for the seat, whereas the operating carrier is the airline that transports the passenger on its plane. A *product* is a unique combination of ticketing carrier(s), operating carrier(s), and itinerary. Similar to Gayle (2008), we focus on three types of air travel products: pure online; traditional codeshare; and virtual codeshare.[21]

Table 2.1 provides examples of the three different types of products, each using an itinerary that requires travel from Atlanta (ATL) to Los Angeles (LAX) with one stop in Houston (IAH). In the case of a *pure online* product, the same airline is the ticketing and operating carrier on all segments of the trip. Note Delta is the ticketing carrier for both segments of the trip, denoted by DL:DL in the table. Furthermore, Delta is also the operating carrier for both segments of the trip—Atlanta to Houston and Houston to Los Angeles.

Table 2.1 Examples of Airline Product Type

Product Type	Ticketing Carrier	Operating Carrier	Origin	Intermediate Stop	Destination
Pure Online	DL:DL	DL:DL	ATL	IAH	LAX
Traditional Codeshare	DL:DL	DL:CO	ATL	IAH	LAX
Virtual Codeshare	DL:DL	CO:CO	ATL	IAH	LAX

[21] Also see Ito and Lee (2007) for a discussion of these types of air travel products.

Codeshare products are identified as those having different ticketing and operating carriers. There are two types of codeshare products: (1) Traditional Codeshare; and (2) Virtual Codeshare. A traditional codeshare product is defined as having a single ticketing carrier, but multiple operating carriers, one of which is the ticketing carrier. Referring to the table, while Delta is the ticketing carrier for both segments, it only operates on the first leg of the trip. Continental (CO) operates the Houston to Los Angeles leg. A virtual codeshare product is defined as having the same operating carrier for all segments of the trip, but the ticketing carrier is different from the operating carrier. The key distinction between a traditional and a virtual codeshare product is that the operating carrier does not change across trip segments in a virtual codeshare product, while the operating carrier changes across trip segments in a traditional codeshare product.

Data Construction

The data we use come from the Office of Airline Information of the Bureau of Transportation Statistics. The dataset is the Airline Origin and Destination Survey (DB1B). DB1B is a 10 percent sample of all airline tickets issued by carriers in the United States. Each observation in the dataset is an itinerary. It includes information such as: (i) the identities of origin, destination, and intermediate stop(s) airports on an itinerary; (ii) the identities of ticketing and operating carriers on the itinerary; (iii) the price of the ticket; (iv) the number of passengers who bought the ticket at that price; (v) total itinerary distance flown from origin to destination; and (vi) the nonstop distance between the origin and destination. The data are quarterly. Since the DNC alliance was implemented in June 2003, we use the third and fourth quarters of 2002 as the pre-alliance period and the third and fourth quarters of 2004 as the post-alliance period.

Following Aguirregabiria and Ho (2012), we focus on air travel between the 65 largest US cities based on the Census Bureau's Population Estimates Program (PEP), which produces estimates of population for the United States. We use data from the category "Cities and Towns". We group cities that belong to the same metropolitan areas and share the same airport. Tables 2.2 and 2.3 provides a list of the cities and corresponding airport groupings. As in Berry,

Carnall and Spiller (2006) and Berry and Jia (2010), we use the geometric mean of a market's origin city population and destination city population as a measure of market size.[22]

In selecting itineraries for estimation, we drop all itineraries with real prices less than $50 or greater than $2,000. Eliminating fares that are too low helps avoid discounted fares that may be due to passengers using their frequent-flyer miles to offset the full price of the trip. We also drop itineraries with the following characteristics: (i) travel outside the 48 mainland U.S.; (ii) one-way tickets; (iii) more than two intermediate stops; and (iv) if there are multiple ticketing carriers.

Table 2.2 Cities, Airports and Population

City, State	Airports	2002 Population	2004 Population
New York[1]	LGA, JFK, EWR	8,606,988	8,682,908
Los, Angeles, CA	LAX, BUR	3,786,010	3,796,018
Chicago, IL	ORD, MDW	2,886,634	2,848,996
Dallas, TX[2]	DAL, DFW	2,362,046	2,439,703
Houston, TX	HOU, IAH, EFD	2,002,144	2,058,645
Phoenix, AZ[3]	PHX	1,951,642	2,032,803
Philadelphia, PA	PHL	1,486,712	1,514,658
San Antonio, TX	SAT	1,192,591	1,239,011
San Diego, CA	SAN	1,251,808	1,274,878
San Jose, CA	SJC	896,076	901,283
Denver-Aurora, CO	DEN	841,722	848,227
Detroit, MI	DTW	922,727	924,016
San Francisco, CA	SFO	761,983	773,284
Jacksonville, FL	JAX	758,513	778,078
Indianapolis, IN	IND	783,028	787,198
Austin, TX	AUS	671,486	696,384
Columbus, OH	CMH	723,246	735,971
Charlotte, NC	CLT	577,191	614,446
Memphis, TN	MEM	674,478	681,573
Minneapolis-St. Paul, MN	MSP	660,771	653,872
Boston, MA	BOS	585,366	607,367
Baltimore, MD	BWI	636,141	641,004
Raleigh-Durham, NC	RDU	503,524	534,599
El Paso, TX	ELP	574,337	582,952
Seattle, WA	SEA	570,166	570,961

[1] New York-Newark-Jersey;
[2] Dallas-Arlington-Fort Worth-Plano, TX
[3] Phoenix-Temple-Mesa, AZ

[22] Since we find that many products have extremely small product shares based on the definition of market size used, we scaled up all products shares in the data set by a common factor. The common factor used is the largest integer such that the outside good share $\left(\boldsymbol{S}_0 = 1 - \sum_{j=1}^{J} \boldsymbol{S}_J\right)$ in each market remains positive. In our data set the common factor is 40. It turns out that estimation results are qualitatively similar with or without using this scaling factor.

Table 2.3 Cities, Airports and Population Continued

City, State	Airports	2002 Population	2004 Population
Nashville, TN	BNA	544,375	570,068
Milwaukee, WI	MKE	589,975	601,081
Washington, DC	DCA, IAD	564,643	579,976
Las Vegas, NV	LAS	506,695	534,168
Louisville, KY	SDF	553,049	558,389
Portland, OR	PDX	537,752	533,120
Oklahoma City, OK	OKC	518,516	526,939
Tucson, AZ	TUS	501,332	517,246
Atlanta, GA	ATL	419,476	468,839
Albuquerque, NM	ABQ	464,178	486,319
Kansas City, MO	MCI	443,390	458,618
Sacramento, CA	SMF	433,801	446,295
Long Beach, CA	LGB	470,398	470,620
Omaha, NE	OMA	399,081	426,549
Miami, FL	MIA	371,953	378,946
Cleveland, OH	CLE	468,126	455,798
Oakland, CA	OAK	401,348	394,433
Colorado Springs, CO	COS	369,945	388,097
Tula, OK	TUL	390,991	382,709
Wichita, KS	ICT	354,306	353,292
St. Louis, MO	STL	347,252	350,705
New Orleans, LA	MSY	472,540	461,915
Tampa, FL	TPA	315,151	320,713
Santa Ana, CA	SNA	341,411	339,319
Cincinnati, OH	CVG	322,278	331,717
Pittsburg, PA	PIT	327,652	320,394
Lexington, KY	LEX	262,706	274,581
Buffalo, NY	BUF	287,469	281,757
Norfolk, VA	ORF	238,343	241,979
Ontario, CA	ONT	164,734	168,068

Collapsing the Data

Each quarter contains millions of itineraries. The data contain many identical itineraries that have different prices and the number of passengers who bought them at each of these prices. Therefore, for each time period, we aggregate the number of passengers and average the prices across unique itinerary-airline(s) combinations, which creates the *quantity* sold and *price* for each defined product.

Because we only want the set of unique itinerary-airline(s) combinations for each quarter, we collapse the data by our product definition. Each product appears only once in the collapsed dataset. Products purchased by less than 9 passengers throughout an entire quarter are

eliminated.[23] The four quarters of cleaned data contain a total of 152,983 products across 2,898 markets.

Creation of Other variables

In the collapsed dataset we create a few more variables. The *observed product share* variable is created by dividing quantity sold by the market size. Measured non-price product characteristic variables include: *Interstop*; *Inconvenience*; and *Opres_demand*. *Interstop* counts the numbers of intermediate stops in a product. This variable constitutes one measure of the travel inconvenience embodied in a product's itinerary. *Inconvenience* is a distance-based measure of the "directness" of travel between the origin and destination that is embodied in a product's itinerary. This variable is computed by dividing a product's itinerary distance flown by the nonstop flight distance between the origin and destination. Therefore, the *Inconvenience* variable has a minimum value of 1, which corresponds to a product that uses a single nonstop flight from the origin to destination.

The *Opres_demand* variable counts the number of different cities that an airline provides service to via a nonstop flight from the origin airport of the market. Figure 2.2 provides an illustration of this variable for a given airline. In the figure, each arrow represents a different city to which the airline provides service leaving from the origin of the market. In this case the *Opres_demand* variable for the airline takes a value of 5. The *Opres_demand* variable is intended to help explain consumers' choice between airlines that offer service from the consumers' origin city.

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

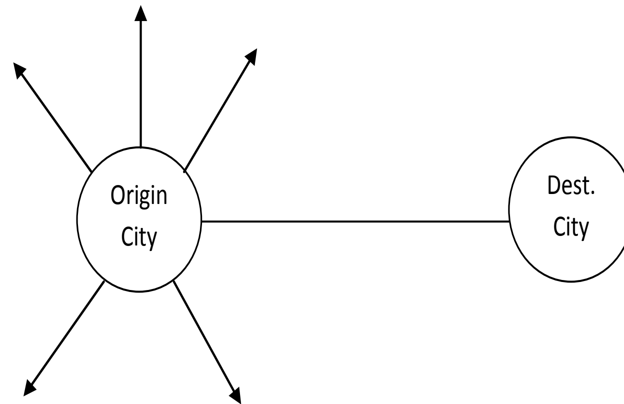

Figure 2.2 Illustration of *Opres_demand* variable

We create two additional variables that measure the size of an airline's presence at the market endpoints. The variables are, *Opres_cost* and *Dpres_cost*. *Opres_cost* counts number of different cities that an airline offers nonstop flights from going into the origin city of the market, while *Dpres_cost* counts the number of different cities that an airline flies to from the destination city of the market using nonstop flight. Figure 2.3 provides an illustration of each of these variables for a given airline. In the figure, each arrow pointing towards the origin city represents a different city from which the airline provides service going into the origin of the market. In this case the *Opres_cost* variable for the airline takes a value of 4. On the other hand, each arrow pointing away from the destination city represents a different city to which the airline provides service leaving from the destination of the market. In this case the *Dpres_cost* variable for the airline takes a value of 6. These two size-of-presence variables are intended to indirectly capture an airlines' ability to benefit from economies of passenger-traffic density in a given origin-destination market, and therefore the variables are intended to help capture cost effects.

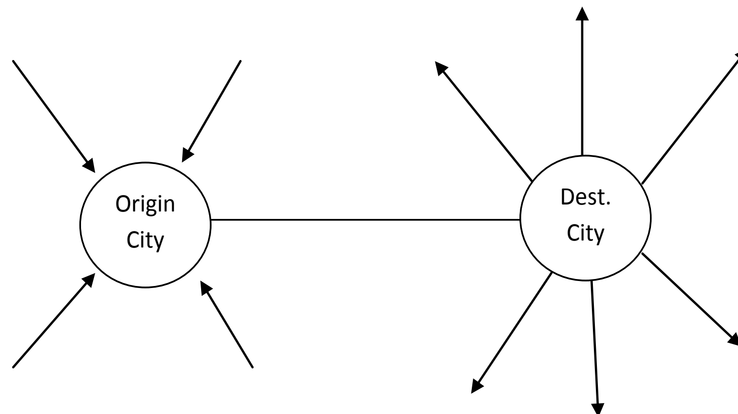

Figure 2.3 Illustration of *Opres_cost* and *Dpres_cost* variables

Dummy variables for quarter, year, origin, destination, and carrier are created to capture unobserved product characteristics that vary across time period, origins, destinations, and carriers. Recall that even though a product may have more than one operating carriers, it has only one ticketing carrier. We use the ticketing carrier as the airline that "owns" the product.

In order to properly identify the different type of products—pure online, traditional codeshare, and virtual codeshare—we recode regional feeder carriers to have their major carriers' code. For example, a product that involves Delta (DL) and Comair Delta Connection (OH), where one of them is the ticketing carrier and the other the operating carrier, Comair Delta Connection is recoded as Delta. Without recoding, this product would mistakenly be considered a codeshare product because the ticketing and operating carriers are different. Once this recoding is done, dummy variables for product types are created.

Finally, we create three variables that pertain to the DNC alliance: *Post-Alliance*; *DNC_demand*; and *DNC_mc*. *Post-Alliance* is a zero-one time period dummy variable that takes the value of 1 to indicate the post-alliance period—the third and fourth quarters of 2004. *DNC_demand* is a zero-one dummy variable that equals to 1 for products that have either Delta, Northwest or Continental as a ticketing carrier. *DNC_mc* is a zero-one dummy variable that takes the value 1 only for products whose operating carrier or operating carrier group is a subset of Delta, Continental, or Northwest. The *DNC_demand* variable is included as a regressor in the demand equation, while *DNC_mc* is more appropriate for the marginal cost equation.

Table 2.4 lists all the carriers in the dataset according to the type of products they offer. While there are 24 airlines that offer pure online products, only 10 are involved in codeshare—traditional or virtual—products. Although regional feeder carriers such as Horizon (QX) and Chautauqua Airlines (RP) are not involved in codeshare products, because we have assigned them to their major carriers' codes, they do offer pure online products where they sell tickets and operate on all segments of the trip.

Table 2.4 List of Airlines in the Data

Airlines Involved in Pure Online Products		Airlines Involved in Codeshare Products	
Airline Name	Code	Airline Name	Code
American Airlines Inc.	AA	American Airlines Inc.	AA
Aloha Air Cargo	AQ	Alaska Airlines Inc.	AS
Alaska Airlines Inc.	AS	Continental Air Lines Inc.	CO
JetBlue Airways	B6	Delta Air Lines Inc.	DL
Continental Air Lines Inc.	CO	Frontier Airlines Inc.	F9
Delta Air Lines Inc.	DL	AirTran Airways Corp.	FL
Frontier Airlines Inc.	F9	Northwest Airlines Inc.	NW
AirTran Airways Corp.	FL	ATA Airlines	TZ
Allegiant Air	G4	United Air Lines Inc.	UA
Hawaiian Airlines Inc.	HA	US Airways Inc.	US
America West Airlines Inc.	HP		
National Airlines	N7		
Vanguard Airlines Inc.	NJ		
Spirit Air Lines	NK		
Northwest Airlines Inc.	NW		
Horizon Air	QX		
Chautauqua Airlines Inc.	RP		
Sunworld International Airlines	SM		
Sun Country Airlines	SY		
ATA Airlines	TZ		
United Air Lines Inc.	UA		
US Airways Inc.	US		
Southwest Airlines Co.	WN		
Midwest Airlines	YX		

Descriptive Statistics

Table 2.5 presents descriptive statistics of the variables used in estimation. We use the consumer price index to deflate the price variable. Thus, it is measured in constant year 1999 dollars. The mean fare and number of passengers are approximately $164 and 144, respectively. The *Opres_demand* variable indicates that, on average, airlines offer nonstop service to approximately 28 distinct cities out of the market origin city.

Similar to Aguirregabiria and Ho (2012), to facilitate estimation of the dynamic entry/exit part of the model, we use a number of passenger threshold to determine whether or not an airline is actively servicing an origin-destination market. Specifically, we define an airline to be active in an origin-destination market during a quarter if at least 130 passengers travel on products offered for sale by the airline in this market during the quarter.[24]

[24] The 130 passenger threshold we use for a directional market is equivalent to the 260 for non-directional market used by Aguirregabiria and Ho (2012).

Table 2.5 Descriptive Statistics

Time period span of data: 2002-Q3-Q4 and 2004-Q3-Q4				
Variable	Mean	Std. Dev.	Min	Max
Price[a]	163.920	59.653	51.15	1,588
Quantity	143.627	457.616	9	10,758
Itinerary Distance Flown (miles)[b]	1,547	701.914	67	3,962
Nonstop Flight Distance (miles)	1,368	652.518	67	2,724
Opres_demand	28.104	27.015	0	145
Opres_cost	27.964	26.861	0	146
Dpres_cost	28.168	27.071	0	145
Inconvenience[c]	1.161	0.221	1	3
Interstop	0.886	0.416	0	2
Pure Online	0.961	0.195	0	1
Traditional Codeshare	0.012	0.107	0	1
Virtual Codeshare	0.028	0.164	0	1
Observed Product Share	0.007	0.023	6.27E-05	0.8764
Number of Products	152,983			
Number of Markets[d]	2,898			

[a] Measured in constant year 1999 dollars.
[b] This variables is reported as "market miles flown" in DB1B database.
[c] Defined as the ratio of itinerary distance to nonstop distance.
[d] Recall that a market is defined as a origin-destination-time period combination.

Table 2.6 shows the number of entry and exit events for each airline. These entries and exits are critical for estimating the fixed and entry cost functions in the dynamic part of the model. The model assumes that airlines will optimally choose which markets to enter and exit in order to maximize their expected discount streams of future profit. Consequently, they will only enter a particular market if the one-time market entry cost does not exceed their expected discounted future profit of entering. Moreover, they will exit a market if the per-period fixed cost exceeds the per-period variable profit of operating in that market. The large number of entry and exit events shows that the airline industry is quite dynamic.

Table 2.6 Number of market entries and exits by airlines

Airlines	Number of markets entered	Number of markets exited
Delta Air Lines Inc.	457	545
Northwest Airlines Inc.	317	375
Continental Air Lines Inc.	214	227
United Air Lines Inc.	413	311
American Airlines Inc.	346	489
Alaska Airlines Inc.	18	6
US Airways Inc.	165	282
Southwest Airlines Co.	193	152
Other Airlines	361	334
Total	2484	2721

2.4 Model

Demand

Travel demand is modeled using a nested-logit model. Potential passenger c chooses among a set of $J_{mt}+1$ alternatives in market m during period t, that is, the potential passenger either chooses one of the J_{mt} differentiated air travel products in the market or the outside option/good $(j=0)$. The outside option includes other modes of transportation besides air travel. Products are organized into $G+1$ mutually exclusive groups, $g=0,1,\ldots,G$ where the outside good is the only member of group 0. A group is a set of products offered by an airline within a market.

Potential passenger c solves the following utility maximization problem:

$$\underset{j\epsilon\{0,1,\ldots J_{mt}\}}{Max}\left\{U_{cjmt}=\mu_{jmt}+\delta\varsigma_{cgmt}+(1-\delta)\varepsilon_{cjmt}^{d}\right\}, \quad (1)$$

where U_{cjmt} is passenger c's indirect utility from choosing product j; μ_{jmt} is the mean level of utility across passengers that choose product j; ς_{cgmt} is a random component of utility common across all products within the same group; and ε_{cjmt}^{d} is an independently and identically distributed (across products, consumers, markets and time) random error term assumed to have type 1 extreme value distribution. The parameter δ lies between 0 and 1 and measures the correlation of consumer utility across products belonging to the same group/airline. The correlation of preferences across products within a group increases as δ approaches 1. In the case where δ is 0, the model collapses to the standard logit model where products compete symmetrically.

The mean utility, μ_{jmt}, is specified as:

$$\mu_{jmt}=x_{jmt}\phi^{x}+\phi^{p}p_{jmt}+\eta_{j}+\upsilon_{t}+origin_{m}+dest_{m}+\xi_{jmt}, \quad (2)$$

where x_{jmt} is a vector of observed non-price product characteristics. The variables in x_{jmt} were briefly defined in the previous section, they include: (1) the number of intermediate stops in a product (*Interstop*); (2) an alternate measure of itinerary convenience (*Inconvenience*); (3) a measure of the size of an airline's presence at the origin city (*Opres_demand*); (4) product-level

zero-one codeshare dummy variables (*Traditional* and *Virtual* codeshare); (5) a zero-one time-period dummy variable that takes the value 1 in the post-alliance period (*Post-Alliance*); and (6) a dummy variable that takes the value 1 for products offered for sale by either Delta, Northwest, or Continental (*DNC_demand)*. The vector of parameters, ϕ^x, measures passengers' marginal utilities associated with the measured non-price product characteristics. The price passengers pay for the product is represented by p_{jmt}, and associated parameter, ϕ^p, captures their marginal utility of price. Ticketing carrier fixed effects, η_j, are captured by airline dummy variables. Time period effects, υ_t, are captured by quarter and year dummy variables. $origin_m$ and $dest_m$ are origin and destination city fixed effects. ξ_{jmt} is the unobserved (by researchers) component of product characteristics that affect consumer utility. For notational convenience, we drop the market and time subscripts in some subsequent equations.

The demand for product j is given by:

$$d_j = POP \times s_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^p, \phi^x, \delta), \quad (3)$$

where POP is the geometric mean between the origin city population and destination city population, which is our measure of market size. $s_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^p, \phi^x, \delta)$ is the predicted product share function that has functional form based on the nested logit model.[25] $\mathbf{x}$, $\mathbf{p}$, and $\boldsymbol{\xi}$ are vectors of observed non-price product characteristics, price, and unobserved product characteristics respectively. ϕ^p, ϕ^x, and δ are demand parameters to be estimated.

Variable Profit, Product Markups and Product Marginal Costs

The way in which a codeshare agreement commonly works is that the ticketing carrier markets and sets the final price for the round-trip ticket and compensates the operating carrier for operating services provided. However, partner airlines do not publicize details on their compensation mechanisms actually used, which may even differ across partnerships. Our challenge as researchers is to specify a modeling approach that captures our basic understanding of what is commonly known about how a codeshare agreement works without imposing too

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[25] The nested logit model has the following well-known predicted product share function: $s_j = \frac{\exp\left(\frac{\mu_j}{1-\delta}\right)}{D_g} \times \frac{D_g^{1-\delta}}{\left[1+\sum_{g=1}^{G} D_g^{1-\delta}\right]}$, where $D_g = \sum_{j \in G_g} \exp\left(\frac{\mu_j}{1-\delta}\right)$ and G_g is the set of products belonging to group g.

much structure on a contracting process about which we have few facts. To achieve this balance we adopt the modeling approach outlined in Chen and Gayle (2007) and Gayle (2013).

As suggested in Chen and Gayle (2007) and Gayle (2013), it is useful to think of a codeshare agreement as a privately negotiated pricing contract between partners (w, Γ), where w is a per-passenger price the ticketing carrier pays over to an operating carrier for transporting the passenger, while Γ represents a potential lump-sum transfer between partners that determines how the joint surplus is distributed. We do not attempt to econometrically identify an equilibrium value of Γ since its value is not essential for the purposes of this paper. However, in laying out the dynamic part of the model, we do show where Γ enters the model.

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

Each ticketing carrier i offers a set of B_i products for sale. Thus, ticketing carrier i solves the following profit maximization problem:

$$\text{Max}_{p_j} VP_i = \text{Max}_{p_j} \left[\sum_{j \epsilon B_i} (p_j - mc_j) q_j \right], \tag{4}$$

where VP_i is variable profit of ticketing carrier i; p_j and q_j are the respective price and quantity sold of product j; while mc_j is the effective marginal cost ticketing carrier i incurs by offering product j for sale.

Let $f = 1, \dots, F$ index the corresponding operating carriers. In the event that product j is a traditional codeshare product, then $mc_j = c_j^i + w_j^f$, where c_j^i is the marginal cost that ticketing carrier i incurs by using its own plane to provide transportation services on some segment(s) of the trip needed for product j, while w_j^f is the price ticketing carrier i pays to operating carrier f for its transportation services on the remaining trip segment(s). If instead product j is a virtual

codeshare product, then $mc_j = w_j^f$, where w_j^f is the price the ticketing carrier pays to operating carrier f for its exclusive transportation services in the provision of product j.[26] Last, if product j is a pure online product, then $mc_j = c_j^i$. Note that in the pure online product case the ticketing carrier is also the sole operating carrier of product j, i.e., $i = f$.

In summary, the effective marginal cost that ticketing carrier i incurs by providing product j to consumers is given by:

$$mc_j = \begin{cases} c_j^i + w_j^f & \text{if product } j \text{ is traditional codeshare;} \\ w_j^f & \text{if product } j \text{ is virtual codeshare;} \\ c_j^i & \text{if product } j \text{ is pure online.} \end{cases} \quad (5)$$

Note that c_j^i directly constitutes per-passenger expenses incurred by ticketing carrier i when it contributes operating services with its own plane to product j, while w_j^f is correlated with per-passenger expenses incurred by operating carrier f when it contributes operating services to product j. But why is the price, w_j^f, that operating carrier f charges ticketing carrier i for carrier $f's$ operating services correlated with marginal cost incurred by carrier f? This is an implication of the assumed sequential price-setting game that determines equilibrium prices of codeshare products. The reason is as follows. In the first stage of the sequential price-setting game, operating carriers each optimally choose w_j^f, i.e., each operating carrier f solves the following profit maximization problem: $\text{Max}_{w_j^f} \left[\sum_{j \epsilon A_f} (w_j^f - c_j^f) q_j\right]$, where A_f is the set of products in the market to which carrier f contributes its transportation services, while c_j^f is the marginal cost that carrier f incurs by using its own plane to provide transportation services to product j. In equilibrium, w_j^f is positively correlated with c_j^f. So both c_j^i and w_j^f in equation (5) are a function of factors that influence the marginal cost of operating carriers. Therefore, when we subsequently specify a parametric marginal cost function for econometric estimation, mc_j will be a function of factors that influence the marginal cost of operating carriers.

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

In equilibrium, the amount of product j an airline sells equals to the quantity demand, that is, $q_j = d_j = POP \times s_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^p, \phi^x, \delta)$, which implies that the optimization problem in (4) for each airline can be re-written as:

$$\text{Max}_{p_j}\left[\sum_{j \epsilon B_i}(p_j - mc_j) \times POP \times s_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \phi^p, \phi^x, \delta)\right] \tag{6}$$

Such optimizing behavior yields the following system of J first-order equations:

$$\sum_{k \epsilon B_i}(p_k - mc_k)\frac{\partial s_k}{\partial p_j} + s_j = 0 \text{ for all } j = 1, \ldots, J. \tag{7}$$

The system of first-order equations in (7) can be represented compactly in matrix notation:

$$(\Omega.* \Delta) \times (p - mc) + s = 0, \tag{8}$$

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

Equation (8) can be rearranged to compute product markups:

$$\boldsymbol{Mkup}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}\right) = (p - mc) = -(\Omega.* \Delta)^{-1} \times s, \tag{9}$$

where $\widehat{\Phi^{\mathrm{d}}} = (\widehat{\phi^p}, \widehat{\phi^x}, \hat{\delta})$ is the vector of demand parameter estimates. Let $markup_j(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d})$ be an element in $\boldsymbol{Mkup}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}\right)$. Note that $markup_j(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d})$ is the product markup function which depends exclusively on demand-side variables and parameter estimates.

With computed product markups in hand, product marginal costs can be recovered by:

$$\widehat{mc}_{jmt} = p_{jmt} - markup_{jmt}(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}). \tag{10}$$

In addition, an airlines' variable profit in a market can be computed by:

$$VP_{imt} = \sum_{j \epsilon B_i} markup_{jmt}\left(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^d}\right) * q_{jmt}. \tag{11}$$

2.5 Dynamic Entry/Exit Game

In every period (quarter), each airline decides which market(s) to be active in to maximize its expected inter-temporal profits. An airline being active in a market means that the airline actually sells products to consumers in the market even though a subset of those products may use the operating services of the airline's codeshare partner carriers.

Let airlines be indexed by i, markets by m, and period by t. An airline's expected discounted stream of profit in market m is given by:

$$E_t\left(\sum_{r=0}^{\infty} \beta^r \Pi_{im,t+r}\right), \tag{12}$$

where $\Pi_{im,t+r}$ is the per-period profit of the airline in market m and $\beta \in (0,1)$ is the time discount factor. Each airline's per-period profit is specified as the difference between variable profit and the sum of recurrent fixed and one-time market entry costs:

$$\Pi_{imt} = R_{imt}^{*} - a_{imt}\left\{FC_{imt} + \epsilon_{imt}^{FC} + (1 - s_{imt})\left[EC_{imt} + \epsilon_{imt}^{EC}\right]\right\}, \tag{13}$$

where $R_{imt}^{*} = s_{imt} VP_{imt}$ is the variable profit of airline i in market m during period t. The value VP_{imt} is computed from the short-run price-setting game described previously. s_{imt} is a zero-one indicator variable that equals to 1 if airline i had decided in period $t-1$ to be active in market m during period t. a_{imt} is also a zero-one indicator variable, but unlike s_{imt}, a_{imt} equals 1 if airline i decides in period t to be active in $t+1$. Therefore, by definition $s_{imt} = a_{im,t-1}$.

After deciding to be active in a market, we assume that it takes time (one period) for airline i to actually begin offering products to consumers in market m - time-to-build assumption. This time-to-build assumption implies that if $a_{imt} = 1$ and $s_{imt} = 0$, then airline i pays fixed and entry costs in period t even though it does not actually begin offering products to consumers until $t+1$. Note that in period t, a_{imt} is a decision variable, while s_{imt} is a state

variable. So we use different letters (a_{imt} versus s_{imt}) to make the distinction between an airline's decision versus a state variable.

FC_{imt} and EC_{imt} are the deterministic portions of fixed and entry costs functions respectively and are common knowledge for all airlines. ϵ_{imt}^{FC} and ϵ_{imt}^{EC} represent private information shocks to fixed and entry costs respectively. The composite shock $\varepsilon_{imt} = \epsilon_{imt}^{FC} + (1 - s_{imt})\epsilon_{imt}^{EC}$ is assumed to be independent and identically distributed (i.i.d) over airlines, markets, and time period based on a specific probability distribution function, which we assume is the type 1 extreme value distribution.

We specify the deterministic portions of fixed and entry costs functions as follows:

$$\begin{aligned} FC_{imt} = {} & \theta_0^{FC} + \theta_1^{FC} Presence_{imt} + \theta_2^{FC} Post_Alliance_Period_t + \\ & \theta_3^{FC} Alliance_Firm_{imt} + \\ & \theta_4^{FC} Post_Alliance_Period_t \times Alliance_Firm_{imt}, \end{aligned} \tag{14}$$

$$\begin{aligned} EC_{imt} = {} & \theta_0^{EC} + \theta_1^{EC} Presence_{imt} + \theta_2^{EC} Post_Alliance_Period_t + \\ & \theta_3^{EC} Alliance_Firm_{imt} + \\ & \theta_4^{EC} Post_Alliance_Period_t \times Alliance_Firm_{imt}, \end{aligned} \tag{15}$$

where $Presence_{imt}$ is a measure of the size of an airline's presence at the endpoint airports of origin-destination market *m*, which we define as the mean across *Opres_cost* and *Dpres_cost* variables. $Post_Alliance_Period_t$ is a zero-one time-period dummy variable that takes the value 1 only during the post-alliance period. $Alliance_Firm_{imt}$ is a zero-one airline dummy variable that takes the value 1 if the airline is one of the airlines that is a part of the alliance, i.e., Delta, Northwest or Continental. The structural parameters to be estimated are:

$$\{\theta_0^{FC}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}\}'$$

θ_0^{FC} and θ_0^{EC} measure the mean fixed and entry costs across airlines, markets and time, respectively. θ_1^{FC} and θ_1^{EC} capture the effects of the size of an airlines' airport presence on its market-level fixed and entry costs. θ_2^{FC} and θ_2^{EC} capture how fixed and entry costs change for all other airlines except the alliance partners across the pre- and post-alliance periods. θ_3^{FC} and θ_3^{EC}

measure any persistent systematic difference in mean fixed and entry costs of the alliance partners relative to other airlines. The coefficients of key interest are $\theta_4^{FC}$and θ_4^{EC}, which identify changes in fixed and entry costs resulting from the implementation of the DNC alliance, that is, these parameters capture the possible fixed and entry cost efficiency gains associated with the alliance.

The mean recurrent fixed cost parameter θ_0^{FC} may comprise fixed expenses incurred by a ticketing carrier when the carrier markets a codeshare product to potential consumers. In addition, recall that (w, Γ) represents a privately negotiated codeshare contract between partner carriers, where w is a per-passenger price the ticketing carrier pays over to an operating carrier for transporting the passenger, while Γ represents a potential lump-sum transfer between partners that determines how the joint surplus is distributed. We have already shown that w enters the effective marginal cost of the ticketing carrier. However, the lump-sum transfer between partners, Γ, is nested in θ_0^{FC}, but we do not attempt to separately identify Γ since knowing its value is not essential for the purposes of our paper.

Reducing the Dimensionality of the State Space

Recall that the variable profit function is defined as:

$$R_{imt}^{*} = a_{im,t-1} VP_{imt}, \tag{16}$$

where $VP_{imt}(\mathbf{x}, \boldsymbol{\xi}; \widehat{\Phi^{d}})$ is computed based on equation (11). Note that variable profits are functions of state variables $(\mathbf{x}, \boldsymbol{\xi})$. Aguirregabiria and Ho (2012) suggest that these state variables can be aggregated into a single state variable, R_{imt}^{*}, rather than treating $(\mathbf{x}, \boldsymbol{\xi})$ as separate state variables, which serves to significantly reduce the dimensionality of the state space. The vector of payoff-relevant state variables is the following:

$$y_{imt} = \{s_{imt}, R_{imt}^{*}, Presence_{imt}, Post_Alliance_Period_t\}. \tag{17}$$

Each airline has the same vector of state variables, which it takes into account when making decisions. Decision-making of each airline also depends on the strategies and actions of other airlines via R_{imt}^{*}. Recall that 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. Thus, the dynamic entry-exit game does implicitly take into account strategic interaction among competitors.

Markov Perfect Equilibrium (MPE)

For notational convenience, we drop the market subscript. Let $\sigma \equiv \{\sigma_i(y_{it}, \varepsilon_{it})\}$ be the vector of strategies for each airline where $y_{it} = \{s_{it}, R_{it}^*, Presence_{it}, Post_Alliance_Period_t\}$ is a vector of common knowledge state variables and ε_{it} is assumed to be *i.i.d.* In a Markov Perfect Equilibrium each airline behaves according to its best response strategy, which maximizes its own value function given the state and strategies of other airlines.

Let $V_i^\sigma(y_t, \varepsilon_{it})$ be the value function for airline i. This value function is the unique solution to the following Bellman equation:

$$V_i^\sigma(y_t, \varepsilon_{it}) = \underset{a_{it}\epsilon\{0,1\}}{Max} \left\{ \begin{array}{c} \Pi_{it}^\sigma(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ +\beta \int V_i^\sigma\big(y_{t+1}, \varepsilon_{i,t+1}\big) dG_i(\varepsilon_{i,t+1}) F_i^\sigma(y_{t+1}|y_t, a_{it}) \end{array} \right\}, \tag{18}$$

where $\Pi_{it}^\sigma(a_{it}, y_t)$ is the expected per-period profit function and $F_i^\sigma(y_{t+1}|y_t, a_{it})$ is the expected transition of state variables. We describe how state variables transition in Appendix C. The profile of strategies in σ is a MPE if, for every airline *i* and every state (y_t, ε_{it}), we have:

$$\sigma_i(y_t, \varepsilon_{it}) = \underset{a_{it}\epsilon\{0,1\}}{argmax} \left\{ \begin{array}{c} \Pi_{it}^\sigma(a_{it}, y_t) - \varepsilon_{it} * a_{it} \\ +\beta \int V_i^\sigma\big(y_{t+1}, \varepsilon_{i,t+1}\big) dG_i(\varepsilon_{i,t+1}) F_i^\sigma(y_{t+1}|y_t, a_{it}) \end{array} \right\}. \tag{19}$$

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 $\mathbf{P} = \Psi(\theta, \mathbf{P})$, where $\mathbf{P} = \{P_i(\mathbf{y})\text{: for every firm and state } (i, \boldsymbol{y})\}$. $\mathbf{P} = \Psi(\theta, \mathbf{P})$ is a vector of best response probability mapping, where $\Psi(\cdot)$ is the CDF of the type 1 extreme value distribution.

2.6 Estimation of Demand and Marginal Cost Functions

Our strategy for estimating the demand parameters (ϕ^p, ϕ^x, δ) is such that the observed market shares, $\mathbf{S}_{jmt}$, are equal to the market shares predicted by the model s_{jmt}. As shown in

Berry (1994), in the case of the nested logit model, such an estimation strategy implies the following linear equation:

$$\ln(\mathbf{S}_{jmt}) - \ln(\mathbf{S}_{0mt}) = x_{jmt}\phi^{x} + \phi^{p}p_{jmt} + \delta\ln(\mathbf{S}_{jmt/g}) + \eta_{j} + \upsilon_{t} + origin_{m} + dest_{m} + \xi_{jmt}, \tag{20}$$

where $\boldsymbol{S}_{0mt}$ is the observed share of the outside good and $\boldsymbol{S}_{jmt/g}$ is the observed within group share of product *j*. Equation (20) can be estimated by Two Stage Least Squares (2SLS) given that the equation is linear, and p_{jmt} and $\ln(\mathbf{S}_{jmt/g})$ are endogenous.

We use the following linear specification for the marginal cost function:

$$\begin{aligned}\widehat{mc}_{jmt} = \tau_{0} + \tau_{1}W_{jmt} + \tau_{2}Opres_cost_{jmt} + \tau_{3}(Opres_cost_{jmt})^{2} + \tau_{4}Dpres_cost_{jmt} \\ + \tau_{5}(Dpres_cost_{jmt})^{2} + \tau_{6}Post\ Alliance_{t} + \tau_{7}DNC_mc_{jmt} \\ + \tau_{8}Post\ Alliance_{t} \times DNC_mc_{jmt} \\ + \tau_{9}Post\ Alliance_{t} \times DNC_mc_{jmt} \times Opres_cost_{jmt} \\ + \tau_{10}Post\ Alliance_{t} \times DNC_mc_{jmt} \times Dpres_cost_{jmt} \\ + \psi_{j} + \lambda_{t} + origin_{m} + dest_{m} + \varepsilon_{jmt}^{mc},\end{aligned} \tag{21}$$

where $\widehat{mc}_{jmt}$ represents product-level marginal cost estimates that were recovered using equation (10). W_{jmt} is a vector of observed marginal cost-shifting variables and τ_{1} is the associated vector of parameters to be estimated.

Parameters $\tau_{2}$and τ_{3} measure how marginal cost changes as an airline's presence increases at the market origin city (*Opres_cost*). *Opres_cost* counts the number of different cities that an airline has nonstop flights from going into the origin city of the market. Similarly, $\tau_{4}$and τ_{5} measure how marginal cost changes as an airline's presence increases at the market destination city (*Dpres_cost*) measured by the number of different cities that an airline flies to from the destination city of the market using nonstop flight. Parameters τ_{2}, τ_{3}, τ_{4}, and τ_{5} should indirectly capture the effects of economies of passenger-traffic densities, i.e., the existence of economies of passenger-traffic density implies the following sign pattern: $\tau_{2} > 0$, $\tau_{3} < 0$,

$\tau_4 > 0$, and $\tau_5 < 0$. This sign pattern of the parameters suggests that an airline's marginal cost of transporting a passenger in a market decreases as its measure of *Opres_cost* and *Dpres_cost* increases beyond a certain level. The reasonable presumption here is that, as an airline's measures of *Opres_cost* and *Dpres_cost* increase for a given market, the airline is likely to channel more passengers through this market who are on their way to various destinations.

$Post\ Alliance_t$ is a zero-one time-period dummy variable that equals 1 during post-alliance time periods. DNC_mc_{jmt} is a product-dummy indicator variable that equals to 1 for all products where the operating carrier or the operating carrier group is a subset of the three carriers, Delta, Continental, or Northwest. Given that interaction variable $Post\ Alliance_t \times DNC_mc_{jmt}$ is included in the model, parameter τ_6, which is the coefficient on $Post\ Alliance_t$, measures, on average, how marginal cost changes over the pre-post DNC alliance periods for products that are not associated with Delta, Northwest or Continental. Parameter τ_7 , which is the coefficient on DNC_mc_{jmt}, measures how the mean marginal cost of the alliance partners over the entire sample period differs from other airlines. Parameter τ_8, which is the coefficient on interaction variable $Post\ Alliance_t \times DNC_mc_{jmt}$, measures whether the three partner airlines' marginal cost changed differently over the pre-post alliance periods relative to other airlines. Thus τ_8 should pick up marginal cost effects of the alliance. For example, $\tau_8 < 0$ suggests that the alliance reduces partner carrier's marginal cost.

We also include three-way interaction variables, $Post\ Alliance_t \times DNC_mc_{jmt} \times Opres_cost_{jmt}$ and $Post\ Alliance_t \times DNC_mc_{jmt} \times Dpres_cost_{jmt}$. These variables are used to capture whether marginal cost effects associated with the alliance depend on the size of the partner carriers' presence at the market origin and market destination cities, respectively. For example, it is possible that the alliance may have a larger impact on marginal cost the larger the partner airlines' presence at endpoint airports of the relevant market. In the event that economies of passenger-traffic density is the key driving force for marginal cost effects of the alliance, we expect the coefficients associated with these three-way interaction variables to be negative, i.e., $\tau_9 < 0$, and $\tau_{10} < 0$.

ψ_j is an airline-specific component of marginal cost captured by operating carrier/operating carrier group dummy variables. λ_t captures time-varying effects on marginal cost that are unobserved by us the researchers. These unobserved time-varying effects are

measured using quarter and year dummy variables. $origin_m$ and $dest_m$ are sets of origin and destination city dummy variables respectively. Finally, ε_{jmt}^{mc} is an unobserved random component of marginal cost. The marginal cost equation (equation (21)) is estimated via ordinary least squares (OLS).

Instruments

The product price (p_{jmt}) and the within group share ($\mathbf{S}_{jmt/g}$) variables are likely to be correlated with unobserved product characteristics, ξ_{jmt}. Therefore, consistent estimation of coefficients associated with these variables in the demand equation (equation (20)) requires a set of instruments that are uncorrelated with the demand residual but correlated with price and within group share.

The instruments that we use are: (1) itinerary distance; (2) interaction of jet fuel price with itinerary distance; (3) an airline's market sum itinerary inconvenience measure; and (4) mean number of intermediate stops across products offered by an airline in a market.

As discussed in Gayle (2007 and 2013), instruments (1) and (2) are motivated by the fact that a product's price is influenced by the marginal cost of providing the product. The intuition for instrument (1) is that flying distance covered by an air travel product is likely to be correlated with the marginal cost of providing the product. For instrument (2), airlines' marginal costs are likely to change differently when there are shocks to jet fuel price.[27] These two instruments should be valid since itinerary distance and fuel price shocks are unlikely to be correlated with ξ_{jmt}.

Instruments (3) and (4) are primarily used to deal with the endogeneity of within group product share. Instrument (3) measures the sum of itinerary inconvenience associated with products offered by an airline in a market. Itinerary inconvenience is a flight distance-based measure we previously define in the data section of the paper. For the nested logit demand model, we group products by airline. Since passengers may prefer the set of products offered by an airline in a market because these products offer relatively more convenient travel itineraries, then it is likely that within group share is correlated with instrument (3). Similarly, instrument (4) is likely to be correlated with within group share because passengers may prefer a set of

[27] Jet fuel price data are drawn from the U.S. Energy Information Administration.

products offered by a particular airline to other airlines' products owing to differences in number of intermediate stops associated with the products.

The instruments rely on the fact that the menu of products offered by airlines in a market is predetermined at the time of shocks to demand. Furthermore, unlike price and within group product share, the menu of products offered and their associated non-price characteristics are not routinely and easily changed during a short period of time, which mitigates the influence of demand shocks on the menu of products offered and their non-price characteristics.

2.7 Results from Estimation of Demand, Markup and Marginal Cost Functions

Demand Results

Table 2.7 shows estimation results for Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS). Both regressions include sets of dummy variables for ticketing carriers, origin cities, destination cities and time periods, although associated coefficient estimates for the dummy variables are not reported in the table.

Focusing on the first two variables—*Price* and within group share, $\ln(S_{j/g})$- there are considerable differences in terms of the sign and magnitude of the associated coefficient estimates across the OLS and 2SLS results. The coefficient on *Price* has the wrong sign (positive) in the OLS regression. Furthermore, although the estimates on the within group share variable are between 0 and 1 in both regressions, the OLS estimate is more than fifteen times the size of the 2SLS estimate. These differences indicate that OLS is biased and inconsistent. The Durbin-Wu-Hausman test rejects the null hypothesis that *Price* and within group share are exogenous with over 99 percent confidence. Therefore, the need to use instruments is justified.

We regress each endogenous variable against the instruments using OLS as a check on how well the instruments can explain variations in the endogenous variables. We find that the R^2 measures for the regressions of price against instruments and within group product share against instruments are 0.128 and 0.409 respectively, which suggest that the instruments do explain variations in the endogenous variables. Therefore, the following discussion is based on results from the 2SLS regression.

The coefficient on the *Price* variable now has the expected negative sign. Although the coefficient on $\ln(S_{j/g})$ is statistically greater than zero, the magnitude is closer to 0 than 1. This suggests that even though products offered by the same airline are closer substitutes relative to the cross substitutability of products offered by different airlines, the degree of brand-loyalty to a given airline's products is weak.

Table 2.7 Demand Estimation

152,983 observations. 2002-Q3-Q4 and 2004-Q3-Q4				
	2SLS		OLS	
Variable	Estimates	Std. Error	Estimates	Std. Error
Price	-0.0078***	0.0002	0.0004***	0.00004
$\ln(S_{j/g})$	0.0334***	0.0052	0.5103***	0.0019
Opres_demand	0.0083***	0.0002	0.0136***	0.0001
Interstop	-1.185***	0.0096	-0.6797***	0.0062
Inconvenience	-0.9983***	0.0141	-1.0421***	0.0110
Traditional Codeshare	-0.7435***	0.0275	-0.3871***	0.0213
Virtual Codeshare	-0.9560***	0.0181	-0.7084***	0.0139
Post Alliance	-0.2007***	0.0078	-0.0417***	0.0058
DNC_demand	-0.3660***	0.0134	-0.4639***	0.0103
Post Alliance × DNC_demand	0.0143	0.0118	-0.0708***	0.0092
Constant	-1.7697***	0.0478	-3.2277***	0.0312
Ticketing carrier effects	YES		YES	
Market Origin effects	YES		YES	
Market Destination effects	YES		YES	
Quarter effects	YES		YES	
R-squared	0.3746		0.6188	
Durbin-Wu-Hausman: 18274***	$\chi^2(2)$	Prob_Value = 0.0000		

***indicates statistical significance at 1%.

The coefficient on *Opres_demand* is positive as expected. Passengers prefer to fly with an airline that offers nonstop service to more destinations out of their origin city. Frequent-travelers might benefit the most since they are more likely to join a frequent-flyer program offered by an airline that flies to many nonstop destinations out of their origin city. Participation in such programs allows these passengers to accumulate miles and therefore renders them less likely to use other airlines for future travel from their home airport.

The negative coefficients on the variables *Interstop* and *Inconvienience* are also expected. Passengers prefer traveling to their destinations using nonstop flights compare to flights that have intermediate stops. *Inconvenience* is the ratio of the itinerary distance to nonstop distance between the origin and destination cities. It measures the relative itinerary convenience that the variable *Interstop* does not capture. The level of convenience flying from Atlanta to New York

with one stop in Washington DC is likely to be very different than flying from Atlanta to New York with one stop in Denver. Although both itineraries have a single intermediate stop, depending on where that intermediate stop is relative to the origin and destination city, the two itineraries may yield different levels of convenience for the passenger [Gayle (2007)].

The coefficients on the *Traditional* and *Virtual Codeshare* variables are negative. The product type dummy variable excluded from the regression is *Pure Online*. The negative coefficient estimate on the *Traditional Codeshare* variable suggests that traditional codeshare products are less preferred compare to pure online products. Traditional codeshare products have more than one operating carriers, whereas pure online products are ticketed and operated by the same carrier. It may be easier for the same airline to organize and streamline its products more efficiently than multiple airlines can. This organization and streamlining may take the form of the airline's ability to position its gates at more convenient locations and reducing the layover time for passengers. Despite efforts of partner carriers, the negative coefficient estimate on the *Traditional Codeshare* variable suggests that these conveniences are difficult to achieve in a traditional codeshare product [Gayle (2013)]. Similarly, the negative coefficient estimate on the *Virtual Codeshare* variable suggests that these codeshare products are associated with lower utilities relative to pure online products. Ito and Lee (2007) argue that because the ticket was purchased from a partner carrier, passengers using virtual codeshare products typically cannot get first-class upgrades using their frequent-flyer miles. This makes virtual codeshare products less attractive compare to pure online products.

Post Alliance is a time period dummy variable that equals to one for the post-alliance period. This variable captures the mean change in consumers' utilities associated with non-DNC products over the pre-post alliance periods. The negative coefficient estimate suggests that over the pre and post-alliance periods, the mean level of utility decreases for non-DNC products. The variable *DNC_demand* is a dummy variable that equals to one for all products where the ticketing carrier is either Delta, Northwest or Continental. The negative coefficient estimate suggests that, throughout the entire sample period, DNC products are associated with a lower mean utility level relative to non-DNC products.

The coefficient of the interaction variable, $Post\ Alliance \times DNC_demand$, captures how consumers' utility change differently for DNC products relative to non-DNC products over the pre and post-alliance periods. While the coefficient estimate is positive, it is not statistically

significant, suggesting that, on average, mean utility obtained from DNC products did not change differently relative to change in mean utility of non-DNC products over the pre-post alliance period.

Our demand model yields a mean own-price elasticity estimate of -1.3. A reasonable range for own-price elasticity in the airline industry is from -1.2 to -2.0 as pointed out by Oum, Gillen and Noble (1986), and Brander and Zhang (1990). Berry and Jia (2010) in their 2006 sample find own-price elasticity estimates ranging from -1.89 to -2.10, while Gayle and Wu (2012) estimates range from -1.65 to -2.39. Even though our demand model seems to produce a relatively low mean own-price elasticity, we believe that it is reasonable and consistent with the existing literature.

Computed Product Markups, Marginal Costs, and Variable Profits

Summary statistics on price, markup, marginal cost, and the number of passengers per product are computed for each airline. The overall mean product price and markup are $163.92 and $132.83, respectively. The Lerner index— a measure of the product markup as a percentage of price—indicates that overall, airlines are able to raise their price above marginal costs by a mean of 89.85%. Mean marginal cost is $31.09. Even though this level of markup over marginal cost seems high, it is necessary for their overall profitability because the airline industry has relatively high fixed costs.

Quarterly market-level variable profits for each airline are computed using equations (9) and (11) along with the demand estimates. Recall that the original database, before any cleaning, is only a 10% sample of air travel tickets sold. This implies that the magnitudes of variable profit estimates are at most roughly 10% of actual variable profits. Overall median quarterly market-level variable profit for an airline is approximately $43,810. The quarterly median market-level variable profit for Delta and Northwest is approximately $37,000, while Continental is a little higher, almost $45,000.

Results from Estimation of Product Markup Function

Table 2.8 shows estimation results for a reduced-form product markup equation. Here, we examine whether the markup for DNC products changes differently compare to markup for non-DNC products due to formation of the DNC alliance. The sign and magnitude of the coefficient on $\text{Post Alliance} \times \text{DNC_demand}$ suggests that even though the formation of the

DNC alliance has a negative effect on the three partner carriers product markup compare to their competitors, the reduction in markup is quite small, only about 38 cents reduction. So there is no evidence that implementation of the DNC alliance increased market power of the three alliance partners [Gayle and Brown (2013)].

Table 2.8 Estimation Results for Product Markup Regressed on Several of its Determinants

152,983 observations. 2002-Q3-Q4 and 2004-Q3-Q4		
Variable	Estimate	Std. Error
Post Alliance	0.1242*	0.0647
DNC_demand	-1.1932***	0.1145
Post Alliance × DNC_demand	-0.3808***	0.1020
Opres_demand	0.1174***	0.0012
Interstop	-0.4976***	0.0617
Traditional Codeshare	-0.8920***	0.2369
Virtual Codeshare	-1.800***	0.1550
Constant	128.6452***	0.3098
Ticketing carrier effects	YES	
Market Origin effects	YES	
Market Destination effects	YES	
Quarter effects	YES	

*, *** indicate statistical significance at the 10% and 1% levels respectively. Equation is estimated using ordinary least squares.

All other control variables in Table 2.8 have the expected sign. First, the positive coefficient estimate on the *Opres_demand* variable suggests that the size of an airlines' presence at the origin airport of a market is positively related to markup. This evidence is suggestive of the existence of a hub premium, i.e., airlines have higher market power at their hub airports and thus are able to charge higher markups on flights out of their hub airports [Borenstein (1989)]. Second, we know from our demand results that passengers prefer nonstop flights to their destinations. Therefore, we expect products with intermediate stops have lower markup, as indicated by the negative coefficient estimate on the *Interstop* variable in Table 2.8. Finally, our demand results suggest that traditional and virtual codeshare products are less preferred to pure online products. Therefore, it is not surprising that codeshare products have lower markup compare to pure online products, as indicated by the negative coefficient estimates on *Traditional Codeshare* and *Virtual Codeshare* variables in Table 2.8.

Results from Estimation of Marginal Cost Function

Table 2.9 presents estimation results for two marginal cost specifications, labeled in columns of the table as Specification 1 and Specification 2, respectively. The two specifications help us better assess how the size of market endpoint presence of the alliance partners might affect marginal cost effects of the alliance. By using variables *Opres_cost* and *Dpres_cost*, we are able to capture the marginal cost effects of an airline's scale of operation or "hub-size" at the respective origin and destination airports of the market. We anticipate that these variables will reveal the forces of economies of passenger-traffic density that an airline can enjoy as the airline is likely to channel higher volumes of passengers through the market due to its large presence at the market's endpoints. As expected, the sign pattern of these variables and their squares suggest that a carrier's marginal cost initially increases with the size of its presence at the market endpoints, but once its presence increases beyond a certain threshold, the carrier's marginal cost declines with further increases in its presence at the market endpoints. This result suggests that economies of passenger-traffic density can be achieved by an airline.

How "big" should the hub-size be before an airline is able to enjoy economies of passenger-traffic density? The magnitude of the coefficient estimates on *Opres_cost* and $(Opres_cost)^2$ suggest that an airline can enjoy economies of passenger-traffic density within the market if the number of different cities that an airline has nonstop flights from going into the origin city of the market exceeds 453. Similarly, the coefficient estimates on *Dpres_cost* and $(Dpres_cost)^2$ suggest that an airline has to provide nonstop service to more than 301 different cities from the destination city of the market before it can enjoy economies of passenger-traffic density within the market. The "slight" problem is that a single airline typically does not connect that many different cities to the market endpoints via nonstop flights. In our sample, the mean number of different cities an airline connects to a given market endpoint using nonstop flights is 28 and a maximum of 145.

Still focusing on the estimates in Specification 1, the negative coefficient estimate on $Post\ Alliance_t$ suggests that the marginal cost of products that are not associated with Delta, Northwest or Continental declined (by $11.34) over the pre-post DNC alliance periods. However, the negative coefficient estimate on DNC_mc_{jmt} suggests that, over the entire sample period, the marginal cost of products offered by Delta, Northwest or Continental is on average lower ($13.64 lower) than that of products offered by other airlines. An unexpected result is that

the coefficient estimate on the interaction variable $Post\ Alliance_t \times DNC_mc_{jmt}$ is positive. The fact that the positive coefficient estimate on $Post\ Alliance_t \times DNC_mc_{jmt}$ (2.66) is not large enough to outweigh the negative coefficient estimate on $Post\ Alliance_t$ (-11.34), this suggests that over the pre-post alliance periods the marginal cost of products offered by Delta, Northwest or Continental declined, but did not decline as much as the decline in marginal cost of products offered by other airlines.[28] This result surprisingly suggests that the alliance attenuated an apparent industry-wide decline in marginal cost for the partner carriers' rather than precipitated the decline.

In Specification 2 of the marginal cost function we added three-way interaction variables, $Post\ Alliance_t \times DNC_mc_{jmt} \times Opres_cost_{jmt}$ and $Post\ Alliance_t \times DNC_mc_{jmt} \times Dpres_cost_{jmt}$. The coefficient estimates on these variables are negative, suggesting that implementation of the alliance may have precipitated a decline in marginal cost for the partner carriers in some markets. In particular, the alliance seems to precipitate a decline in the partner carriers' marginal cost in markets where they have sufficiently large hub-size presence at the origin or destination airports of the relevant market. The magnitudes of the coefficient estimates on three-way interaction variables relative to the coefficient estimate on $Post\ Alliance_t \times DNC_mc_{jmt}$, suggest that the alliance will precipitate the decline in the partners' marginal cost in markets where the partners provide nonstop service from more than 75 (= 14.38/0.19) different cities going into the market origin airport, or more than 68 (= 14.38/0.21) different cities via nonstop flights from the destination airport.

The endpoint airport hub-size thresholds are satisfied by each of the three partner carriers at several airports during the post-alliance period. For Delta, Atlanta Hartsfield-Jackson (ATL) and Cincinnati (CVG) satisfy both market origin and destination thresholds, while Dallas/Fort-Worth (DFW) International Airport satisfies the market destination threshold. For Northwest, Detroit Metropolitan (DTW), Memphis (MEM), and Minneapolis–Saint Paul International (MSP) satisfy both thresholds, while the destination threshold is satisfied at George Bush Intercontinental (IAH). Finally, for Continental, Cleveland Hopkins (CLE), Ellington International (EFD), Newark Liberty (EWR), George Bush Intercontinental (IAH), LaGuardia (LGA), William Hobby Airport (HOU), and John F. Kennedy (JFK) satisfy both thresholds.

[28] Marginal cost of Delta, Northwest and Continental products declined by $8.68 (= $11.34 - $2.66), while the marginal cost of products offered by other airlines declined by $11.34.

Table 2.9 Marginal Cost Function Estimation

152,983 observations. Pre-alliance period: 2002:Q3 2002:Q4. Post-alliance period 2004:Q3 and 2004:Q4		
	Coefficient Estimates (Std. Error)	
Variable	Specification 1	Specification 2
Opres_cost	0.5440***	0.5129***
	(0.0242)	(0.0242)
$(\text{Opres_cost})^2$	-0.0006***	0.0002
	(0.0002)	(0.0002)
Dpres_cost	0.6025***	0.5662***
	(0.0233)	(0.0232)
$(\text{Dpres_cost})^2$	-0.0010***	-0.0002
	(0.0002)	(0.0002)
Post Alliance	-11.34***	-11.37***
	(0.3314)	(0.3311)
DNC_mc	-13.64***	-14.22***
	(0.5077)	(0.5052)
Post Alliance × DNC_mc	2.66***	14.38***
	(0.5480)	(0.7616)
Post Alliance × DNC_mc × Opres_cost	---	-0.1907***
		(0.0164)
Post Alliance × DNC_mc × Dpres_cost	---	-0.2077***
		(0.0003)
Itinerary distance flown (miles)	0.0380***	0.0378***
	(0.0003)	(0.0003)
Codeshare product	-12.43***	-12.35***
	(0.8290)	(0.8304)
Constant	-29.72***	-30.37***
	(1.3855)	(1.3852)
Operating carrier/group effects	YES	
Market Origin effects	YES	
Market Destination effects	YES	
Quarter effects	YES	
R-squared	0.2860	0.2886

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

The crucial "take-away" result to note here is that the alliance enables the partner carriers to achieve economies of passenger-traffic density that might not be otherwise achievable. Recall that Specification 1 of the marginal cost function suggests that the hub-size threshold required for a single carrier to achieve economies of passenger-traffic density was well beyond the hub-size of a typical carrier. However, the results in Specification 2 suggest that once the carrier belongs to an alliance, then the hub-size threshold needed to exploit economies of passenger-traffic density is significantly less, and achievable. These findings fit squarely with our

expectation of how an alliance may influence marginal cost via economies of passenger-traffic density.

In terms of the remaining regressors, *Itinerary Distance Flown* measures the number of miles flown from the origin to destination city. The coefficient is positive as expected, suggesting that itinerary distance positively impact marginal cost. The variable *Codeshare Product* is a dummy variable that equals to one if the product is either traditional or virtual codeshare. The coefficient estimate suggests that the marginal cost of offering a codeshare product is on average $12.35 less than offering a pure online product.

Results from Estimation of Reduced-form Price Regression

Since standard oligopoly theory predicts that equilibrium price is equal to marginal cost plus markup, this implies that changes in markup and marginal cost should be reflected in price. An advantage of directly using a reduced-form price regression is that it does not embed the strong assumptions required for a structural model. Of course, the strong assumptions of the structural model buy us the advantage of being able to separately analyze markup and marginal cost. So both approaches, reduced-form versus structural, have advantages and disadvantages. In an attempt to exploit the advantages of both approaches, we now estimate a simple reduced-form price regression to achieve two objectives: (i) provide a useful rough "reality check" on inferences already drawn from the structural model; and (ii) provide additional economic insights on the relative magnitudes of markup versus marginal cost effects.

Table 2.10 shows the estimation results for a reduced-form price regression. The negative coefficient estimate on $Post\ Alliance_t$ suggests that prices of non-DNC products decrease over the pre-post alliance periods. Results from our structural analysis suggest that, over the pre-post alliance periods, the markup of non-DNC products increase, but their marginal cost decrease. The fact that the reduced-form price regression reveals that price of non-DNC products decrease over the pre-post alliance periods, we can infer that the decrease in marginal cost outweigh the increase in markup for these products.

Table 2.10 Estimation Results for Reduced-form Price Regression

152,983 observations. Pre-alliance period: 2002:Q3 2002:Q4. Post-alliance period 2004:Q3 and 2004:Q4		
Variable	Coefficient Estimate	Robust Std. Error
Opres_cost	0.5202***	0.0231
$(\text{Opres_cost})^2$	0.0011***	0.0002
Dpres_cost	0.5638***	0.0002
$(\text{Dpres_cost})^2$	0.0008***	0.0002
Post Alliance	-11.38***	0.3252
DNC_mc	-15.25***	0.5024
Post Alliance × DNC_mc	14.50***	0.7325
Post Alliance × DNC_mc × Opres_cost	-0.2018***	0.0152
Post Alliance × DNC_mc × Dpres_cost	-0.2188***	0.0152
Itinerary distance flown (miles)	0.0354***	0.0003
Interstop	-1.85***	0.4064
Traditional Codeshare	-6.19*	3.618
Virtual Codeshare	-15.41***	0.8113
Constant	104.36***	1.418
Operating carrier/group effects	YES	
Market Origin effects	YES	
Market Destination effects	YES	
Quarter effects	YES	
R-squared	0.3090	

***, * indicate statistical significance at the 1% and 10% levels respectively. Equation is estimated using ordinary least squares.

The negative coefficient estimate on the variable *DNC_mc* in the reduced-form price regression suggests that, on average, DNC products have lower prices relative to non-DNC prices. The joint results from the reduced-form price regression and the structural analysis therefore imply that DNC products have a lower price than non-DNC products due to DNC products having both lower markup and lower marginal cost.

The sign pattern of coefficient estimates on interaction variables, $Post\ Alliance_t \times DNC_mc_{jmt}$, $Post\ Alliance_t \times DNC_mc_{jmt} \times Opres_{jmt}$, and $Post\ Alliance_t \times DNC_mc_{jmt} \times Dpres_{jmt}$ in the reduced-form price regression suggest that implementation of the alliance precipitated a decline in the partner carriers' price only in markets where they have sufficiently large hub-size presence at the origin or destination airports of the relevant market. We now see that such price changes reflect changes in the partner carriers' marginal cost, and therefore likely driven by alliance partners being better able to exploit economies of passenger-traffic density.

As expected, distance has a positive effect on price. For every 100 miles increase in itinerary distance the price increases by \$3.54. Since passengers prefer nonstop products, prices

are lower for products with more intermediate stops. Codeshare products (traditional and virtual) are also priced lower because these products are seen as inferior compare to pure online products.

2.8 Estimation of Dynamic Entry/Exit Game

Consider the following pseudo log likelihood function:

$$Q(\theta, \mathbf{P}) = \sum_{m=1}^{M} \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ \begin{array}{c} a_{imt} \ln\Psi\left(\tilde{Z}_{imt}^{\mathbf{P}} \boldsymbol{\theta} + \tilde{e}_{imt}^{\mathbf{P}}\right) \\ + (1 - a_{imt}) \ln\Psi\left(-\tilde{Z}_{imt}^{\mathbf{P}} \boldsymbol{\theta} - \tilde{e}_{imt}^{\mathbf{P}}\right) \end{array} \right\}, \quad (22)$$

where $Q(\theta, \mathbf{P})$ is called the "pseudo" log likelihood function because players' conditional choice probabilities (CCPs) in vector $\mathbf{P}$ are arbitrary and do not represent the equilibrium probabilities associated with parameter vector θ implied by the model. Recall that θ represents the vector of parameters in the fixed and entry cost functions.

We begin by implementing a two-step pseudo maximum likelihood estimator (PML). The first step involves estimating the relevant state transition equations and obtaining nonparametric estimates of the choice probabilities, $\widehat{\mathbf{P}}_0$. Nonparametric estimates of choice probabilities allow us to construct consistent estimates of $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$. Appendix E describes construction of $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$. With $\tilde{Z}_{imt}^{\widehat{\mathbf{P}}_0}$ and $\tilde{e}_{imt}^{\widehat{\mathbf{P}}_0}$ in hand, we can construct the pseudo log likelihood function, $Q\left(\theta, \widehat{\mathbf{P}}_0\right)$.

In the second step, we estimate the vector of parameters by solving the following problem:

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

where $\hat{\theta}_{PML}$ is the two-step pseudo maximum likelihood estimator (PML). The computation in the second step is simple as it only involves estimation of a standard discrete choice model. The main advantage of the two-step estimator is its computational simplicity because it does not require solving for an equilibrium in the dynamic game, which greatly reduces the computational burden. However, as discussed in Aguirregabiria and Mira (2007), the two-step PML estimator may have large finite sample bias. One reason for the bias is that the nonparametric probabilities, $\widehat{\mathbf{P}}_0$, enter nonlinearly in the sample objective function that defines the estimator,

and the expected value of a nonlinear function of $\widehat{\mathbf{P}}_0$ is not equal to that function evaluated at the expected value of $\widehat{\mathbf{P}}_0$. Second, the nonparametric probability estimates themselves can have large finite sample bias, which in turn causes bias in the PML estimator. These potential problems with the PML estimator lead us to implement the Nested Pseudo Likelihood (NPL) estimator proposed by Aguirregabiria and Mira (2002, 2007). In Appendix F we provide more discussion on implementing the NPL estimator.

2.9 Results from Estimation of Fixed and Entry Cost Functions

Table 2.11 presents estimation results for the recurrent fixed and sunk market entry cost functions. We are better able to identify the coefficients in the entry cost function than the coefficients in the fixed cost function. In the fixed cost function, the parameters that measure mean fixed cost and the coefficient on the size of an airline's airport presence are unreasonably small and not precisely estimated. We expected the coefficient estimate associated with airport presence to be positive, suggesting that fixed cost increases with the size of an airline's operation at an airport. As the scale of operation increases, fixed expenses such as the addition of gates and facilities should be higher.

The negative fixed cost coefficient on the dummy variable $Alliance_Firm_{imt}$ suggests that the alliance partner carriers have a lower mean fixed cost relative to the mean fixed cost of other airlines over the pre and post-alliance periods. For a typical origin-destination market, the mean quarterly fixed cost of Delta, Northwest and Continental is approximately \$15,400 lower than the mean quarterly fixed cost across other airlines.

The coefficient on the variable $Post_Alliance_Period_t$ in the fixed cost function measures how the fixed cost of airlines that are not Delta, Northwest or Continental changes over the pre and post-alliance periods. Since this coefficient estimate is not statistically different from zero, it suggests that non-DNC airlines' fixed cost does not change between the pre and post-alliance periods.

Table 2.11 Parameter Estimates for Recurrent Fixed and Sunk Market Entry Cost Functions

Pre-alliance period - 2002:Q3-Q4 Post-alliance period - 2004:Q3-Q4	Parameter Estimates (in $10,000)	Standard Errors	T-statistics
Fixed Cost Function			
Mean Fixed Cost	4.40e-10	0.00574	7.68e-08
$Presence_{imt}$	-2.10e-12	0.00016	-1.32e-08
$Alliance_Firm_{imt}$	-1.54***	0.04281	-36.08
$Post_Alliance_Period_t$	1.81e-09	0.00711	2.54e-07
$Post_Alliance_Period_t \times Alliance_Firm_{imt}$	0.9907***	0.05350	18.52
Entry Cost Function			
Mean Entry Cost	3.3318***	0.04027	82.74
$Presence_{imt}$	-0.0082***	0.00034	-24.52
$Alliance_Firm_{imt}$	1.30***	0.07029	18.53
$Post_Alliance_Period_t$	-0.9634***	0.04486	-21.48
$Post_Alliance_Period_t \times Alliance_Firm_{imt}$	-0.7494***	0.08703	-8.61

*** indicates statistical significance at the 1% level. The alliance firms are Delta, Northwest, and Continental airlines.

The coefficient of primary interest is on the interaction variable $Post_Alliance_Period_t \times Alliance_Firm_{imt}$ because it measures how the fixed cost of partner carriers in the DNC alliance changes relative to other airlines between the pre and post-alliance periods. Therefore, it captures fixed cost effects associated with formation of the alliance. Interestingly, the coefficient estimate is positive and statistically significant, suggesting that the formation of the DNC alliance has resulted in higher recurrent fixed costs for the alliance partners. In a typical origin-destination market, the DNC alliance is associated with an increase in partner carriers' quarterly fixed cost by an average of $9,907. As we previously suggested, the alliance is likely to increase the volume of passengers that travel on each partner carriers' network. Accommodating a higher volume of passengers may require partner carriers to acquire more airport gates and a larger airport staff to handle more intensive airport operations. This is a plausible explanation for the increase in partners' recurrent fixed cost.

We now turn to discussing results for the entry cost function. Recall that entry cost is the one-time sunk cost that an airline incurs if it wants to begin offering service in a market. The mean one-time market entry cost is estimated to be $33,318. As previously computed from the Nash price-setting equilibrium part of the model, overall median quarterly market-level variable

profit of an airline is $43,810. Therefore, the one-time mean entry cost is more than 75 percent of median quarterly variable profit.

The coefficient estimate on the size of market endpoint airport presence is negative as expected, suggesting that an airline's market entry cost decreases as size of the airline's presence at the endpoint airports increases. This result is consistent with much of the airline literature that discusses the determinants of market entry [for example see Berry (1992) and Goolsbee and Syverson (2008)].

The positive coefficient estimate on the dummy variable $Alliance_Firm_{imt}$ suggests that for a typical origin-destination market, the mean entry cost for Delta, Northwest, and Continental is higher than the mean entry cost of other airlines by $13,000. The coefficient on $Post_Alliance_Period_t$ dummy variable in the entry cost function measures how the market entry cost of other airlines—airlines that are not Delta, Northwest or Continental—change between the pre-and post-alliance periods. The coefficient estimate on this variable suggests that their market entry costs decreased about $9,634 between the pre and post-alliance periods.

The variable of primary interest in the entry cost function is $Post_Alliance_Period_t \times Alliance_Firm_{imt}$, as the coefficient on this interaction variable measures if entry cost changes differently for the alliance partners relative to other carriers over the pre and post-alliance periods. Essentially, this interaction variable allows us to measure whether entry cost savings are associated with the alliance. The negative coefficient estimate on this variable suggests that the DNC alliance has resulted in a decrease of the market entry costs for the alliance partners relative to other airlines. The partner carriers' market entry cost decrease, on average, by an additional $7,494 due to the alliance. As we previously discussed in the introduction of the paper, an alliance effectively allows an airline to enter several new origin-destination markets more cheaply by leveraging its partners' network rather than having to exclusively use its own planes to enter these markets. So our empirical finding of market entry cost savings for partner carriers is consistent with our expectation. We are unaware of any other paper in the literature that has shown evidence of entry cost savings associated with an alliance.

In sum, we find that although the formation of the DNC codeshare alliance has decreased one-time sunk market entry costs for the alliance partners, their recurrent market fixed costs increased.

2.10 Concluding Remarks

The literature on codeshare alliances is extensive. But an important aspect of codeshare alliances that has received little empirical analysis is their effect on partner airlines' cost, perhaps due to the difficulty of obtaining cost data at the route-level. The studies that have examined cost effects use aggregate measures of cost that do not distinguish between marginal, recurrent fixed, and sunk market entry costs, which makes it difficult to draw inferences for short-run price changes versus medium to long-run market structure changes. For example, while changes in marginal cost more quickly influence short-run equilibrium pricing, changes in recurrent fixed cost and sunk market entry cost will influence the ease with which alliance partners can enter new markets in the medium to long-run. Furthermore, since an alliance may differentially affect different components of cost, the use of aggregated cost data can cause researchers to mistakenly find that alliances have very little impact on airlines' costs.

Our study sets out to address the above-mentioned shortcomings in the existing literature by empirically estimating marginal, recurrent fixed, and sunk market entry costs effects associated with an airline alliance using a structural econometric model that does not require the researcher to have cost data. Therefore, our study offers two crucial distinguishing features from others in the literature. First, our methodology does not require having actual cost data to draw inference on changes in cost associated with an alliance. Second, our methodology separately identifies changes in economically relevant components of cost associated with an alliance.

Our empirical results suggest that implementation of the Delta-Northwest-Continental alliance resulted in: (1) a decrease in marginal costs for the alliance partners in markets where the airlines have a large presence at their market endpoints; (2) reduced sunk market entry costs for the alliance partners; and (3) the alliance however is associated with higher recurrent fixed costs for the partners. It is interesting that we find that the partners' recurrent fixed costs are higher following implementation of the DNC alliance. Perhaps it is the case that the overall effect on cost is small since higher recurrent fixed costs may negate some of the savings from reductions in marginal and sunk market entry costs. But the broader, and conceivably more important, point is that an alliance does influence partner airlines' cost components differentially, and each of these cost components may have different implications for short-run versus medium to long-run equilibrium market effects.

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Appendix A - Transition Rules for State Variables

The vector of state variables: $y_t = \{s_{it}, R_{it}^*, Pres_{it}, Post_Merger_Period_t\}$. The following are the state transition equations:

$$s_{i,t+1} = a_{it}, \tag{A1}$$

$$R_{i,t+1}^* = a_{it}(\alpha_0^R + \alpha_1^R R_{it}^* + \xi_{it}^R), \tag{A2}$$

$$Pres_{i,t+1} = \alpha_0^{Pres} + \alpha_1^{Pres} Pres_{it} + \xi_{it}^{Pres}. \tag{A3}$$

Variable profit and airline presence follow an exogenous Markov process with probability distribution $F_{\xi_{it}^R}$ and $F_{\xi_{it}^{Pres}}$, respectively, that we assume to be normally distributed.

We assume that the probability that next period (*t+1*) is a post-merger period for the relevant merger being studied is exogenously determined by information firms have about the current state. Furthermore, we assume that the parametric probability distribution governing this process is normal, which implies the following probit model:

$$Pr\ (Post_Merger_Period_{t+1} = 1|y_t) = \Phi(\alpha_0^T + \alpha_1^T s_{it} + \alpha_2^T R_{it}^* + \alpha_3^T Pres_{it}). \tag{A4}$$

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

Recall that the per-period profit function is given as:

$$\Pi_{imt}(a_{it}, y_t) = R_{imt}^* - a_{imt}(FC_{imt} + (1 - s_{imt})EC_{imt}),$$

which implies that,

$$\Pi_{imt}(0, y_t) = R_{imt}^*, \tag{B1}$$

$$\Pi_{imt}(1, y_t) = R_{imt}^* - FC_{imt} - (1 - s_{imt})EC_{imt}. \tag{B2}$$

Let

$$z_{imt}(0, y_t) = \{R_{imt}^*, 0,0,0,0,0,0,0,0,0,0\}, \tag{B3}$$

$z_{imt}(1, y_t)$ =
$\{R^*_{imt},\ -1,\ -Pres_{imt},\ -\ Post_Merger_Period_t, -A_Merging_Firm_{imt},$
$-Post_Merger_Period_t \times A_Merging_Firm_{imt},\ -(1 - s_{imt}),\ -(1 - s_{imt})Pres_{imt},$
$-(1 - s_{imt})Post_Merger_Period_t,\ \ -(1 - s_{imt})A_Merging_Firm_{imt},\ -(1 -$
$s_{imt})Post_Merger_Period_t \times A_Merging_Firm_{imt}\}$

(B4)

and

$$\theta = \{1, \theta_0^{FC}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}\}'. \quad \text{(B5)}$$

Therefore, we can rewrite the per-period profit function as:

$$\Pi_{imt}(0, y_t) = z_{imt}(0, y_t) \times \theta, \quad \text{(B6)}$$

$$\Pi_{imt}(1, y_t) = z_{imt}(1, y_t) \times \theta. \quad \text{(B7)}$$

An MPE can also be represented as a vector of conditional choice probabilities (CCPs) that solves the fixed point problem $\mathbf{P} = \Psi(\theta, \mathbf{P})$, where $\mathbf{P} = \{P_i(\mathbf{y})\text{: for every firm and state } (i, \boldsymbol{y})\}$. $\mathbf{P} = \Psi(\theta, \mathbf{P})$ is a vector of best response probability mapping:

$$\left\{\Psi\left(\tilde{Z}_i^{\mathbf{P}}(\boldsymbol{y})\frac{\theta}{\sigma_\varepsilon} + \tilde{e}_i^{\mathbf{P}}(\mathbf{y})\right)\text{: for every firm and state } (i, \mathbf{y})\right\} \quad \text{(B8)}$$

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

$$\tilde{Z}_i^{\mathbf{P}}(\mathbf{y}) = Z_i(1, y_t) - Z_i(0, y_t) + \beta[\mathbf{F}_{iy}^{\mathbf{P}}(1) - \mathbf{F}_{iy}^{\mathbf{P}}(0)] \times \mathbf{W}_{z,i}^{\mathbf{P}} \quad \text{(B9)}$$

$$\tilde{e}_i^{\mathbf{P}}(\mathbf{y}) = \beta[\mathbf{F}_{iy}^{\mathbf{P}}(1) - \mathbf{F}_{iy}^{\mathbf{P}}(0)] \times \mathbf{W}_{e,i}^{\mathbf{P}}, \quad \text{(B10)}$$

where

$$\mathbf{W}_{z,i}^{\mathbf{P}} = (\mathbf{I} - \beta * \overline{\mathbf{F}_{iy}^{\mathbf{P}}})^{-1} \times [\mathbf{P}_i(\boldsymbol{y}) * \boldsymbol{Z}_i(1, y) + (1 - \mathbf{P}_i(\mathbf{y})) * \boldsymbol{Z}_i(0, y)], \quad \text{(B11)}$$

$$\mathbf{W}_{e,i}^{\mathbf{P}} = (\mathbf{I} - \beta * \overline{\mathbf{F}_{iy}^{\mathbf{P}}})^{-1} \times [\mathbf{P}_i(\mathbf{y}) * \mathbf{e}_i^{\mathbf{P}}], \quad \text{(B12)}$$

and

$$\overline{\mathbf{F}_{iy}^{\mathbf{P}}} = [(\mathbf{P}_i(\mathbf{y}) \times \mathbf{1}'_M) * \mathbf{F}_{iy}^{\mathbf{P}}(1) + \left((1 - \mathbf{P}_i(\mathbf{y})) \times \mathbf{1}'_M\right) * \mathbf{F}_{iy}^{\mathbf{P}}(0)]. \quad \text{(B13)}$$

$\mathbf{W}_{z,i}^{\mathbf{P}}$ and $\mathbf{W}_{e,i}^{\mathbf{P}}$ are vectors of valuations that depend on CCPs and transition probabilities, but not on the dynamic parameters being estimated. Since ε_{it} is assumed to be distributed extreme value type 1, $\mathbf{e}_i^{\mathbf{P}}(\mathbf{P}_i(\boldsymbol{y})) = \gamma - \ln(\mathbf{P}_i(\mathbf{y}))$, , where $\gamma = 0.577215665$ is Euler's constant.

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

As discussed in Aguirregabiria and Mira (2007), the two-step PML estimator may be subjected to finite sample bias. One reason for the bias is that the nonparametric probabilities, $\widehat{\mathbf{P}}_0$, enter nonlinearly in the sample objective function that define the estimator, and the expected value of a nonlinear function of $\widehat{\mathbf{P}}_0$ is not equal to that function evaluated at the expected value of $\widehat{\mathbf{P}}_0$. Second, the nonparametric probability estimates themselves can have finite sample bias, which in turn causes bias in the PML estimator. These potential problems with the PML estimator lead us to implement the Nested Pseudo Likelihood (NPL) estimator proposed by Aguirregabiria and Mira (2002, 2007).

Aguirregabiria and Mira (2002, 2007) consider a recursive K-step extension of the two-step PML estimator, which they refer to as the NPL estimator. Since we have the two-step estimator $\hat{\theta}_{PML}$ and the initial nonparametric estimates of CCPs, $\widehat{\mathbf{P}}_0$, we can construct new CCP estimates, $\widehat{\mathbf{P}}_1$, using the best response CCPs equation:

$$\widehat{\mathbf{P}}_1 = \Psi\left(\widehat{\mathbf{P}}_0, \hat{\theta}_{PML}\right). \tag{C1}$$

We then solve the pseudo log likelihood function again using $\widehat{\mathbf{P}}_1$instead of $\widehat{\mathbf{P}}_0$ to obtain new estimates for θ, that is, we solve: $\hat{\theta}_2 = \arg\max_{\theta} \; Q\left(\theta, \widehat{\mathbf{P}}_1\right)$. We again construct new CCP estimates, $\widehat{\mathbf{P}}_2$, using: $\widehat{\mathbf{P}}_2 = \Psi\left(\widehat{\mathbf{P}}_1, \hat{\theta}_2\right)$. This process is repeated K times:

$$\hat{\theta}_K = \arg\max_{\theta} \; Q\left(\theta, \widehat{\mathbf{P}}_{K-1}\right) \tag{C2}$$

and

$$\widehat{\mathbf{P}}_K = \Psi\left(\widehat{\mathbf{P}}_{K-1}, \hat{\theta}_K\right), \tag{C3}$$

where on the Kth iteration the choice probability vector $\widehat{\mathbf{P}}_K$ is sufficiently close to $\widehat{\mathbf{P}}_{K-1}$ based on a tolerance level that we chose. The result is an NPL fixed point, which can be define as a pair $(\theta, \mathbf{P})$ where θ maximizes the pseudo likelihood function, and $\mathbf{P}$ is an equilibrium probability vector associated with θ. Aguirregabiria and Mira (2002, 2007) argue that the NPL algorithm significantly reduces the bias of the two-step PML estimator.

Appendix D - Transition Rules for State Variables

The vector of state variables: $y_t = \{s_{it}, R^*_{it}, Presence_{imt}, Post_Alliance_Period_t\}$. The following are the state transition equations:

$$s_{i,t+1} = a_{it}, \quad \text{(D1)}$$

$$R^*_{i,t+1} = a_{it}(\alpha_0^R + \alpha_1^R R^*_{it} + \xi^R_{it}), \quad \text{(D2)}$$

$$Presence_{i,t+1} = \alpha_0^{Pres} + \alpha_1^{Pres} Presence_{it} + \xi^{Pres}_{it}. \quad \text{(D3)}$$

Variable profit and airline presence follow an exogenous Markov process with probability distribution $F_{\xi^R_{it}}$ and $F_{\xi^{Pres}_{it}}$, respectively, that we assume to be normally distributed.

We assume that the probability that next period (*t+1*) is a post-alliance period for the relevant alliance being studied is exogenously determined by information firms have about the current state. Furthermore, we assume that the parametric probability distribution governing this process is normal, which implies the following probit model:

$$\Pr\,(Post_Alliance_Period_{t+1} = 1|y_t) = \Phi(\alpha_0^T + \alpha_1^T s_{it} + \alpha_2^T R^*_{it} + \alpha_3^T Presence_{it}) \quad \text{(D4)}$$

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

Recall that the per-period profit function is given as:

$$\Pi_{imt}(a_{it}, y_t) = R^*_{imt} - a_{imt}(FC_{imt} + (1 - s_{imt})EC_{imt}),$$

which implies that,

$$\Pi_{imt}(0, y_t) = R^*_{imt}, \quad \text{(E1)}$$

$$\Pi_{imt}(1, y_t) = R^*_{imt} - FC_{imt} - (1 - s_{imt})EC_{imt}. \quad \text{(E2)}$$

Let

$$z_{imt}(0, y_t) = \{R^*_{imt}, 0,0,0,0,0,0,0,0,0,0\}, \quad \text{(E3)}$$

$z_{imt}(1, y_t) \ =$
$\{R^*_{imt},\ -1,\ -Presence_{imt},\ -\ Post_Alliance_Period_t, -Alliance_Firm_{imt},$
$-Post_Alliance_Period_t \times Alliance_Firm_{imt},\ -(1-s_{imt}),$
$-(1-s_{imt})Presence_{imt},$
$-(1-s_{imt})Post_Alliance_Period_t,\ \ -(1-s_{imt})Alliance_Firm_{imt},\ -(1-$
$s_{imt})Post_Alliance_Period_t \times Alliance_Firm_{imt}\}$

(E4)

and

$$\theta = \{1, \theta_0^{FC}, \theta_1^{FC}, \theta_2^{FC}, \theta_3^{FC}, \theta_4^{FC}, \theta_0^{EC}, \theta_1^{EC}, \theta_2^{EC}, \theta_3^{EC}, \theta_4^{EC}\}'. \quad \text{(E5)}$$

Therefore, we can rewrite the per-period profit function as:

$$\Pi_{imt}(0, y_t) = z_{imt}(0, y_t) \times \theta, \quad \text{(E6)}$$

$$\Pi_{imt}(1, y_t) = z_{imt}(1, y_t) \times \theta. \quad \text{(E7)}$$

A MPE can also be represented as a vector of conditional choice probabilities (CCPs) that solves the fixed point problem $\mathbf{P} = \Psi(\theta, \mathbf{P})$, where $\mathbf{P} = \{P_i(\mathbf{y})\text{: for every firm and state } (i, \boldsymbol{y})\}$. $\mathbf{P} = \Psi(\theta, \mathbf{P})$ is a vector of best response probability mapping:

$$\left\{\Psi\left(\tilde{Z}_i^{\mathbf{P}}(\mathbf{y})\frac{\theta}{\sigma_\varepsilon} + \tilde{e}_i^{\mathbf{P}}(\mathbf{y})\right)\text{: for every firm and state } (i, \mathbf{y})\right\}, \quad \text{(E8)}$$

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

$$\tilde{Z}_i^{\mathbf{P}}(\mathbf{y}) = Z_i(1, y_t) - Z_i(0, y_t) + \beta[\mathbf{F}_{iy}^{\mathbf{P}}(1) - \mathbf{F}_{iy}^{\mathbf{P}}(0)] \times \mathbf{W}_{z,i}^{\mathbf{P}}, \quad \text{(E9)}$$

$$\tilde{e}_i^{\mathbf{P}}(\mathbf{y}) = \beta[\mathbf{F}_{iy}^{\mathbf{P}}(1) - \mathbf{F}_{iy}^{\mathbf{P}}(0)] \times \mathbf{W}_{e,i}^{\mathbf{P}}, \quad \text{(E10)}$$

$$\mathbf{W}_{z,i}^{\mathbf{P}} = (\mathbf{I} - \beta * \overline{\mathbf{F}_{iy}^{\mathbf{P}}})^{-1} \times [\mathbf{P}_i(\boldsymbol{y}) * \boldsymbol{Z}_i(1, y) + (1 - \mathbf{P}_i(\mathbf{y})) * \boldsymbol{Z}_i(0, y)], \quad \text{(E11)}$$

$$\mathbf{W}_{e,i}^{\mathbf{P}} = (\mathbf{I} - \beta * \overline{\mathbf{F}_{iy}^{\mathbf{P}}})^{-1} \times [\mathbf{P}_i(\mathbf{y}) * \mathbf{e}_i^{\mathbf{P}}], \quad \text{(E12)}$$

$$\overline{\mathbf{F}_{iy}^{\mathbf{P}}} = [(\mathbf{P}_i(\mathbf{y}) \times \mathbf{1}'_M) * \mathbf{F}_{iy}^{\mathbf{P}}(1) + \left(\left(1 - \mathbf{P}_i(\mathbf{y})\right) \times \mathbf{1}'_M\right) * \mathbf{F}_{iy}^{\mathbf{P}}(0)], \quad \text{(E13)}$$

where $\mathbf{F}_{iy}^{\mathbf{P}}(0)$ and $\mathbf{F}_{iy}^{\mathbf{P}}(1)$ are state transition probability matrices for $a_{it} = 0$ and $a_{it} = 1$ respectively; while $\mathbf{W}_{z,i}^{\mathbf{P}}$ and $\mathbf{W}_{e,i}^{\mathbf{P}}$ are vectors of valuations that depend on CCPs and transition probabilities, but not on the dynamic parameters being estimated. Since ε_{it} is assumed to be distributed extreme value type 1, $\mathbf{e}_i^{\mathbf{P}}(\mathbf{P}_i(\boldsymbol{y})) = \gamma - \ln(\mathbf{P}_i(\mathbf{y}))$, where $\gamma = 0.577215665$ is Euler's constant.

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

Aguirregabiria and Mira (2002, 2007) consider a recursive K-step extension of the two-step PML estimator, which they refer to as the NPL estimator. Since we have the two-step estimator $\hat{\theta}_{PML}$ and the initial nonparametric estimates of CCPs, $\hat{\mathbf{P}}_0$, we can construct new CCP estimates, $\hat{\mathbf{P}}_1$, using the best response CCPs equation:

$$\hat{\mathbf{P}}_1 = \Psi\left(\hat{\mathbf{P}}_0, \hat{\theta}_{PML}\right). \tag{F1}$$

We then solve the pseudo log likelihood function again using $\hat{\mathbf{P}}_1$ instead of $\hat{\mathbf{P}}_0$ to obtain new estimates for θ, that is, we solve: $\hat{\theta}_2 = \arg\max_{\theta} \; Q\left(\theta, \hat{\mathbf{P}}_1\right)$. We again construct new CCP estimates, $\hat{\mathbf{P}}_2$, using: $\hat{\mathbf{P}}_2 = \Psi\left(\hat{\mathbf{P}}_1, \hat{\theta}_2\right)$. This process is repeated *K* times:

$$\hat{\theta}_K = \arg\max_{\theta} \; Q\left(\theta, \hat{\mathbf{P}}_{K-1}\right) \tag{F2}$$

and

$$\hat{\mathbf{P}}_K = \Psi\left(\hat{\mathbf{P}}_{K-1}, \hat{\theta}_K\right), \tag{F3}$$

where on the Kth iteration the choice probability vector $\hat{\mathbf{P}}_K$ is sufficiently close to $\hat{\mathbf{P}}_{K-1}$ based on a tolerance level that we chose. The result is an NPL fixed point, which can be defined as a pair $(\theta, \mathbf{P})$ where θ maximizes the pseudo likelihood function, and **P** is an equilibrium probability vector associated with θ. Aguirregabiria and Mira (2002, 2007) argue that the NPL algorithm significantly reduces the bias of the two-step PML estimator.