ESSAYS ON PRODUCT QUALITY IN COMMERCIAL AVIATION

by

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B.S., University of Buea, 2006

M.B.A., Alabama A&M University, 2010

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

2016

Abstract

This dissertation consists of three essays on product quality in commercial aviation. Since the mid-1990s, major airlines that serve the U.S. domestic market have increasingly found it appealing to form alliances. Amidst the recent emergence of airline alliance formation, this dissertation has sought to answer questions on the product quality implications of policies regarding cooperation among airlines in the U.S. domestic air travel industry. A challenge that empirical work faces in studying the relationship between airline alliances and product quality is to find reasonable measure(s) of product quality.

The first essay sheds light on whether the route network integration that comes with an airline alliance provides sufficient extra incentive to partner carriers to improve their flight routing quality. Evidence suggests that routing quality for Delta/Continental/Northwest's—our alliance of interest—products decreases in markets where pre-alliance competition among alliance partners exists, resulting in substantial negative welfare effects for passengers. In fact, routing quality for Delta/Continental/Northwest products decreased by 0.256% below the mean routing quality of the entire sample's products. More interestingly, the codeshare effects in specific markets where the alliance firms competed prior to the alliance, are also negatively associated with routing quality of the alliance firms' products, resulting in a fall in consumer utility of $0.5 per consumer.

The second essay explores the potential relationship between on-time performance and airline code-sharing. Although flight delay has always received much attention, we are unaware of any empirical research that measures the on-time performance effects of airline alliances. We empirically investigate the on-time performance effects of the largest U.S. domestic alliance that began in June 2003—an alliance between Delta Air Lines, Northwest Airlines and Continental Airlines. We find evidence that code-sharing improves alliance

partners' on-time performance and that the size of the alliance effect on on-time performance depends on pre-alliance competition in a market, with the effect being larger in markets where the partners competed in prior to the alliance.

Using a structural econometric model, the third essay attempts to provide an alternative explanation to a long-standing question: why are airlines late? Airlines usually claim that air travel delays are out of their control, placing the blame on adverse weather or air traffic control as the most common reasons. Despite these claims, data on causes of flight delay reveal that the share of delay caused by weather and air traffic control has been on the decline while the share of delay caused by airlines has been on the rise. This suggests that on-time performance improvement is well within the reach of carriers. We investigate why airlines have little or no incentive to improve on-time performance. We also measure the cost of delay borne by consumers in terms of how much monetary value they are willing to pay to avoid delay. We find that consumers are willing to pay \$0.78 for every minute of arrival delay which after extrapolation, amounts to consumer welfare effects of \$1.76 billion. Our findings suggest that airlines have little to no incentive because their markups do not increase when they improve on-time performance. In fact, the marginal increase in price resulting from on-time performance improvement is offset by an increase in marginal cost causing a zero net effect on markup.

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Acknowledgments

The following dissertation, while it bears the single name of the student, benefited from the insights and direction of several people. I wish to acknowledge my appreciation to certain people.

First, my Dissertation Chair, Dr. Philip Gayle, exemplifies the high quality scholarship to which I aspire. Dr. Philip Gayle provided timely and instructive comments and evaluation at every stage of the dissertation process, allowing me to complete this project on schedule. It is not often that one finds an advisor that always finds the time for listening to the little roadblocks that unavoidably crop up in the course of performing research. His technical and editorial advice was essential to the completion of this dissertation and has taught me countless lessons and insights on the workings of academic research in general.

Next, I wish to thank the complete Dissertation Committee, including my outside chair, respectively: Dr. Yang-Ming Chang, Dr. Tian Xia, Dr. Jin Wang, and Dr. Chwen Sheu for providing many valuable comments during my dissertation proposal defense that substantially improved the presentation and contents of the finished product. To Dr. Yang-Ming Chang, his microeconomic theory class sparked my research interest in microeconomics. I am grateful to Dr. Tian Xia for insights gained while taking his class on demand estimation. Special thanks go to Dr. Jin Wang, who was willing to join my dissertation committee at the last moment. I also want to thank my outside chair for his time, Dr. Chwen Sheu. I also want to thank Dr. William Blankenau who believed in my ability to teach from the first day I gave a practice lecture on the price elasticity of demand.

In addition to the technical and instrumental assistance above, I received equally important assistance from family and friends. I especially want to thank my mom, Julienne Sami whose endearing love kept me going every day. My sister, Nathalie Yimga, receives my deepest gratitude and love for her dedication and the many years of support during my undergraduate studies that provided the foundation for this work. To my uncle, Dr. Senwo and his wife, I cannot express to you how grateful I am for your kindness, encouragement and mentorship. To Abed Kouamen, a true brother, thank you for keeping me grounded. Thanks to Shawne York for being my solace during moments of frustration. Special thanks to Reina for being a voice of reason and bringing out the best in me.

My immense gratitude goes to my colleagues in the economics department with whom I have shared thoughts and ideas. First with Sheryll Namingit, thank you for being an amazing office mate. To Dr. Bebonchu Atems, Dr. Huubinh Le, Dr. Hedieh Shadmani, Dr. Tyson Thomas and Dr. Jason Walter, for sharing great job market tips. To Yang, for being such a good friend. To Moayad, Iqbal, Akbar, Karen, Anna, Tennecia, Sandra, Farah, Nick, Han, Atika, Manaf, Robert, Ying, Adeel, Dr. Cheawenet Bunchai, Dr. Mercy Palamuleni and others I have not mentioned have all been part of this wonderful journey.

I would like to express my full appreciation to the staff of the Department of Economics at Kansas State University, especially Crystal Strauss for her reliability and promptitude during my job search, thank you for the countless recommendation letters you sent out on my behalf. I thank Susan Koch for her professionalism, Sean Pittman for setting up my profile page on the department website and Samantha Moore for helping me with printing. To the rest of the economics faculty, particularly Dr. Kuester, Dr. Babcock, Dr. Da Silva and Dr. Al-Hamdi, you made the department a place to belong.

Special thanks to Scott Velasquez for offering me my first on-campus job. Scott was there for me when I needed help the most. I thank Dr. Kathleen Greene for her encouragement and Dr. Dina Bennett for being a friend and letting me work with the McNair scholars.

Finally, the completion of my dissertation, and success in graduate school in general, was possible thanks to the generous financial support from the Economics Department in the form of tuition waiver and stipend, and additional support from the Graduate School and the College of Arts and Sciences in the form of research travel grants to present this work at many conferences.

Dedication

In Loving Memory of My Dad, Zachée Yimga

Chapter 1

Airline Alliance and Product Quality: The Case of the U.S. Domestic Airline Industry

1.1 Introduction

Airline alliance formation has a long history in the international air travel market and has been hailed by some economists for providing airlines with the opportunity to extend their networks overseas when the alliance agreement is entered with a foreign airline (Pels, 2001; Brueckner and Whalen, 2000). Airline alliance partners in international air travel link up their existing complementary networks and build a new network providing an interlining service to their passengers[1]. Park (1997) and Hassin and Shy (2004), among others, show that alliance formations on these kinds of networks are welfare improving.

However, unlike international aviation, alliance formation in the U.S. domestic air travel market may involve parallel or overlapping networks. In this instance, the cooperation between alliance partners encompasses markets in which they actually compete. These

[1] Park (1997)

overlapping markets have been a source of concern for policy analysts. They argue that cooperation in these markets is likely to reduce the competitive pressure on the alliance partners, and therefore curbs the incentive to improve product quality.

The objective of this paper is to estimate the product quality effects of an airline alliance, particularly in markets the partners competed prior to the alliance formation. The literature on airline alliances is vast, spanning from why they exist[2] to how they affect prices (Brueckner and Whalen, 2000; Zou et al., 2011), costs (Gayle and Le, 2013; Goh and Yong, 2006) and market entry (Gayle and Xie, 2014; Lin, 2008). However, questions on potential product quality effects of airline alliances remained unanswered. This is surprising given the increasing customer's awareness of service quality in air travel. Perhaps, this vacuum results from the difficulty to find a reasonable measure of service/product quality. From a passenger's viewpoint, service quality entails a combination of various attributes, some of which are tangible and others intangible or subjective. These subjective attributes are difficult to measure since every individual passenger might have a wide range of perceptions vis-à-vis service quality. In this paper, we examine the relationship between airline alliance and product quality by empirically investigating the Delta/Northwest/Continental codeshare alliance.

1.2 Delta/Northwest/Continental Codeshare Alliance

The codeshare alliance between Delta Air Lines, Northwest Airlines and Continental Airlines of August 23, 2003 represented the largest domestic codeshare agreement ever approved in the United States. This agreement involves code sharing, reciprocal frequent-flyer programs and reciprocal access to airport lounges. In a press release on the alliance, the U.S. Department of Justice (DoJ) believed that:

[2]Among others, Tarola (2007) argue that airline alliances in the U.S. soared over the years because of the increased competition from low-cost carriers, following the Airline Deregulation Act of 1978.

"The codeshare agreement could result in lower fares and better service for passengers"[3]

However, it is worth mentioning that this approval came with some strings attached due to some anti-competitive concerns expressed by the U.S. Department of Transportation (DoT). First, regulators worry about the large number of markets in which potential partners' service overlap since these carriers are direct competitors on some segments of their respective networks that overlap. Thus, an alliance between them, which often requires optimal integration of their route networks may involve collusion (explicit or tacit) on prices and/or service levels in the partners' overlapping markets. A review of the proposed alliance by the DoT shows that the three airlines' service overlap in 3,214 markets, accounting for approximately 58 million annual passengers. This large number of overlapping markets contrasts vividly to the next largest alliance at that time, between United Airlines and US Airways with overlapping service in only 543 markets, accounting for 15.1 million annual passengers. Secondly, the combined market share of the three airlines at the time of the proposed alliance, was 35 percent—18 percent for Northwest and Continental combined, and 17 percent for Delta—measured by domestic revenue passenger miles. Again, this seems substantial when compared to the 23 percent market share of the United/US Airways alliance. The above two main concerns prompted the DoT to impose some conditions 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[4].

On a separate evaluation, the DoJ banned any conduct the alliance carriers could use to collude on fares or otherwise reduce competition among themselves. Specifically, the carriers are forbidden from code sharing on each other's flights wherever they offer competing nonstop service, such as service between their hubs. The carriers are also required to continue to act independently when setting award levels or other benefits of their respec-

[3] U.S. Department of Justice (2003). "Department of Justice Approves Northwest/Continental/Delta Marketing Alliance with Conditions." *www.justice.gov/atr/public/press_releases/2003/200645.htm*

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

tive frequent-flier programs. Although the DoJ anticipated lower fares as a result of the codeshare agreement, it is difficult to predict what would happen to product quality.

1.3 Measuring Airline Product Quality

To examine the relationship between airline alliance formation and product quality, it is essential to find a reasonable measure of product quality. Product quality is like beauty in the eyes of the beholder and hence a matter of perception (Rhoades and Waguespack, 2004). As such, its measurement constitutes a challenge for empirical work. One measure of quality used by airline carriers is quality ratings. However, most quality ratings in the airline industry are based on subjective surveys about consumer opinions[5] and consumers are usually asked to evaluate the sum of all service interactions with a specific airline. Nonetheless, when an airline alliance is involved, things get more complex since an airline alliance's services are not an individual service activity but rather a group activity characterized by a set of service complexities (Janawade, 2011). Hence, it is assumed that service complexities in an airline alliance context, can be difficult to define and measure. This issue can be well understood, when passengers book flights from one airline, but might experience services from a partner airline (Janawade, 2011).

The literature on the quality effects of airline alliances is very limited. In this vein, Tsantoulis and Palmer (2008) look at service quality effects of a co-brand alliance. Their measure of service quality is based on an index constructed using some technical and functional aspects of quality. In their paper, the choice of these technical and functional components to include in the index, and their relative weighting, was informed by a panel of so-called experts. Goh and Uncles (2003), on the other hand, carry out an empirical study of the perceptions that business travelers have of the benefits of global alliances. To measure qual-

[5]Some studies have used the SERVQUAL service quality model. This entails the use of a questionnaire that measures both the customer expectations of service quality in terms of five quality dimensions, and their perceptions of the service they receive. When customer expectations are greater than their perceptions of received delivery, service quality is deemed low.

ity, they use a cross-sectional self-completion survey that was administered to a sample of Australian business travelers.

Tiernan et al. (2008) investigate the service quality of E.U. and U.S. members of main airline alliances. They consider three measures of airline service quality: on-time flight arrival percentage, percentage of flights not canceled and percentage of passengers filing baggage reports (bags lost, damaged, delayed or pilfered). Their examination of the international airline alliances indicates no significant differences in the quality of service indicators.

Unlike other measures of quality in airline alliance studies, which are based on a subjective approach, our measure of air travel product quality is typically constructed using itinerary distance data. Following Chen and Gayle (2013), we refer to this measure as *Routing Quality* which is defined as the ratio of nonstop fight distance to the product's itinerary fight distance used to get passengers from the origin to destination. Distance-based measure for product quality has been used by some studies.[6] These studies used this measure as a proxy for itinerary convenience/inconvenience. Based on our routing quality measure, a nonstop flight between the origin and destination will have the shortest itinerary flight distance. Hence, air travel products that require intermediate airport stop(s) that are not on a straight path between the origin and destination, will have an itinerary flight distance that is longer than the nonstop flight distance. Our rationale for choosing this measure is that the greater the itinerary flight distance of an intermediate stop product relative to the nonstop flight distance, the lower the routing quality of this intermediate stop product. A limitation with our measure of routing quality is that it does not capture any delays the passenger may have experienced.

[6] See Reiss and Spiller (1989), Borenstein (1989), Ito and Lee (2007), Färe et al. (2007) and Gayle (2007, 2013)

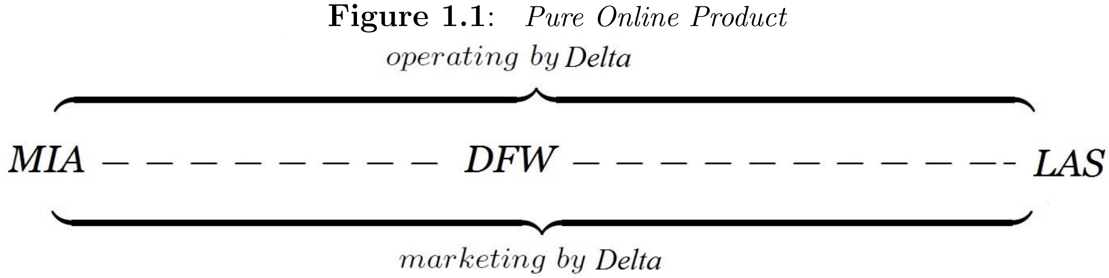
1.4 Definitions and Data

1.4.1 Definitions

A *market* is a directional, round-trip air travel between an origin city and a destination city during a specific time period. By directional, we mean that a round-trip air travel from Miami to Las Vegas is a distinct market from a round-trip air travel from Las Vegas to Miami. This directional definition of a market controls for origin city fixed effects that may influence market demand (Berry et al., 2006; Gayle, 2007). An *itinerary*, which also refers to a ticket, is a planned route from an origin city to a destination city.

An itinerary comprises one or more flight coupons, each coupon typically representing travel on a particular flight segment between two airports. Each flight itinerary has, by definition, a single ticketing/marketing carrier (the airline that issues and sells the ticket for the seat) and one or more operating carriers (the airline whose aircraft and crew are used to operate the flight). An air travel product is defined as a unique combination of ticketing carrier, operating carrier(s) and itinerary. Following Gayle (2008) and Ito and Lee (2007), we focus on three types of air travel products: pure online; traditional codeshare; and virtual codeshare. Figure 1.1 depicts a pure online air travel product using an itinerary that requires travel from Miami (MIA) to Las Vegas (LAS) with one intermediate stop in Dallas (DFW). Thus, for a pure online product, the same airline is the ticketing and operating carrier on all segments of the trip. In Figure 1.1, the itinerary is marketed by Delta Air Lines and both segments of the itinerary are also operated by Delta Air Lines.

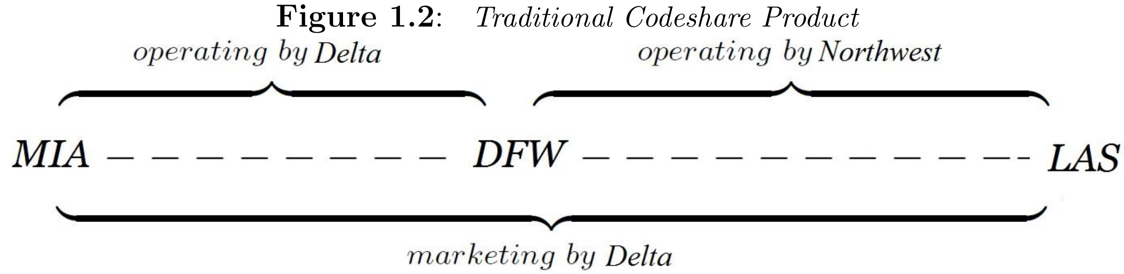
Figure 1.1: *Pure Online Product*



An air travel product is said to be code-shared if the operating and ticketing carriers for that itinerary differ. In this case, we consider two types of codeshare products: (1) *traditional codeshare*; and (2) *virtual codeshare*. We define a traditional codeshare product as one having a single ticketing carrier, but multiple operating carriers, one of which is the ticketing carrier.

Figure 1.2 shows an illustration of a traditional codeshare air travel product for an itinerary that requires travel from Miami (MIA) to Las Vegas (LAS) with one intermediate stop in Dallas (DFW). Delta Air Lines is the ticketing/marketing carrier for both segments and only operates the first leg of the itinerary (Miami to Dallas), while Northwest Airlines operates the Dallas-Las Vegas segment.

Figure 1.2: *Traditional Codeshare Product*

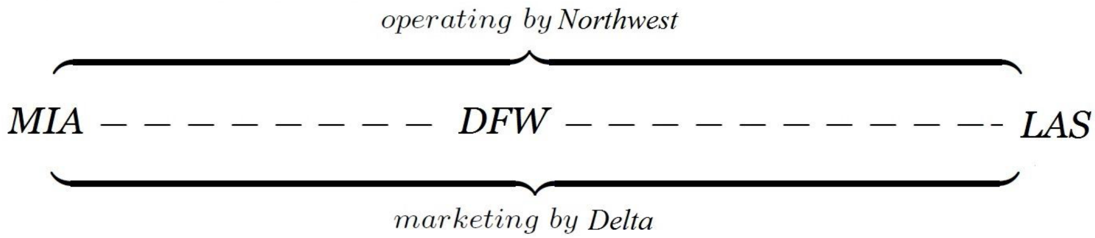


A *virtual codeshare* air travel product is defined as having the same operating carrier for all segments of the itinerary, however the ticketing carrier is different from the operating carrier. An illustration of a virtual codeshare product is shown in Figure 1.3 with an itinerary that requires travel from Miami (MIA) to Las Vegas (LAS) with one intermediate stop in Dallas (DFW). The connecting itinerary is entirely operated by Northwest Airlines but solely marketed by Delta Air Lines.

1.4.2 Data

We use data from the Airline Origin and Destination Survey (DB1B) collected by the Office of Airline Information of the Bureau of Transportation Statistics. The data are quarterly

Figure 1.3: *Virtual Codeshare Product*



and represent a 10 percent sample of airline tickets from reporting carriers. A record in this survey represents a flight itinerary. Each record or itinerary contains information on; *(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 DB1B data does not include passenger-specific information, that would facilitate the estimation of a richer demand model than the one we use based on available data. Also missing, is information on ticket restrictions such as advance-purchase and length-of-stay requirements. Given that the Delta/Northwest/Continental alliance was formed in August of 2003, the third and fourth quarters of 2002 represent the pre-alliance period whereas the third and fourth quarters of 2004 represent the post-alliance period[7].

The raw DB1B data set contains millions of itineraries for each quarter. For example, the third quarter of 2002 consists of 7,759,221 observations. In order to construct our data set, we place some restrictions on the raw data. First, we restrict our analysis to U.S. domestic flights operated by U.S. domestic carriers. Second, we only consider, passengers purchasing round-trip, coach class tickets. Third, inflation-adjusted fares less than \$25 or greater than \$2,000 are excluded. Excluding real fares that are too low gets rid of discounted fares that may be due to passengers using their frequent-flier miles to offset the full price of the trip or employee travel tickets. Similarly, excluding fares that are too high gets rid of first-class or

[7]Using data from the same quarters for both years will control for potential seasonal effects in demand.

business-class tickets. Fourth, we also limit our analysis to air travel products possessing at least 9 passengers per quarter to exclude products that are not part of the regular offerings by an airline. Fifth, we restrict our analysis to itineraries with the following characteristics: *(i)* within the 48 states in U.S. mainland; *(ii)* no more than two intermediate stops; and *(iii)* with a single ticketing carrier.

Finally, in the spirit of Aguirregabiria and Ho (2012), the selection of markets focuses on air travel amongst the 65 largest U.S. cities. The size of these cities is based on the Census Bureau's Population Estimates Program (PEP), which produces estimates of U.S. population. Data are drawn from the category "Cities and Towns." We use the size of population in the origin city as a proxy for potential market size. We group cities that belong to the same metropolitan areas and share the same airport. Table 1.1 presents a list of the cities and corresponding airport groupings. Given that there are often multiple records for the same itinerary because different passengers paid different prices, we construct the price and quantity variables by averaging the airfares and aggregating the number of passengers, respectively, based on our product definition, and then collapse the data by product. Therefore, in the collapsed dataSET that we use for analyses, a product appears only once during a given time period. Our final working data set includes a total of 55 metropolitan areas ("cities") and 63 airports representing 153,794 air travel products bought by over 22.8 million passengers across 11, 534 different directional city-pair markets.

Table 1.2 presents pre- and post-alliance service levels (number of passengers). While service levels decreased for some carriers, Delta, Northwest and Continental actually experienced an increase in service levels of 4.8 percent, 15.87 percent and 64.69 percent respectively over the pre-post alliance periods.

Table 1.1: *Cities, airports and population*

City, State	Airports	City Population	
		2002	2004
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
Nashville, TN	BNA	544,375	570,068
Milwaukee, WI	MKE	589,975	601,081
Washington, DC	DCA, IAD	564,643	579,796
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
Tulsa, 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

[1] *New York-Newark-Jersey*

[2] *Dallas-Arlington-Fort Worth-Plano, TX*

[3] *Phoenix-Temple-Mesa, AZ*

Table 1.2: *Airlines # of passengers pre- and post-alliance*

Code	Airline	# of Passengers	
		2002 Q3-Q4	2004 Q3-Q4
AA	American Airlines[(a)]	1,931,322	1,938,342
AQ	Aloha Air Cargo	1,909,012	1,784
AS	Alaska Airlines[(a)]	1,491,700	334,158
B6	JetBlue Airways	1,441,918	219,431
CO	Continental Air Lines[(a)]	877,425	919,919
DL	Delta Air Lines[(a)]	839,691	1,382,877
F9	Frontier Airlines[(a)]	737,908	252,340
FL	AirTran Airways[(a)]	723,832	233,486
G4	Allegiant Air	327,628	6,070
HA	Hawaiian Airlines	194,920	–
HP	America West Airlines	151,134	789,576
N7	National Airlines	130,970	–
NJ	Vanguard Airlines	99,145	–
NK	Spirit Air Lines	72,343	40,370
NW	Northwest Airlines[(a)]	53,305	899,116
QX	Horizon Air	47,506	–
RP	Chautauqua Airlines	12,008	–
SM	Sunworld International Airlines	11,631	–
SY	Sun Country Airlines	4,126	31,272
TZ	ATA Airlines[(a)]	2,272	251,231
UA	United Air Lines[(a)]	600	1,583,078
US	US Airways[(a)]	334	704,561
WN	Southwest Airlines	287	2,090,517
YX	Midwest Airlines	32	92,513
	Total	11,061,049	11,770,641

Note: All carriers offer pure online itinerary

[(a)] *Carrier is involved in codeshare product*

Table 1.3 shows that among the airlines offering a codeshare products, Delta, Northwest and Continental account for a whopping 38.91 percent of all codeshare products in our sample.

Table 1.4 reports the number of codeshare tickets sold by type. It shows that 58.18 percent of Delta codeshare products are virtual in nature. Virtual codeshare tickets represent 85.60 percent and 76.91 percent of Northwest and Continental codeshare product offerings

Table 1.3: *Airlines Involved in Codeshare Products*

Code	Airline	% of codeshare products
UA	United Air Lines	26.64
NW	Northwest Airlines	21.21
US	US Airways	19.28
CO	Continental Air Lines	14.96
AA	American Airlines	5.70
AS	Alaska Airlines	3.89
TZ	ATA Airlines	3.64
DL	Delta Air Lines	2.74
FL	AirTran Airways	1.86
F9	Frontier Airlines	0.08
		100.00

Table 1.4: *Frequency of Codeshare Tickets*

Code	Airline	Number of tickets			% virtual
		Traditional	Virtual	Total	
UA	United Air Lines	528	1,076	1,604	67.08
NW	Northwest Airlines	184	1,093	1,277	85.60
US	US Airways	196	965	1,161	83.12
CO	Continental Air Lines	208	693	901	76.91
AA	American Airlines	221	122	343	35.57
AS	Alaska Airlines	77	157	234	67.09
ATA	ATA Airlines	205	14	219	6.39
DL	Delta Air Lines	69	96	165	58.18
FL	AirTran Airways	102	10	112	8.93
F9	Frontier Airlines	0	5	5	100.00
	Total	1,790	4,231	6,021	

Note: Data are from the third and fourth quarters of 2002 and 2004, U.S. Bureau of Transportation Statistics DB1B database. Data include round-trip, coach-class tickets with less than three intermediate stops per itinerary.

respectively. In Table 1.5, we summarize our data according to the three types of air travel product groupings described in Section 1.4.1. We denote a connection between two flights with an arrow. For example, DL/DL $\rightarrow$ DL/DL denotes a connecting itinerary between two

Table 1.5: *Classification of Cooperative Agreements in Data Set*

Product Classification	Example	Observations Frequency	Observations Percent	Passengers Frequency	Passengers Percent
1. Pure online	DL/DL → DL/DL	147,773	96.09	22,603,001	98.99
2. Virtual codeshare	DL/NW → DL/NW	4,231	2.75	177,286	0.78
3. Traditional codeshare	DL/DL → DL/NW	1,790	1.16	51,403	0.23
Total		153,794	100.00	22,831,690	100.00

Note: Data are from the third and fourth quarters of 2002 and 2004, U.S. Bureau of Transportation Statistics DB1B database. Data include round-trip, coach-class tickets with less than three intermediate stops per itinerary. Examples denote connecting itineraries between marketing carrier i.e. Delta (DL) and operating carrier(s)—DL and NW.

flights in which both the marketing and operating carrier is Delta Air Lines.

Likewise, DL/NW → DL/NW denotes a connecting itinerary where both segments are marketed by Delta and both segments operated by NW. Finally DL/DL → DL/NW denotes a connecting itinerary between two flights in which the marketing carrier for both segments is Delta which also operates the first leg of the trip and NW operates the second segment of the trip.

Our working sample shows that, of the 153,794 itineraries, close to 4 percent—accounting for .23 million passengers—involve at least one code-shared segment. Table 1.5 shows that the overwhelming majority of passengers—about 99 percent—in our sample travel on pure online itineraries. This is expected and consistent with the literature[8] since whenever an operating carrier is involved in a virtual code-shared product with a given ticketing carrier in a market, the same ticketing carrier is probably offering its own pure online product in the same market. Importantly, we observe that among code-shared itineraries, virtual code sharing is twice more prevalent than traditional code sharing.

Figure 1.4 shows the increase in code sharing activity over the sample time span, third and fourth quarters of 2002 and 2004, and consistent with Tables 1.4 and 1.5, airline carriers show an apparent inclination to engage more in virtual as opposed to traditional code

[8]See Ito and Lee (2007)

sharing.

Figure 1.4: *Frequency of Domestic Codeshare Tickets, 2002:Q3-Q4 and 2004:Q3-Q4*

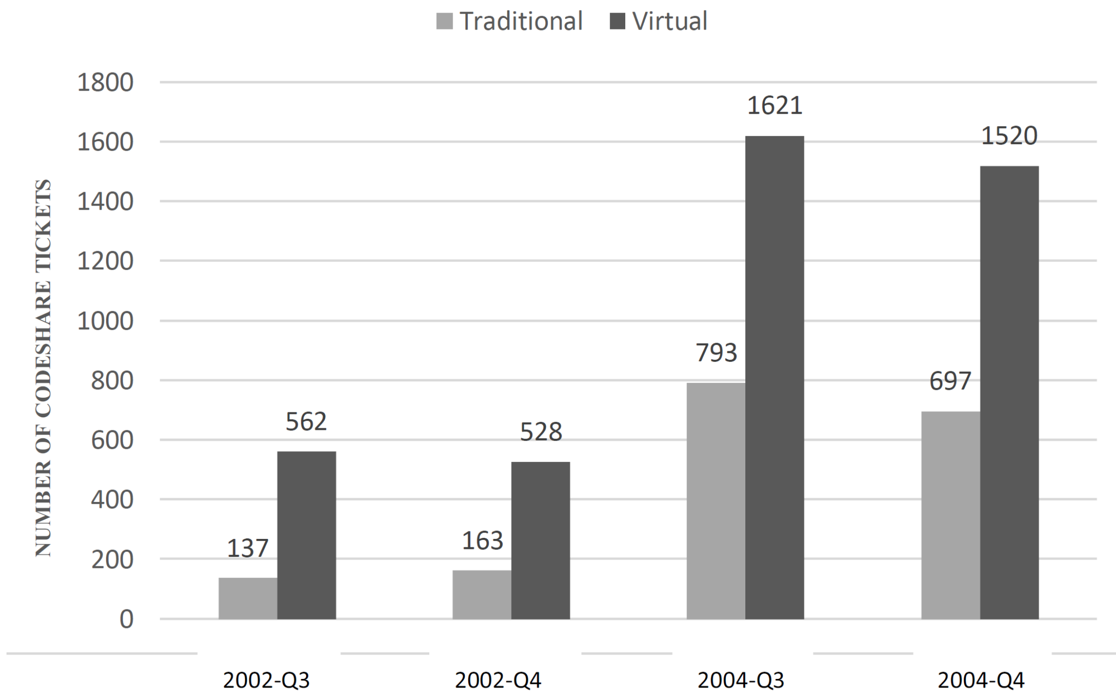


Table 1.6 presents the summary statistics for variables used in our demand estimation. The price variable is measured in constant year 1999 U.S. dollars. The *Origin Presence* variable represents the number of cities an airline serves from any given origin city with direct origin-destination flights. Thus, on average, airlines serve approximately 28 distinct cities with direct flights from the market origin city. We describe the rest of the variables in Table 1.7 and in the demand model section (1.5.1).

1.5 The Model

Air travel demand is specified based on a discrete choice framework. The estimation of air travel demand is of particular interest since it permits us to confirm whether consumers' choice behavior is consistent with our presumption that the better the routing quality, the

Table 1.6: *Summary Statistics*

Variable	Mean	Std. Dev.	Min	Max
Price[a]	162.36	59.5342	27.11	1,593.51
Quantity	148.4563	457.616	9	12,349
Observed Product Share	.000221	.00085	1.04e-06	.0482414
Origin presence	28.0691	26.9782	0	145
Destination presence	28.0480	26.9259	0	146
Nonstop (dummy variable)	.150	.357	0	1
Itinerary distance flown (miles)[b]	1,542.992	701.483	67	4,084
Nonstop flight distance (miles)	1,364.168	653.058	67	2,724
Routing Quality[c]	.8853	.1291	.3388	1
Traditional Codeshare	.012	.107	0	1
Virtual Codeshare	.028	.164	0	1
Pure Online	0.96	0.194	0	1
N_comp_nonstop	2.367	2.575	0	21
N_comp_connect	15.092	12.407	0	96
Number of Products	153,794			
Number of Markets[d]	11,534			

[a] *Adjusted for inflation*

[b] *Reported as "market miles flown" in the DB1B database*

[c] *Defined as the ratio of non-stop distance to itinerary distance*

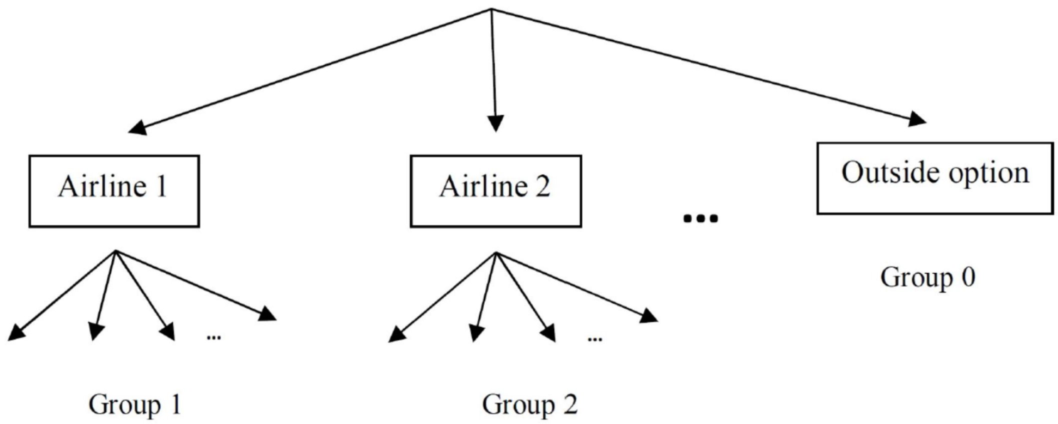
[d] *A market is an origin-destination-time period combination*

more desirable the itinerary to the passenger. Following Chen and Gayle (2013), we estimate pre-alliance cross-price elasticities of demand between any pair of the three alliance partners in markets where they directly competed. These cross-price elasticities gauge the pre-alliance competition intensity among the alliance partners in various markets. We later estimate a reduced-form regression of routing quality to identify the alliance routing quality effects.

1.5.1 Demand

The nested logit model is used to specify air travel demand. Here, a typical passenger i may either buy one of J products (air travel products), $j = 1, \ldots, J$ or otherwise choose the outside good 0 ($j = 0$), for example driving or using another transportation means. Thus, passenger i makes a choice among $J_{mt}+1$ alternatives in market m during time period t. The nested logit model classifies products into G groups, and one additional group for the outside good. Therefore, products are organized into $G+1$ mutually exclusive groups. Figure 1.5 illustrates the choice set faced by a typical passenger. Note that a group is a set of products offered by an airline within a market.

Figure 1.5: *The Choice Set*



The passenger solves the following utility maximization problem:

$$\underset{j\in\{0,1,\cdots,J_{mt}\}}{Max} U_{ijmt} = \delta_{jmt} + \sigma\varsigma_{imtg} + (1-\sigma)\varepsilon_{ijmt} \tag{1.1}$$

$$\delta_{jmt} = x_{jmt}\beta + \alpha p_{jmt} + \eta_j + \upsilon_t + origin_m + dest_m + \xi_{jmt} \tag{1.2}$$

where U_{ijmt} is passenger i's utility from choosing product j; δ_{jmt} is the mean level of utility across passengers that choose product j; ς_{imtg} represents a random component of utility common across all products within the same group; ε_{ijmt} is an independently and identically distributed (across products, consumers, markets and time) random error term assumed to have an extreme value distribution.

In Equation (1.2), x_{jmt} represents a vector of observed non-price product characteristics described below; p_{jmt} is the price; η_j captures airline-specific fixed effects; υ_t captures time period fixed effects; $origin_m$ and $dest_m$ are origin and destination city fixed effects and

ξ_{jmt}, the unobserved (by the researcher) component of product characteristics that affects consumer utility.

The vector x_{jmt} includes *Routing Quality*[9], *Origin Presence*, which is a measure of the size of an airlines airport presence, product-level zero-one codeshare dummy variables (*traditional and virtual codeshare*) and a zero-one dummy variable that equals to unity only if the product uses a nonstop flight to get passengers from the origin to destination. The origin city presence variable is measured by the number of different cities an airline provides service to using nonstop flights from the relevant market origin to destination cities.

The vector β measures the passenger's marginal utilities associated with the product characteristics. The parameter α captures the marginal utility of price. The parameter σ lies between 0 and 1 and measures the correlation of consumer utility across products belonging to the same airline. The correlation of preferences increases as σ approaches 1. In the case where σ is equal to 0, the model collapses to the standard logit model where products compete symmetrically. For notational convenience, we drop the market and time subscripts to complete the derivation of the model.

Let there be G_g products in group g. If product j is in group g, then the conditional probability of choosing product j given that group g is chosen, is given by:

$$S_{j/g} = \frac{e^{(1-\sigma)^{-1}\delta_j}}{D_g} \quad \text{where,} \quad D_g = \sum_{j \in G_g} e^{(1-\sigma)^{-1}\delta_j} \tag{1.3}$$

The probability of choosing group g or group g's predicted share is given by:

$$S_g = \frac{D_g^{1-\sigma}}{D_0^{1-\sigma} + \sum_{g=1}^{G} D_g^{1-\sigma}} \tag{1.4}$$

The outside good is the only good in group 0. Therefore, $D_0^{1-\sigma} = e^{\delta_0}$. We normalize

[9]Note that including *Routing Quality* in our demand model is paramount since a positive estimate on this variable would empirically validate that consumers' choice behavior is consistent with the fact that better routing quality is associated with a more desirable itinerary.

the mean utility of the outside good to zero. This implies $D_0^{1-\sigma} = 1$. Equation (1.4) can be rewritten as:

$$S_g = \frac{D_g^{1-\sigma}}{1 + \sum_{g=1}^{G} D_g^{1-\sigma}} \tag{1.5}$$

The unconditional probability of choosing product j or the market share of product j is:

$$S_j = S_{j/g} \times S_g = \frac{e^{(1-\sigma)^{-1}\delta_j}}{D_g} \times \frac{D_g^{1-\sigma}}{1 + \sum_{g=1}^{G} D_g^{1-\sigma}} \quad \text{or} \quad S_j = \frac{e^{(1-\sigma)^{-1}\delta_j}}{D_g^{\sigma}\left[1 + \sum_{g=1}^{G} D_g^{1-\sigma}\right]} \tag{1.6}$$

Therefore, the demand for product j is given by:

$$d_j = M \times S_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \alpha, \beta, \sigma) \tag{1.7}$$

where M is a measure of market size—the population in the origin city. The predicted market share of product j is S_j while $\mathbf{x}$, $\mathbf{p}$ and $\boldsymbol{\xi}$ are vectors of observed non-price product characteristics, price, and the unobserved vector of product characteristics. α, β and σ are parameters to be estimated. The estimation strategy of the demand parameters (α, β, σ) is such that the observed market shares $\mathbf{S}_{jmt}$ are equal to the market shares predicted by the model S_{jmt}. Empirical industrial organization shows that the model presented above results in a linear equation:

$$ln(\mathbf{S}_{jmt}) - ln(\mathbf{S}_{0mt}) = x_{jmt}\beta - \alpha p_{jmt} + \sigma ln(\mathbf{S}_{jmt/g}) + \eta_j + \upsilon_t + origin_m + dest_m + \xi_{jmt} \tag{1.8}$$

where $\mathbf{S}_{jmt}$ is the observed within group share of product j computed from the data by $\mathbf{S}_{jmt} = \frac{q_{jmt}}{M}$ where q_{jmt} is the quantity of air travel product j sold and M is the population of the origin city. $\mathbf{S}_{0mt} = 1 - \sum_{j \in J_m} S_{jmt}$ is the observed share of the outside good. $\mathbf{S}_{jmt/g}$

is the observed within-group share of product j and the other variables are described as in equation (1.2). Equation (1.8) can be estimated using Two Stage Least Squares (2SLS) since price p_{jmt} and $\mathbf{S}_{jmt/g}$ are endogenous.

The instruments we use for the 2SLS estimation are: (1) number of competitors' products in the market; (2) number of competing products offered by other airlines with an equivalent number of intermediate stops; (3) number of other products offered by an airline in a market; and (4) average number of intermediate stops across products offered by an airline in a market. The rationale for using these instruments is discussed in Gayle (2007, 2013) Instruments (1) - (3) are motivated by supply theory, which predicts that a product's price and within-group product share are affected by changes in its markup. Instruments (1) and (2) capture the degree of competition facing a product, which in turn affects the size of a product's markup. The use of instrument (3) is justified by the fact that, all else constant, as an airline offers more substitute products in a given market, the more capable the airline is to charge a higher markup on each of these products. The intuition for instrument (4) is as follows. Since we are using the nested logit demand model, we group products by airline. So, instrument (4) is likely to be correlated with the 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.

1.5.2 Routing Quality Equation

To evaluate the effects of the Delta/Northwest/Continental alliance on the routing quality of the alliance firms' products, we use a reduced-form regression of *Routing Quality*. Possible alliance effects on routing quality are identified using a difference-in-differences strategy. This strategy enables us to compare pre-post alliance periods' changes in routing quality of products offered by the alliance firms, relative to changes in routing quality of products offered by non-alliance firms over the same pre-post alliance periods. Given that the alliance was formed in August 2003, we use the third and fourth quarters of 2002 as the pre-alliance period while the third and fourth quarters of 2004 are used as the post-alliance period. The empirical model specification in equation (1.9) is similar to that used by Chen and Gayle (2013)[10] .The baseline reduced-form specification of the Routing Quality equation is as follows and variables are defined in Table 1.7:

$$
\begin{aligned}
&Routing\ \ Quality_{jmt} = \\
&\qquad \theta_0 + \theta_1 OriginPresence_{jmt} + \theta_2 DestinationPresence_{jmt} \\
&\qquad + \theta_3 NonStopFlightDistance_{jmt} + \theta_4 N\_comp\_connect_{jmt} \\
&\qquad + \theta_5 N\_comp\_nonstop_{jmt} + \theta_6 T_t^{dnc} + \theta_7 DNC_{jmt} + \theta_8 T_t^{dnc} \times DNC_{jmt} \\
&\qquad + \eta_j + \upsilon_t + origin_m + dest_m + \mu_{jmt}
\end{aligned} \tag{1.9}
$$

In equation (1.9), while the presence variables are supposed to control for the size of an airline's presence at the endpoint airports of the market, the $NonStopFlightDistance$ variable controls for the effect of distance between the origin and destination. $N\_comp\_connect$ and $N\_comp\_nonstop$ are used to control for the level of product-type-specific competition faced by a given product in a market.

The coefficient on T_t^{dnc} in equation (1.9), θ_6, explains how routing quality of products offered by airlines other than Delta, Northwest or Continental changes over the DL/NW/CO pre-post alliance periods. θ_7, which is the coefficient on DNC_{jmt}, tells us whether the routing quality of Delta, Northwest or Continental products systematically differs from the routing quality of products offered by other airlines. θ_8, the coefficient on the interaction variable $T_t^{dnc} \times DNC_{jmt}$, identifies whether routing quality of products offered by any of the alliance carriers changed differently relative to routing quality changes of products offered by other airlines over the DL/NW/CO pre- and post-alliance periods. Thus, θ_8 captures changes in routing quality in DL/NW/CO products due to the alliance.

[10] They used this model specification to identify merger quality effects. Furthermore, using almost identical specifications to Chen and Gayle (2013) makes it easy to the reader to compare results across papers

Table 1.7: *Description of Routing Quality Determinants*

Variable	*Definition*
Routing quality	Itinerary's direct distance divided by the travel's distance
Origin presence	Number of cities an airline serves from origin city with direct origin & destination (O&D) flights
Destination presence	Number of cities an airline serves with direct O&D flights going into the destination city.
Nonstop Flight Distance	Direct flight distance (in miles)
N_comp_connect	Number of connecting itineraries offered by an airline's competitors in the market
N_comp_nonstop	Number of direct itineraries offered by an airline's competitors in the market
T_t^{dnc}	Time period dummy variable, equals unity for post-alliance period.
DNC_{jmt}	Dummy for products marketed and operated by Delta, Northwest and Continental or any combination of the alliance carriers
MKT_{bm}^{dnc}	Market-specific dummy variable, equals unity for O&D markets in which any two of three alliance carriers competed (each offering their own substitute products) prior to alliance.

1.6 Empirical Results

1.6.1 Demand Results

We estimate the demand equation (1.8) and report the results in Table 1.8. As mentioned above, price and within-group product shares $\mathbf{S}_{jmt/g}$ are endogenous variables in the demand equation. Thus, OLS estimation in column 1 of Table 1.8 produces biased and inconsistent estimates of the price coefficient and σ. We re-estimate the demand equation using 2SLS and perform a Hausman exogeneity test. The Hausman test rejects the exogeneity of price and within-group product share at conventional levels of statistical significance. First-stage reduced-form regressions where we regress p_{jmt} and $ln(\mathbf{S}_{jmt/g})$ against the instruments suggest that the instruments explain variations in the endogenous variables. We find that the R^2 measures for the regressions of price against the instruments and within-group product share against the instruments are 0.0544 and 0.4202 respectively. While we control for carrier-specific effects in both models, we suppress the estimates in Table 1.8 for brevity and since the use of instruments is justified, we only discuss the 2SLS estimates. The coefficient estimate on the price variable has the expected sign. Thus, an increase in the product's price reduces the probability that a typical passenger will choose the product.

The coefficient estimate on $ln(\mathbf{S}_{jmt/g})$, which is an estimate of σ should lie between zero and one. σ measures the correlation of consumers' preferences for products offered for sale by the same airline. Here, the estimate is 0.1088 and is closer to zero indicating that passenger's choice behavior shows weak levels of brand loyalty to airlines. Airlines use customer loyalty programs to strengthen relationships with their customers but as pointed by Dowling and Uncles (1997), the launch of a loyalty program does not provide exceptional advantages mostly when any potential gain differential can be quickly eroded by competitive forces. This might explain the weak level of brand loyalty.

The importance of serving a large number of non-stop routes out of a given city is measured by the *Origin Presence* variable. The positive coefficient estimate on *Origin Presence* shows that, ceteris paribus, more customers choose airlines that have large operations out of the origin city. Similar findings were obtained by Chen and Gayle (2013) Gayle and Le (2013) and Berry (1990) among others. A possible explanation has to do with benefits of marketing devices such as frequent-flyer programs.

The positive coefficient estimate on the *Nonstop* variable suggests that direct flights are associated with higher levels of utility compared to connecting flights. Thus, ceteris paribus, passengers prefer products with nonstop flight itineraries to those with intermediate stop(s)

Table 1.8: *Demand Estimation*

Regressors	OLS	2SLS
Price	.000741***	– .01165***
	(.00004)	(.00051)
$ln(\mathbf{S}_{jmt/g})$	.537825***	.10882***
	(.00175)	(.00659)
Origin Presence	.01238***	.00959***
	(.00011)	(.00023)
Nonstop Dummy	.82532***	1.12242***
	(.00705)	(.01077)
Routing Quality	1.78093***	1.93739***
	(.01894)	(.02704)
Traditional Codeshare	– .30573***	– .66719***
	(.02045)	(.02925)
Virtual Codeshare	– .70304***	– .97949***
	(.01342)	(.02055)
Constant	– 10.4485***	– 9.0109***
	(.03101)	(.08215)
Carrier Fixed Effects	Yes	Yes
Quarter and Year fixed effects	Yes	Yes
Market Origin fixed effects	Yes	Yes
Market Destination fixed effects	Yes	Yes
R^2	0.6964	0.4013
Endogeneity Test. H_0: *Price* and $ln(\mathbf{S}_{jmt/g})$ are exogenous		
Wu-Hausman: F(2, 153652)= 3371.11*** ($p = 0.0000$)		

Note: Standard errors are in parentheses.

****p < 0.01; **p < 0.05; *p < 0.10*

when traveling from origin to destination. Furthermore, consumers are willing to pay up to \$96.35 extra,[11] on average, to obtain a product with a nonstop itinerary in order to avoid products with intermediate stop(s).

Consumers show preference for products with itinerary fight distances as close as possible

[11] This is obtained by dividing the coefficient estimate on the *Nonstop* dummy variable by the coefficient estimate on Price.

to the nonstop flight distance between the origin and destination. This result is explained by the positive coefficient estimate on the Routing Quality variable and underscores our premise that consumers' choice behavior is consistent with the fact that better routing quality is associated with a more passenger-desirable itinerary. Furthermore, consumers are willing to pay up to $2.38 extra,[12] on average, for each percentage point increase that the nonstop flight distance is of the actual itinerary flight distance.

The demand effects of each type of code sharing are identified by interpreting the coefficient estimates on the codeshare variables ($Traditional$ and $Virtual$). The coefficient estimates on codeshare variables measure utility differentials vis-à-vis the *Pure Online* product type. The negative coefficient estimates strongly suggest that traditional and virtual code sharing result in lower consumer utility levels. A drawback of a code-shared product, unlike a pure online product, is the change in operating carrier(s) across trip segments (traditional) or that the ticketing carrier differs from the operating carrier (virtual). Consumers may perceive the cooperation between two carriers less attractive than flying on a single airline. The demand model yields a mean own-price elasticity of demand estimate of -2.03. This estimate falls well within the range for estimated own-price elasticity of demand in the airline industry. In fact, Berry and Jia (2010) find own-price elasticity estimates ranging from -1.89 to -2.10 while Gayle and Wu (2011)'s estimates range from -1.65 to -2.39.

In the spirit of Chen and Gayle (2013), we estimate mean cross-price elasticities of demand between any two of the three alliance partners in the pre-alliance period. The demand model yields mean cross-price elasticity of demand estimates of 0.00021 between Delta and Northwest products, 0.000197 between Delta and Continental products, and 0.000165 between Northwest and Continental products. We later use the cross-price elasticities of demand to proxy the intensity of pre-alliance competition between alliance firms' products. This competition intensity measure is essential for the formulation and estimation of our

[12] This is obtained by dividing the coefficient estimate on the *Routing Quality* variable by the coefficient estimate on Price.

disaggregated reduced-form routing quality equation (1.10) specified in section 1.7.

1.6.2 Routing Quality Results - Aggregated Analysis

Table 1.9 presents coefficient estimates of the reduced-form routing quality equation (1.9). There are 2 columns of coefficient estimates. Coefficient estimates in the first column correspond to the baseline model, and those in the second column, evaluate how routing quality changes in markets the alliance partners competed prior to the alliance. The coefficient estimate of the constant term across specifications is approximately 0.86. This means that, assuming all determinants of routing quality in the regressions are held at zero, the mean routing quality measure across all products in the sample is approximately 0.86. Thus, nonstop flight distances between origin cities and destination cities are on average 86% of the flight distances associated with product itineraries used by passengers in the sample markets.

Presence variables : The effects on routing quality of serving a large number of non-stop routes into and out of a given city is measured by the Destination and Origin Presence variables, respectively. The positive coefficient estimates on both presence variables show that, ceteris paribus, for each additional city that an airline connects to either endpoints of a market using nonstop service, routing quality of the airline's products within the market will increase by approximately 0.06%.

Nonstop distance : The positive coefficient estimate on this variable indicates that products with longer nonstop flight distance between a market's origin and destination, tend to have better routing quality.

Number of competing products with intermediate stop(s) in a market: The negative coefficient estimate on *N_comp_connect* indicates that the higher the number of competing products with intermediate stop(s) a given product faces, the better its routing quality.

Number of competing non-stop products in a market: The coefficient estimate on *N_comp_nonstop*

Table 1.9: *Routing Quality Estimation: Aggregated Analysis*

Regressors	Specification 1	Specification 2
Constant	.8562***	.8614***
	(.0041)	(.0041)
Origin Presence	.00058***	.00057***
	(.000014)	(.000014)
Destination Presence	.00058***	.00057***
	(.000014)	(.000014)
Nonstop Distance	.000069***	.00007***
	(7.76e-07)	(9.07e-07)
N_comp_connect	– .00038***	– .0004***
	(.00005)	(.00005)
N_comp_nonstop	– .00017	– .0002
	(.0002)	(.0002)
DNC_{jmt}	– .1383***	– .1367***
	(.00212)	(.00211)
T_t^{dnc}	.00356***	.00359***
	(.00075)	(.00075)
$T_t^{dnc} \times DNC_{jmt}$	– .00259***	– .0165***
	(.00118)	(.00348)
MKT^{dnc}		– .0277***
		(.00151)
$T_t^{dnc} \times DNC_{jmt} \times MKT^{dnc}$		.0144***
		(.00341)
Carrier Fixed Effects	Yes	Yes
Quarter and Year fixed effects	Yes	Yes
Market Origin fixed effects	Yes	Yes
Market Destination fixed effects	Yes	Yes
R^2	0.2457	0.2474

Note: Standard errors are in parentheses.

****p < 0.01; **p < 0.05; *p < 0.10*

is not significant, implying that there on significant effect on the routing quality of a product as the product faces increasing number of products with no intermediate stops.

1.6.3 Persistent Differences in Routing Quality of Products offered by the Alliance Partners

These persistent differences in routing quality are captured by the coefficient estimate (approximately -14%) on the DNC dummy variable. This suggests that ceteris paribus, the mean routing quality of products offered by Delta, Northwest and Continental is 14 points less than the mean routing quality across all products in the sample. Holding all determinants of routing quality at their sample mean values, the mean routing quality measure of DL/NW/CO products is 0.8359.[13] Thus, nonstop flight distances between origins and destinations are on average only 83.59% of the flight distances associated with Delta/Northwest/Continental product itineraries used by passengers.

1.6.4 Routing Quality Effects of the DL/NW/CO Alliance

The positive coefficient estimate on T_t^{dnc} indicates that routing quality of products offered by airlines other than Delta, Northwest and Continental increased by 0.36% above the sample mean routing quality from pre- to post-alliance periods. In other words, non-DL/NW/CO itinerary flight distances decreased relative to nonstop flight distances by 0.36% over the relevant pre-post alliance periods.

The coefficient estimate on the interaction variable $T_t^{dnc} \times DNC_{jmt}$ represents the difference-in-differences estimate that identifies whether routing quality of products offered by any of

[13]This is computed using specification 1:
$RoutingQuality^{dnc} = .8562 - .1383 + 0.00058(28.4106) + 0.00058(28.2689) + 0.000069(1321.997) - 0.00038(14.898) - 0.00017(2.295)$

where the numbers in parentheses are means of the regressors for DL/NW/CO products, while the other numbers are the coefficient estimates.

the allied carriers changed differently relative to routing quality changes of products offered by other airlines over the DL/NW/CO pre- and post-alliance periods. It captures changes in routing quality in DL/NW/CO products due to the alliance. The estimate is negative, suggesting that the alliance caused the mean routing quality in DL/NW/CO products to fall over the pre- and post-alliance periods. However, over the pre-post alliance periods, routing quality of products offered by the Delta/Northwest/Continental trio witnessed a net increase of 0.097% (0.356% − 0.259%) even though this increase is less than the increase in routing quality witnessed by the other airline by 0.259%.

1.6.5 Routing Quality Effects based on Existence of Pre-alliance Competition between Alliance Firms

As defined in table 1.7, MKT^{dnc} is a market-specific dummy variable that equals unity for origin and destination markets in which any two of the three alliance partners competed prior to the alliance. MKT^{dnc} is used in specification (2) in the second column of Table 1.9. We include this dummy variable to find out whether the alliance effects on routing quality differ in markets where the alliance partners competed prior to the alliance. Our dataset shows that there is a total of 2896 directional origin-destination combinations prior to the DL/NW/CO alliance. Table 1.10 shows that all three carriers simultaneously competed in 1624 (56.1%) of these directional origin-destination combinations prior to the alliance.

Table 1.10: *Number of overlapping directional O&D combinations with pre-alliance competition*

	Number of O&Ds
Delta Air Lines (DL) / Northwest Airlines (NW)	1,924
Delta Air Lines (DL) / Continental Air Lines (CO)	1,896
Northwest Airlines (NW) / Continental Air Lines (CO)	1,669
Delta Air Lines (DL) / Northwest Airlines (NW) / Continental Air Lines (CO)	1,624

The effects of the DL/NW/CO alliance on routing quality in markets where the alliance firms competed before the alliance is determined by summing the coefficients on interaction variables $T_t^{dnc} \times DNC_{jmt}$ and $T_t^{dnc} \times DNC_{jmt} \times MKT^{dnc}$ in Specification 2 (column 2 in Table 1.9). Specification 2 suggests that the DL/NW/CO alliance is associated with 0.21% ($|-0.0165 + 0.0144|$) decline in routing quality of products offered by the alliance firms in the markets where they competed with each other prior to their alliance. This result is consistent with the premise that routing quality decreases in markets where the alliance firms competed prior to alliance because of the decrease in competitive pressure.

Our structural demand estimates from equation (1.8) can be used to monetize consumer welfare effects of the routing quality decrease associated with the DL/NW/CO alliance. We estimate in section (1.6.1) that consumers are willing to pay \$2.38 extra, on average, for each percentage point increase that the nonstop flight distance is of the actual itinerary flight distance.

So, in markets where the alliance firms competed prior to the alliance, routing quality effects of the alliance imply that each consumer's utility falls by an average of \$0.5 ($= 0.21 \times$ \$2.38).[14] These consumer welfare effects can be substantial given the origin city population sizes in our sample. The coefficient estimate on the interaction variable $T_t^{dnc} \times DNC_{jmt}$ in Specification 2 of Table 1.9 captures the alliance routing quality effects in markets where the alliance partners did not compete prior to the alliance. Evidence shows that each consumer experienced a fall in utility as a result of routing quality deterioration equivalent to \$3.93 ($= 1.65 \times$ \$2.38).

[14] As pointed out by Chen and Gayle (2013), this method of calculating welfare effects fails to consider second-order welfare effects that can occur due to routing quality influencing other variables such as price that in turn may affect welfare.

1.7 Routing Quality Equation: Disaggregated Analysis

To allow for the possibility that the market effects of an alliance may depend on the identity of the partner carriers code sharing a given product, we replace the product-specific dummy variable (DNC_{jmt}) in equation (1.9) with three variables: DN_{jmt}, DC_{jmt} and NC_{jmt}. Recall that DNC_{jmt} is a dummy variable equals to 1 for itineraries marketed and operated by one or any combination of the alliance firms. We define the three variables as follows: DN_{jmt} is a dummy variable equals to 1 for products marketed and operated by Delta and Northwest, whereas DC_{jmt} equals 1 for products marketed and operated by Delta and Continental. Similarly, NC_{jmt} equals 1 for products marketed and operated by Northwest and Continental. Therefore, DN_{jmt} is a dummy variable for code-shared products between Delta and Northwest, DC_{jmt} is a dummy variable for code-shared products between Delta and Continental. NC_{jmt} is analogously defined if the product is codeshared by Northwest and Continental.

The above disaggregation is important in two aspects. First, it permits us to identify routing quality changes in markets where two of the three partner carriers competed prior to the alliance. This is relevant because Northwest and Continental have been operating as codeshare partners since their 1998 codeshare agreement and were joined by Delta in August 2003. Secondly, this pairwise disaggregation makes it convenient to use our measure of pre-alliance competition intensity since cross-price elasticities of demand can only be computed for a pair of firms. So, measures of pre-alliance competition intensity will clearly vary across markets. Consequently, the sign on DNC_{jmt} in equation (1.9) is ambiguous a priori since it might be capturing the overall routing quality effect on DL/NW/CO products whereby masking existing pairwise competitive effects among the alliance firms. As such the prevailing total effect on routing quality may depend on the degree of competition intensity among any pair of the alliance partners.

The baseline model for our disaggregated analysis is specified as follows:

$$
\begin{aligned}
&Routing\ \ Quality_{jmt} = \\
&\qquad \theta_0 + \theta_1 OriginPresence_{jmt} + \theta_2 DestinationPresence_{jmt} \\
&\qquad +\theta_3 NonStopFlightDistance_{jmt} + \theta_4 N\_comp\_connect_{jmt} \\
&\qquad +\theta_5 N\_comp\_nonstop_{jmt} + \theta_6 T_t^{dnc} + \phi_1 DN_{jmt} + \phi_2 DC_{jmt} \\
&\qquad +\phi_3 NC_{jmt} + \phi_4 T_t^{dnc} \times DN_{jmt} + \phi_5 T_t^{dnc} \times DC_{jmt} + \phi_6 T_t^{dnc} \times NC_{jmt} \\
&\qquad +\eta_j + \upsilon_t + origin_m + dest_m + \mu_{jmt}
\end{aligned}
\tag{1.10}
$$

To identify whether routing quality of products offered by any pair of alliance firms changed differently relative to routing quality changes of products offered by other airlines over the pre- and post-alliance periods, we interact the variables DN_{jmt}, DC_{jmt} and NC_{jmt} with the time period dummy variable T_t^{dnc} which equals unity for post-alliance period.

1.7.1 Routing Quality Results: Disaggregated Analysis

Table 1.11 reports the results of the disaggregated model in equation (1.10). There are 4 columns, each representing a different specification of equation (1.10). The first column reports the baseline specification and the other three columns incrementally assess how various factors influence the routing quality change from each pair of alliance partners. Since the coefficient estimates on measured determinants of *Routing Quality* across specifications are similar to those in Table 1.9, we start by focusing our attention on the persistent differences in routing quality of products offered by each pair of the alliance partners.

Table 1.11: *Routing Quality Estimation - Disaggregated Analysis*

Regressors	Specification 1	Specification 2	Specification 3	Specification 4
Constant	.8347***	.8366***	.8374***	.8377***
	(.00397)	(.00398)	(.00398)	(.00398)
Origin Presence	.00057***	.00056***	.00055***	.00055***
	(.000014)	(.000014)	(.000014)	(.000014)
Destination Presence	.00058***	.00057***	.00056***	.00056***
	(.000014)	(.000014)	(.000014)	(.000014)
Nonstop Distance	.000069***	.000075***	.000075***	.000075***
	(7.76e-07)	(9.00e-07)	(9.00e-07)	(9.00e-07)
N_comp_connect	− .00032***	− .00030***	− .00028***	− .00029***
	(.000047)	(.000047)	(.000047)	(.000047)
N_comp_nonstop	− .00023	− .00057	− .00061	− .00059
	(.0002)	(.0002)	(.0002)	(.0002)
T_t^{dnc}	.0034***	.0035***	.0035***	.0035***
	(.00075)	(.00075)	(.00075)	(.00075)
DN_{jmt}	− .04382***	− .04380***	− .04370***	− .04361***
	(.00138)	(.00138)	(.00138)	(.00138)
DC_{jmt}	− .0575***	− .0568***	− .0569***	− .0570***
	(.00139)	(.00139)	(.00140)	(.00140)
NC_{jmt}	− .08714***	− .0859***	− .0860***	− .0860***
	(.00142)	(.00143)	(.00143)	(.00143)
MKT_{bm}^{dn}		− .00256*	− .00250*	− .00234
		(.00146)	(.00146)	(.00146)
MKT_{bm}^{dc}		− .00723***	− .00758***	− .00782***
		(.0014)	(.0014)	(.0014)
MKT_{bm}^{nc}		− .00907***	− .00902***	− .00893***
		(.00154)	(.00154)	(.00154)
$T_t^{dnc} \times DN_{jmt}$	− .00241***	− .01552***	− .01525***	− .01546***
	(.0015)	(.0028)	(.0029)	(.0029)
$T_t^{dnc} \times DC_{jmt}$	− .00688***	− .00994***	− .00953***	− .00922***
	(.0015)	(.00283)	(.00283)	(.00283)
$T_t^{dnc} \times NC_{jmt}$	.00805***	− .0092***	− .0085***	− .00825***
	(.0015)	(.0027)	(.0027)	(.0027)
$T_t^{dnc} \times DN_{jmt} \times MKT^{dn}$		.0152 ***	.0156***	.01586***
		(.0026)	(.0027)	(.0027)
$T_t^{dnc} \times DC_{jmt} \times MKT^{dc}$		.0037	− .00026	− .00075
		(.0026)	(.0026)	(.0028)
$T_t^{dnc} \times NC_{jmt} \times MKT^{nc}$		.0189***	.0171***	.0144***
		(.0026)	(.0026)	(.0027)
$T_t^{dnc} \times DN_{jmt} \times MKT_{bm}^{dn} \times E_{bm}^{dn}$			− 4.5483***	− 6.901**
			(1.6177)	(2.9226)
$T_t^{dnc} \times DC_{jmt} \times MKT_{bm}^{dc} \times E_{bm}^{dc}$			13.468***	16.921***
			(1.8891)	(3.4705)
$T_t^{dnc} \times NC_{jmt} \times MKT_{bm}^{nc} \times E_{bm}^{nc}$			5.7119***	20.4406***
			(.1.2687)	(2.4955)
$T_t^{dnc} \times DN_{jmt} \times MKT_{bm}^{dn} \times (E_{bm}^{dn})^2$				475.4573
				(495.9267)
$T_t^{dnc} \times DC_{jmt} \times MKT_{bm}^{dc} \times (E_{bm}^{dc})^2$				− 810.4011
				(706.189)
$T_t^{dnc} \times NC_{jmt} \times MKT_{bm}^{nc} \times (E_{bm}^{nc})^2$				− 1810.178***
				(264.0295)
R^2	0.2471	0.2484	0.2487	0.2490

The equations are estimated using ordinary least squares. Fixed effects are included in each specification but were not reported for brevity.

Note: Standard errors are in parentheses.

****p < 0.01; **p < 0.05; *p < 0.10*

The coefficient estimates on the dummy variables terms DN_{jmt}, DC_{jmt} and NC_{jmt} are approximately -0.044, -0.057 and -0.086 respectively, indicating that assuming all determinants of routing quality in the regressions are held constant, the mean routing quality measure of products offered by Delta and Northwest is 4.4 points less than the mean routing quality measure across all products in the sample. The two other coefficient estimates can be interpreted similarly for the DL/NW and NW/CO pairs. However, these results show that the change in mean routing quality is largest for NW/CO products.[15]

The coefficient estimate on T_t^{dnc} is positive and similar to the one in the aggregated analysis, suggesting that the routing quality of products offered by airlines other than Delta, Northwest or Continental increased by 0.34% above the sample average over the DL/NW/CO pre-post alliance periods. Thus, non-DL/NW, non-DL/CO and non-NW/CO itinerary flight distances decreased relative to nonstop flight distances by 0.34% over the relevant pre-post alliance periods. The coefficient estimate on the three interaction variables $T_t^{dnc} \times DN_{jmt}$, $T_t^{dnc} \times DC_{jmt}$ and $T_t^{dnc} \times NC_{jmt}$ represent the difference-in-differences estimates that identify whether routing quality of products offered by any pair of the alliance firms changed differently relative to routing quality changes of products offered by other airlines over the DL/NW/CO pre- and post-alliance periods. It captures changes in routing quality in DL/NW, DL/CO and NW/CO products respectively due to the alliance. The estimate is negative for the first two carrier pairs, suggesting that the alliance caused their products' mean routing quality to fall over the pre- and post-alliance periods. However NW/CO products mean routing quality actually increased by 0.81%.

In summary, coefficient estimates in Specification 1 of Table 1.11 suggest that overall, across all markets in the sample, the airline pairs DL/NW and DL/CO are associated with a decline in routing quality of their products, but the NW/CO pair is associated with an increase in routing quality of its products. Given that these quality effects are likely to

[15]Perhaps because their strategic cooperation started in 1998, couple of years prior to the three-way alliance.

differ across markets based on certain pre-alliance characteristics of a market, we include market-specific dummy variables to find out whether the alliance effects on routing quality differ in markets where each of the carrier pairs competed prior to the three-way alliance. To motivate this scenario, we present the number of directional O&D combinations where each carrier pair directly competed prior to the three-way alliance in Table 1.10. The numbers are substantial and specifications 2, 3 and 4 explore this scenario.

1.7.2 Alliance Effects on Routing Quality based on Existence of Pre-alliance Competition between alliance Firms - Disaggregated Analysis

In specification 2 of Table 1.11, we include three zero-one market-specific dummy variables: MKT_{bm}^{dn}, MKT_{bm}^{dc} and MKT_{bm}^{nc}. MKT_{bm}^{dn} takes the value of one only for origin-destination markets in which Delta and Northwest competed prior to the alliance. Likewise MKT_{bm}^{dc} takes the value of one only for origin-destination markets in which Delta and Continental competed prior to the alliance and MKT_{bm}^{nc} is defined similarly for origin-destination markets in which Northwest and Continental competed prior to the alliance.

The alliance-specific variables in specification 2 indicate that the DL/NW and DL/CO carrier pairs are associated with 0.032% ($|-0.01552+0.0152|$) and 0.994% ($|-0.00994|$) declines, respectively, in routing quality of products offered by the carriers in markets where they competed directly prior to the alliance. However the NW/CO carrier pair witnessed a 0.97% ($|-0.0092+0.0189|$) increase in routing quality of products offered by NW and CO in markets where they competed with each other prior to the alliance. These results are obtained by summing the coefficients on the interaction variables $T_t^{dnc} \times DN_{jmt}$ and $T_t^{dnc} \times DN_{jmt} \times MKT_{bm}^{dn}$ in the case of carrier pair DL/NW. We sum $T_t^{dnc} \times DC_{jmt}$ and $T_t^{dnc} \times DC_{jmt} \times MKT_{bm}^{dc}$ in the case of carrier pair DL/CO and finally for carrier pair

NW/CO, we sum $T_t^{dnc} \times NC_{jmt}$ and $T_t^{dnc} \times NC_{jmt} \times MKT_{bm}^{nc}$.

In our aggregated analysis, we can monetize the consumer welfare effects of routing quality changes associated with the DL/NW/CO alliance using our structural demand estimates from equation (1.8). We recall from section (1.6.1) that consumers are willing to pay \$2.38 extra, on average, for each percentage point increase that the nonstop flight distance is of the actual itinerary flight distance. Therefore, in markets where the carrier pairs competed prior to the alliance, routing quality effects of the alliance imply that each consumer's utility falls by an average of \$0.08 ($= 0.032 \times \$2.38$) in the case for DL/NW and \$2.37 ($= 0.994 \times \$2.38$) in the case for DL/CO. However, in the case of NW/CO, each consumer's utility actually increases by an average of \$2.38 ($= 0.97 \times \$2.38$).

The coefficient estimates on the interaction variables $T_t^{dnc} \times DN_{jmt}$, $T_t^{dnc} \times DC_{jmt}$ and $T_t^{dnc} \times NC_{jmt}$ in specification 2 in Table 1.11 capture the alliance routing quality effects in markets where the carrier pairs did not compete prior to the alliance. Evidence shows that each consumer experiences a fall in utility as a result of routing quality deterioration equivalent to \$3.69 ($= 1.552 \times \$2.38$) in the case for DL/NW and \$2.37 ($= 0.994 \times \$2.38$) in the case for DL/CO and \$2.20 ($= 0.92 \times \$2.38$) in the case of NW/CO.

1.7.3 Alliance Effects on Routing Quality based on Pre-alliance Competition Intensity between the Alliance Firms

Using our disaggregated model in equation (1.10), we examine whether the effect of an alliance on product quality varies with the intensity of pre-alliance competition[16] between products of the alliance firms. The estimated demand model was used to compute pre-alliance cross-price elasticities between Delta and Northwest products, Delta and Continental products and Northwest and Continental products. The variables E_{bm}^{dn}, E_{bm}^{dc} and E_{bm}^{nc} denote pre-alliance cross-price elasticities of demand between Delta and Northwest prod-

[16]Measured using cross-price elasticity of demand

ucts, Delta and Continental products and Northwest and Continental products, respectively. The elasticities in each of these variables vary across origin-destination markets in which the firms forming the pair directly competed prior to the three-way alliance. A cross-price elasticity between the firms' products will only exist in markets where they are competitors prior to the alliance. The pre-alliance cross-elasticity variables discussed above are used to construct the following interaction variables:

$$T_t^{dnc} \times DN_{jmt} \times MKT_{bm}^{dn} \times E_{bm}^{dn} \tag{1.11}$$

$$T_t^{dnc} \times DN_{jmt} \times MKT_{bm}^{dn} \times (E_{bm}^{dn})^2 \tag{1.12}$$

$$T_t^{dnc} \times DC_{jmt} \times MKT_{bm}^{dc} \times E_{bm}^{dc} \tag{1.13}$$

$$T_t^{dnc} \times DC_{jmt} \times MKT_{bm}^{dc} \times (E_{bm}^{dc})^2 \tag{1.14}$$

$$T_t^{dnc} \times NC_{jmt} \times MKT_{bm}^{nc} \times E_{bm}^{nc} \tag{1.15}$$

$$T_t^{dnc} \times NC_{jmt} \times MKT_{bm}^{nc} \times (E_{bm}^{nc})^2 \tag{1.16}$$

We incrementally add these variables to the routing quality regression to obtain Specifications 3 and 4 in Table 1.11.

Delta/Northwest Pair: The segment of the regression equation in Specification 4 that relates to routing quality effects of the Delta/Northwest pair in markets where they directly competed prior to the alliance is given by:

$$\Delta RoutingQuality^{dn} = -0.01546 + 0.01586 - 6.901(E_{bm}^{dn}) \tag{1.17}$$

where the variables T_t^{dnc}, DN_{jmt} and MKT_{bm}^{dn} each takes the value of one. The term $(E_{bm}^{dn})^2$ was suppressed because of statistical insignificance. This sign pattern of the coefficients in equation (1.17) suggests that the Delta/Northwest pair increased routing quality of its products when the pre-alliance competition intensity is less than 0.000058 $\left(\frac{-0.01546+0.01586}{6.901}\right)$ in markets where the two airlines directly competed in prior to the alliance. For pre-alliance competition intensity values above 0.000058, routing quality for Delta/Northwest products decreases in all markets they competed prior to the alliance.

Delta/Continental Pair: The segment of the regression equation in Specification 4 that relates to routing quality effects of the Delta/Continental pair in markets where they directly competed prior to the alliance is given by:

$$\Delta RoutingQuality^{dc} = -0.00922 + 0.00075 + 16.921(E^{dc}_{bm}) \tag{1.18}$$

where the variables T^{dnc}_{t}, DC_{jmt} and MKT^{dc}_{bm} each takes the value of one. The term $(E^{dc}_{bm})^2$ was suppressed because of statistical insignificance. This sign pattern of the coefficients in equation (1.18) suggests that the Delta/Continental pair decreased routing quality of its products when the pre-alliance competition intensity is less than 0.00059 $\left(\frac{-0.00922+0.00075}{16.921}\right)$ in markets where the two airlines directly competed in prior to the alliance. For pre-alliance competition intensity values above 0.00059, routing quality for Delta/Continental products increases in markets they competed prior to the alliance.

The Northwest/Continental Pair: The segment of the regression equation in Specification 4 that relates to routing quality effects of the Northwest/Continental Pair in markets where they directly competed prior to the alliance is given by:

$$\Delta RoutingQuality^{nc} = -0.00922 + 0.00075 + 16.921(E^{nc}_{bm}) - 1810.179(E^{nc}_{bm})^2 \tag{1.19}$$

where the variables T^{dnc}_{t}, BC_{jmt} and MKT^{nc}_{bm} each takes the value of one. This sign pattern of the coefficients in equation (1.19) suggests the effect of the alliance on routing quality varies in an inverted U-shaped manner with pre-alliance competition intensity (measured by cross-elasticity) between the two airlines, where the maximum turning point in the inverted

U-shaped relationship occurs at a cross-elasticity 0.0056 $\left(\frac{20.4406}{2\times 1810.178}\right)$. Specifically, the alliance appears to have increased routing quality more in markets where the pre-alliance cross-elasticities between the two NW/CO products are lower, up to an intermediate pre-alliance cross-elasticity of 0.0056. Markets with pre-alliance cross-elasticity between NW and CO of 0.0056, experienced the largest increase in routing quality of 6.39%.

1.8 Conclusion

This paper investigates the routing quality implications of the Delta, Northwest, Continental codeshare alliance with a particular focus on the alliance effects in markets where the alliance partners competed prior to the alliance.

Examining the alliance partners' products altogether (aggregated analysis), the empirical results show that the alliance decreased routing quality of DL/NW/CO products by 0.256% below the mean routing quality of the entire sample products. More interestingly, the alliance effects in specific markets where the alliance firms directly competed prior the alliance, are also negatively associated with routing quality of the alliance firms' products, resulting in a fall in consumer's utility of $0.5 per consumer. This result supports the premise that routing quality decreases in markets where the alliance firms competed prior to the alliance because of the decrease in competitive pressure in those markets.

We also investigate alliance partners in pairs (disaggregated analysis) to allow for the possibility that the alliance effects in specific pre-alliance markets may differ depending on the degree of pre-alliance competition intensity between the alliance firms. Based on the entire sample, products offered by the carriers pairs DL/NW and DL/CO had a decrease in routing quality due the alliance (0.24% and 0.69%, respectively). However, the NW/CO pairs products witnessed a rise in routing quality of 0.81% due to the alliance. These results are also true in markets where the carriers competed prior to the alliance.

Chapter 2

Airline Code-sharing and its Effects on On-Time Performance

2.1 Introduction

The public outcry and media coverage that ensued in the 1980s over increasing air traffic delays attracted congressional attention on airline on-time performance (OTP). Since 1988, the U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics (BTS) tracks the on-time performance of domestic flights operated by large air carriers. It is now mandatory for airlines with at least one percent of all domestic traffic to disclose flight–by–flight information on delays (Mayer and Sinai, 2003).

Interestingly, even with this flight-by-flight data disclosure, the DOT's Office of Aviation Enforcement and Proceedings[1] showed that the most prevailing consumer air travel complaint in the year 2000, stems from flight problems namely cancellations, delays and missed connections. In fact, 1 out of 4 flights was either delayed, canceled or diverted (Rupp et al., 2006). According to Mayer and Sinai (2003), in 2000, flights that arrived at their destination

[1] US Department Of Transportation Office of Aviation Enforcement and Proceedings (2001). USDTOAEP Feb. 2001 p. 34

within 15 minutes of their scheduled arrival time and without being canceled or diverted, accounted for less than 70 percent.

Given the concerns over OTP and the recent trend of airline alliance formation as a dominant feature of the airline industry, a new and interesting question is: how do airline alliances affect partners' OTP? Answering this question would shed light on whether the recent emergence of airline alliances has made problems related to airline OTP better or worse.

Airline alliances vary from limited cooperation, such as reciprocal frequent flyer programs, to more enhanced agreements, such as code sharing.[2] A codeshare agreement (CSA) is a reciprocal agreement between two or more airlines, through which one airline can sell seats on its codeshare partners' flights using its own reservation code.[3]

Airline alliance formation has a long history in the international air travel market but this practice is a relatively new phenomenon among U.S. domestic carriers. Since the mid-1990s, major airlines that serve the U.S. domestic market have increasingly found it appealing to form alliances. In 1995, Northwest and Hawaiian Airlines announced their intention to create an alliance (Ito and Lee, 2005) and in the first half of 1998, the six largest US carriers[4] followed suit with their own codeshare alliance proposals (Bamberger et al., 2001) This practice proliferated with the implementation of subsequent alliance partnerships such as Alaska/Hawaiian in October 2001, American West/Hawaiian in October 2002, United/US Airways in January 2003 and Delta/Northwest/Continental in June 2003, among others.

For illustration purposes, a CSA between Alaska Airlines (AS) and Hawaiian Airlines (HA) for instance, allows Alaska Airlines (referred to as the "ticketing carrier" or "marketing carrier") to market and sell seats on thousands of flights operated by Hawaiian Airlines

[2] US General Accounting Office (1999)

[3] The International Air Transport Association (IATA) uses two-character codes to identify all airlines; for example the code DL is assigned to Delta Air Lines.

[4] Continental Airlines and Northwest Airlines made alliance announcement in January 1998; Delta Air Lines/United Airlines and American Airlines/US Airways followed in April 1998.

(referred to as the "operating carrier") and vice-versa. In this example, Alaska Airlines may place its code (AS) on this Hawaiian's flight and sell tickets for seats on this flight as if Alaska Airlines operates the flight. So, this same flight will be listed twice in computer reservation systems, once under Alaska Airlines' code (AS) and again under Hawaiian Airlines' code (HA). Therefore, under a CSA, partner airlines are able to expand their flight offerings without adding planes.

We make the following argument. Alliance partners typically coordinate in an attempt to achieve seamless integration of their route networks, which potentially result in more travel-convenient routing across partner carriers' networks. The interdependence across partner carriers' networks caused by the alliance may in turn influence each partner's OTP. It is not clear a priori whether the alliance will improve or worsen a given partner's OTP. On the one hand, a carrier may have a greater incentive to provide better OTP when it joins a codeshare alliance because its OTP not only affects the timeliness of connections within its own network, but also affects the timeliness of connections between its network with its partner carriers' networks. On the other hand, a carriers' OTP could worsen after joining a codeshare alliance since an extra source of a carrier's delay can be due to its partner carriers' delay. While not attempting to study the incentives to form an alliance, the primary objective of this paper is to evaluate the net impact of a codeshare alliance on partner carriers' OTP.

Concerns over poor on-time performance may therefore be exacerbated or improved by airline alliances. Few authors have explored and analyzed the relationship between airline alliances and service quality, both theoretically and empirically. The empirical literature has been largely inconclusive, with some studies suggesting that airline alliances increase product quality (Hassin and Shy, 2004; Gayle and Thomas, 2015), others suggesting that airline alliances decrease product quality (Gayle and Yimga, 2014; Goh and Uncles, 2003), and some studies found no relationship between airline alliances and product quality (Tiernan et al., 2008; Tsantoulis and Palmer, 2008). At the center of these diverging empirical results, reside two main issues: (1) the difficulty in defining quality in a way that is mathematically tractable (Prince and Simon, 2009) and (2) the sensitivity of results to assumptions of a particular theoretical model (Park, 1997).

With respect to the first issue, some measures of service quality have been explored. Goh and Uncles (2003) empirically study the perceptions that business travelers have of the benefits of global alliances. To measure quality, they use a cross-sectional self-completion survey that was administered to a sample of Australian business travelers. Tsantoulis and Palmer (2008) examine service quality effects of a co-brand alliance where service quality is proxied by a quality index they constructed based on some technical and functional aspects of quality. Gayle and Yimga (2014) empirically investigated the routing quality effects[5] of the Delta/Northwest/Continental codeshare alliance, while Gayle and Thomas (2015) investigated the routing quality effect of global alliances, antitrust immunity, and domestic mergers.

Another service quality measure is an airline's on-time performance. Almost no research has been conducted to examine the impact of a codeshare alliance on the on-time performance of its partner members. An exception is the work by Tiernan et al. (2008). They investigate the service quality of E.U. and U.S. members of main airline alliances. Three specific measures of airline service quality were used in their study: on-time flight arrival percentage, percentage of flights not canceled and percentage of passengers filing baggage reports (bags lost damaged, delayed or pilfered). Their examination of the international airline alliances indicates no significant differences in the quality of service indicators.

Apart from Tiernan et al. (2008) who looked at the linkage between on-time performance and airline alliance,[6] most studies on on-time performance have focused on its relationship

[5] Routing Quality is defined as the ratio of nonstop fight distance to the product's itinerary fight distance used to get passengers from the origin to destination.

[6] Their study looked at international airline alliances which contrasts from ours, based on the U.S. domestic air travel market.

with competition (Mayer and Sinai, 2003; Mazzeo, 2003; Rupp et al., 2006), multimarket contact (Prince and Simon, 2009), prices (Forbes, 2008) and entry or threat of entry (Prince and Simon, 2014), among others.

To examine whether and how codeshare partners' product quality provision change in response to a codeshare agreement, we focus on the Delta Air Lines (DL), Northwest Airlines (NW) and Continental Airlines (CO) Codeshare Alliance. We choose this codeshare alliance for the following reasons: (*i*) it involves three major carriers in the U.S. domestic airline industry; (*ii*) the alliance was the largest ever approved in the history of the U.S. commercial aviation; and (*iii*) the alliance turned out to be the most contentious alliance in the U.S. domestic airline industry.

In this paper, we specifically assess how Delta Air Lines (DL), Northwest Airlines (NW) and Continental Airlines' (CO) on-time performance change in response to their codeshare agreement of August 23, 2003. We find that the codeshare agreement (CSA) improved OTP for the alliance firms, and that this improvement occurs in both markets where the codeshare partners had competed prior to the CSA and markets where they did not. However, the OTP effects are larger in markets they competed prior to the CSA.

The rest of the paper is organized as follows. The next section provides an overview of the Delta, Northwest, Continental codeshare alliance. Section 2.3 describes the data used for analysis. Section 2.4 discusses the research methodology and estimation technique used to analyze the OTP effects of the alliance. Results are presented and discussed in Section 2.5, while concluding remarks are gathered in Section 2.6.

2.2 Delta/Northwest/Continental Codeshare Alliance

In August 2002, Delta Air Lines, Northwest Airlines and Continental Airlines submitted the largest domestic codeshare agreement proposal in the United States. This agreement grants some privileges to the partner airlines like reciprocal frequent-flyer programs and reciprocal access to airport lounges. The partner airlines' managers claimed that the CSA will generate benefits to consumers such as increased flight frequencies, broader travel options, improved frequent flyer programs and better route connections. They also claimed that cost savings from the alliance members will be passed on to consumers in terms of lower airfares.

Despite initial assurances by the partner airlines, policy makers have expressed a great deal of skepticism when appraising the Delta/Northwest/Continental alliance proposal, which policy makers believed did not adhere to certain antitrust laws and regulations because of its potential to yield anti-competitive effects:

> *"The Department has determined that the agreements, if implemented as presented by the three airlines, could result in a significant adverse impact on airline competition, unless the airlines formally accept and abide by certain conditions that are intended to limit the likelihood of competitive harm. If the airlines choose to implement the agreements without accepting those conditions, the department will direct its Aviation Enforcement office to institute a formal enforcement proceeding regarding the matter"*[7]

Likewise, the General Accounting Office (GAO) stressed the adverse effects of alliances on competition:

> *"[Proposed alliances] will reduce competition on hundreds of domestic routes if the alliance partners do not compete with each other or compete less vigorously than they did when they were unaffiliated... It will be critical to determine if an airline retains or reduces incentives for alliance partners to compete on price"*[8]

[7]Department of Transportation. Office of the Secretary Termination Review Under 49 U.S.C. 41720 of the Delta/Northwest/Continental Agreements. Federal Register. Vol 68, No.15. Thursday, January 23, 2003. Notices

[8]US General Accounting Office. Aviation Competition: Proposed Domestic Airline Alliances Raise Serious Issues. 1998

The three-way alliance between Delta, Northwest and Continental was the largest domestic alliance at the time, accounting for almost 30% of domestic origin-destination passengers (Ito and Lee, 2005). Given this recent trend towards increased alliance formation and the fact that at the time, carriers comprising the three largest US alliances (Continental/Northwest/Delta, United/US Airways and American/Alaska) accounted for approximately two thirds of all domestic origin and destination passenger traffic, we posit that there could be legitimate policy apprehensions regarding the impact of these cooperative agreements on on-time performance delivery.

Using data on OTP and factors that are likely to influence OTP, this paper uses a reduced-form regression analysis to investigate whether partner airlines' OTP is impacted by them being in a CSA. While arguments can be made to support both views, there is currently no empirical evidence that supports either.

2.3 Data

We use data gathered and published by U.S. Department of Transportation (DOT) Bureau of Transportation Statistics (BTS). The BTS requires all U.S. domestic carriers with revenues from domestic passenger flights of at least one percent of total industry revenues to report flight on-time performance data. The data cover scheduled-service flights between points within the United States.

The data frequency is monthly. A record in this survey represents a flight. Each record or fight[9] contains information on the operating carrier, the origin and destination airports, miles flown, flight times, and departure/arrival delay information.

In this paper, a *market* simply means directional air travel between an origin and a destination city during a specific period. By directional, we mean that an air travel trip

[9]Some flights could be segments of itineraries with intermediate stop(s).

from Miami to Las Vegas is a distinct market from an air travel trip from Las Vegas to Miami. This controls for the number of passengers traveling between the origin and destination.[10]

Moreover, because on-time performance is only measured for individual flights, we restricted our analysis to nonstop service. We collect monthly data for every non-stop domestic flight for the third and fourth quarters of 2002 and 2004 for 19 U.S. carriers. Table 2.1 reports a list of carriers in the data sample. All variables are constructed from the original data set of 6,274,848 flights in the sample. We omitted all canceled and diverted flights.

Table 2.1: *Airlines in Sample*

Code	Airline
AA	American Airlines
AS	Alaska Airlines
B6	JetBlue Airways
CO	Continental Air Lines
DH	Independence Air
DL	Delta Air Lines
EV	Atlantic Southwest
FL	AirTran Airways
HA	Hawaiian Airlines
HP	America West Airlines
MQ	American Eagle
NW	Northwest Airlines
CO	Comair
OO	SkyWest
RU	ExpressJet
TZ	ATA Airlines
UA	United Air Lines
US	US Airways
WN	Southwest Airlines

Given that the Delta/Northwest/Continental codeshare alliance was formed in August of 2003, the third and fourth quarters of 2002 represent the pre-alliance period whereas the third and fourth quarters of 2004 represent the post-alliance period (using data from the

[10]See Berry et al. (2006), Berry et al. (2006) and Gayle (2007). However, unlike these studies, some flights could be segments of itineraries with intermediate stop(s).

same quarters for both years will control for potential seasonal effects in OTP). We choose this particular time period to balance the "before" and "after" periods around the codeshare event and avoid data right after the September 11^{th} terrorist attacks.

To enable a more manageable-sized data set, we place some restrictions on the raw data. We follow the same procedures used by Aguirregabiria and Ho (2012) for the selection of markets. We focus on air travel amongst the 63 largest U.S. cities. Table 2.2 presents a list of the cities and corresponding population sizes. Incomplete data reporting in addition to missing/incorrect on-time performance data slightly reduces the sample.

We use the geometric mean of the populations at the origin and destination to help measure the impact of potential market size. Unlike Aguirregabiria and Ho (2012), we do not group cities that belong to the same metropolitan areas and share the same airport for two reasons: (1) airport grouping will lessen the heterogeneity in OTP data and (2) observations in dataset may not be products but are individual flights, most of which are segments on itineraries with intermediate stop(s).

2.3.1 On-Time Performance (OTP) Measures

We directly use measures of on-time performance from the U.S. DOT BTS' dataset. According to the U.S. DOT, flights that don't arrive at (depart from) the gate within 15 minutes of scheduled arrival (departure) time are late arrivals (departures). This represents performance measured against airlines' published schedules. The three main measures are arrival delay, the percentage of flights arriving at least 15 minutes late and the percentage of flights arriving at least 30 minutes late. We construct the first OTP measure based on the arrival delay of a flight, i.e. the difference between scheduled and actual arrival time.

Table 2.2: *Cities, airports and population*

City, State	Airports	City Population	
		2002	2004
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
Nashville, TN	BNA	544,375	570,068
Milwaukee, WI	MKE	589,975	601,081
Washington, DC	DCA, IAD	564,643	579,796
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
Tulsa, 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

[1] *New York-Newark-Jersey*

[2] *Dallas-Arlington-Fort Worth-Plano, TX*

[3] *Phoenix-Temple-Mesa, AZ*

Following Prince and Simon (2009), our analysis is conducted at the carrier-route-month-year level, so we use the average arrival delay[11] over all of a carrier's flights, on a particular route, during a month and year.

The second OTP measure is constructed from the arrival delay indicator in the dataset for flights arriving at the gate at least 15 minutes late. We use this arrival delay indicator to compute the proportion of a carrier's flights on a route in a month that arrived at least 15 minutes late.

The third OTP measure uses the 30 minutes and more arrival delay indicator. Similar to the second measure, we use this arrival delay indicator to compute the proportion of a carrier's flights on a route in a month that arrived at least 30 minutes late. We use analogous measures for departure OTP. The same 15- and 30-minute rules apply to departure delay. Table 2.3 summarizes OTP measures. Overall, arrival delays are longer than departure delays for all measures, supporting the findings from the Bureau of Transportation Statistics (2011) that indicate that on-time arrival performance has the greatest impact on passengers. Also, arrival measures tend to vary more than departure measures.

Table 2.3: *On-Time Performance Summary Statistics*

	Obs.	Mean	Std. Dev.	Min	Max
Arrival					
Arrival Delay (in minutes)	31748	10.71	8.94	0	440
Fraction of flights arriving at least 15 minutes late (%)	31748	12.13	9.47	0	100
Fraction of flights arriving at least 30 minutes late (%)	31748	6.59	6.10	0	100
Departure					
Departure Delay (in minutes)	31748	9.20	8.90	0	415
Fraction of flights departing at least 15 minutes late (%)	31748	10.22	8.94	0	100
Fraction of flights departing at least 30 minutes late (%)	31748	5.85	5.75	0	100

Note: Early arrivals/departures are counted as zero delays

Figure A.1 and A.2 in the Appendix display the frequency of observations in 15-minute intervals around their scheduled arrival (departure) time. It is surprising to note that a

[11] Early arrivals are counted as zero delays.

sizeable portion of the flights in our sample were "early"—55.4 percent of flights arrived at their gate prior to the scheduled arrival time while 47.6 percent of flights departed from their gate prior to the scheduled departure time. This is indicative of a certain amount of slack that may be built into the airlines' schedules. Prince and Simon (2009) suggests that this may be done strategically by airlines. On the other hand, 17.6 percent of flights in the dataset arrived 15 minutes or more late while 14.7 percent departed from their gate 15 minutes or more late.

Tables 2.4 and 2.5 summarize OTP by month. For all measures, the percentage of flights arriving late peaks in winter. We only consider flights arriving at their destination and do not include cancellations or diversions even though cancellations tend to rise during the winter months in the face of severe weather (Bureau of Transportation Statistics, 2011).

Throughout our study, early arrivals are treated as a delay of zero minutes rather than as a negative delay. Counting early arrivals and departures as zero delays assumes that passengers derive disutility from late arrivals/departures but no utility from early arrivals/departures.

Tables 2.6 & 2.7 summarize OTP by carrier. Hawaiian Airlines performs better than all carriers on arrival delay minutes, while Independence Air has the worst arrival delay minutes. Northwest Airlines has the shortest departure delay minutes while SkyWest has the longest departure delay minutes.

2.3.2 Collapsing the Data

Given that in a specific month, an airline can operate a specific origin-destination multiple times, with different OTP values, we construct our OTP measures by averaging the OTP values for a given origin-destination for a given carrier in a given month and year. We then collapse the data by carrier-origin-destination-month-year combinations. Explanatory variables are averaged and collapsed using the same approach. Our final working data set has 31,748 usable observations, where an observation is at the level of carrier-origin-destination-month-year combination.

Table 2.4: *Mean Values of Arrival Delay Measures by Month*

year	Month	Mean Arrival Delay (minutes)	Percentage of flights delayed more than 15 minutes	Percentage of flights delayed more than 30 minutes
2002	July	10.9	13.9	7.8
	August	9	11.9	6.3
	September	6.1	8	4.2
	October	7.5	11	5.2
	November	7.4	10.6	4.9
	December	11.8	14.8	8.1
2004	July	15.2	14.1	8.4
	August	13.3	13.9	7.6
	September	7.9	7.9	4.2
	October	9.4	11	5.4
	November	11.6	12.2	6.5
	December	15.8	16.8	9.9

Note: Early arrivals are counted as zero delays

Table 2.5: *Mean Values of Departure Delay Measures by Month*

Year	Month	Mean Departure Delay (minutes)	Percentage of flights delayed more than 15 minutes	Percentage of flights delayed more than 30 minutes
2002	July	9.6	12.3	6.9
	August	7.9	10.3	5.7
	September	5.1	6.5	3.7
	October	5.9	8.2	4.3
	November	5.9	7.7	4.1
	December	10.2	12.8	7.2
2004	July	13.2	12.3	7.5
	August	11.3	11.1	6.6
	September	6.9	7	4
	October	7.7	8.7	4.7
	November	9.9	10.1	5.8
	December	14.2	14.8	9

Note: Early departures are counted as zero delays

2.4 Empirical Method and Estimation

To examine whether partner firms' on-time performance is impacted by their participation in a codeshare alliance, we estimate reduced-form regression equations of the various measures

Table 2.6: *Airlines' Mean Arrival Delay*

Code	Airline	Arrival Delay (minutes)	Proportion of Flights Arrivingat Least 15 Minutes Late (%)	Proportion of Flights Arriving at Least 30 Minutes Late (%)
HA	Hawaiian Airlines	0.0	0.00	0.00
WN	Southwest Airlines	8.9	13.92	7.41
UA	United Air Lines	9.4	8.83	5.00
NW	Northwest Airlines	9.5	14.88	7.15
US	US Airways	9.8	13.62	7.45
B6	JetBlue Airways	10.0	12.17	6.61
AA	American Airlines	10.7	10.46	6.27
DL	Delta Air Lines	10.7	13.19	6.60
CO	Continental Air Lines	11.1	12.85	6.76
TZ	ATA Airlines	11.1	12.84	7.08
AS	Alaska Airlines	11.2	12.33	6.65
HP	America West Airlines	11.2	9.64	4.63
RU	ExpressJet	12.9	13.28	7.70
OH	Comair	13.3	12.86	7.68
EV	Atlantic Southwest	13.4	5.05	3.15
FL	AirTran Airways	14.0	5.73	3.99
MQ	American Eagle	14.4	13.38	8.09
OO	SkyWest	16.2	7.73	5.23
DH	Independence Air	17.5	13.01	8.59

Note: Early arrivals are counted as zero delays

of OTP described above. Possible codeshare alliance effects on OTP are identified using a difference-in-differences strategy. This strategy enables us to compare pre-post alliance periods' changes in OTP of flights operated by the alliance firms, relative to changes in OTP of flights operated by non-alliance firms over the same pre-post alliance periods.

We specify our empirical model of product quality effects due to code-sharing. On-time performance (OTP) is used to proxy product quality. We specify a linear regression model in which an OTP measure is a function of: (1) timing of implementation of the codeshare alliance; (2) carrier and airport characteristics; and (3) market structure characteristics. Furthermore, we also examine whether the effect of code-sharing on OTP depends on the existence of pre-alliance competition between alliance firms. Variables are defined in Table 2.8.

The baseline reduced-form specification of the arrival OTP of flight f in market m in

Table 2.7: *Airlines' Mean Departure Delay*

Code	Airline	Departure Delay (minutes)	Proportion of Flights Departing at Least 15 Minutes Late (%)	Proportion of Flights Departing at Least 30 Minutes Late (%)
NW	Northwest Airlines	7.0	9.75	5.55
CO	Continental Air Lines	7.6	7.69	4.58
TZ	ATA Airlines	7.8	9.01	5.09
UA	United Air Lines	7.8	7.03	4.35
DL	Delta Air Lines	8.3	9.25	5.13
US	US Airways	8.5	11.37	6.42
AA	American Airlines	8.8	8.39	5.4
HA	Hawaiian Airlines	8.8	12.53	12.5
RU	ExpressJet	8.9	8.47	5.63
B6	JetBlue Airways	9.3	11.36	5.33
HP	America West Airlines	9.5	6.97	3.89
WN	Southwest Airlines	9.7	16.57	8.33
AS	Alaska Airlines	10.8	11.81	6.69
MQ	American Eagle	11.9	11.23	7.06
FL	AirTran Airways	12.2	5.61	3.62
OH	Comair	12.3	12.18	7.5
EV	Atlantic Southwest	13.2	5.4	3.38
DH	Independence Air	16.6	12.63	8.3
OO	SkyWest	17.0	7.66	5.13

Note: Early departures are counted as zero delays

time period t is as follows:

$$OTP_{fmt} = \alpha + \beta \mathbf{X}_{fmt} + \gamma \mathbf{Z}_{mt} + \delta \mathbf{W}_{fmt} + \lambda_f + \eta_t + origin_m + dest_m + \varepsilon_{fmt}. \qquad (2.1)$$

where $\mathbf{X}_{fmt}$ represent flight characteristics, $\mathbf{Z}_{mt}$ include market characteristics, $\mathbf{W}_{fmt}$ is a vector of dummy variables representing the codeshare effects. λ_f's are airline specific fixed effects, η_t's are time specific fixed effects, origin and destination airport specific fixed effects are denoted by $origin_m$ and $dest_m$, ε_{fmt} is the unobserved part of OTP. The reduced-form OTP regression is estimated using Ordinary Least Squares (OLS). We provide further description of the explanatory variables in the following section.

Table 2.8: *Variable Definitions and Summary Statistics*

Variable	Definition	Mean	Std. Dev.
Codeshare Event			
T_t^{dnc}	Time period dummy variable, equals unity for post-alliance period.	0.566	0.496
Flight, airport and market characteristics			
$DPRESCOST$	Number of different cities that an airline flies to from the destination city of the market using nonstop flight	30.171	30.84
$OPRESCOST$	Number of different cities that an airline offers flights from going into the origin city of the market	30.095	30.792
$INTOHUB$	Dummy Variable = 1 if destination is a hub for that carrier (list of hub/airline combination in Table 2.9)	0.387	0.487
$OUTOFHUB$	Dummy Variable = 1 if origin is a hub for that carrier (list of hub/airline combination in Table 2.9)	0.387	0.487
$DISTANCE$	Nonstop flying distance (in miles) between the origin and destination.	937.118	635.545
$RELSPEED$	Carrier mean speed across its flights in a market as a ratio of market average speed$^{(a)}$	1	0.016
MKT^{dnc}	Market-specific dummy variable, equals unity for O&D$^{(b)}$ markets in which any two of three allied carriers competed prior to alliance.	0.022	0.146
$MKTSIZE$	(logged) Geometric mean of the populations at both endpoint airports	13.483	0.536
DNC_{fmt}	Zero-one dummy variable that takes the value one when the carrier is one of the three alliance carriers, DL, NW, or CO.	0.264	0.441
Market Structure			
$MONOMKT$	Dummy Variable = 1 if only 1 airline serves the directional city-pair market non-stop	0.43	0.495
$NUMCOMP$	Number of competitors in a market	1.817	0.877

$^{(a)}$ *Speed is measured as distance divided by flight air time*

$^{(b)}$ *O&D = origin and destination.*

2.5 Empirical Results

2.5.1 Estimates from Reduced-form Arrival OTP Equation

In this section, we present empirical analyses of the impact of code-sharing on OTP. We start with on-time arrival performance since it has greatest impact on passengers (Bureau of Transportation Statistics, 2011).

Determinants of Arrival OTP

Airport congestion has an influential role in determining on-time performance.[12] One way to control for airport congestion is controlling for hubbing. Effective hubbing implies that flights from different origin airports known as "spokes" of a network arrive at the "hub" airport roughly at the same time. The aircraft at the hub waits for these spoke flights and facilitates the transfer of passengers and baggage. Subsequently, flights depart from the hub airport in quick sequence back out along the spokes.

Essentially, passengers departing from any non-hub origin to other destinations in the network generally proceed first to the hub. Table 2.9 shows that 14 out of the 19 carriers possess at least one hub and 11 have at least 3 hubs. These airlines co-ordinate arrivals and departures at their hubs in order to minimize delays for passengers continuing through the hub to final destinations on spokes other than the one on which they originated. We include a control for hub airlines ($INTOHUB$). This measure is carrier-specific and captures the effect of effective hubbing on arrival OTP. $INTOHUB$ is a dummy variable that equals unity if destination airport is a hub for that carrier. As expected, regression results in Table 2.10 reveal that $INTOHUB$ is a predictor of arrival OTP. The coefficient estimate on $INTOHUB$ is negative and statistically significant suggesting shorter arrival delays for carriers flying into their hubs. Carriers flying into their hubs have a greater incentive to

[12] Flores-Fillol (2010) and Rupp and Sayanak (2008), among others, investigate this relationship.

make sure that passengers get to their intermediate stop on time for their connecting flights since the cost of a missing flight may be quite substantial from rebooking passengers onto new connections to handling missed connection luggage. The disutility[13] experienced by the passenger in terms of inconvenience and frustration may result in loss of future business.

Table 2.9: *Airline Carriers and Their Hubs*

Code	Carrier	Hub Airports
AA	American Airlines	Dallas, O'Hare, Miami, New York, Los Angeles
AS	Alaska Airlines	Seattle, Portland, Los Angeles, San Francisco
B6	JetBlue Airways	New York
CO	Continental Air Lines	Houston, Cleveland, Newark
DL	Delta Air Lines	Atlanta, Cincinnati, New York, Boston, Los Angeles, Minneapolis, Detroit, Seattle
EV	Atlantic Southwest	Dallas, O'Hare, Atlanta, Detroit, Cleveland, Houston, Denver, Kansas City, Newark, Dulles
HP	America West Airlines	Los Angeles, Phoenix
MQ	American Eagle	Dallas, O'Hare, Miami, New York
NW	Northwest Airlines	Minneapolis. Detroit, Memphis
OO	SkyWest	O'Hare, Seattle, Portland, Los Angeles, San Francisco, Detroit, Minneapolis, Denver, Houston, San Francisco, Phoenix
TZ	ATA Airlines	O'Hare, Indianapolis
UA	United Air Lines	Houston, O'Hare, San Francisco, Houston, Denver, Los Angeles, Newark
US	US Airways	Cleveland, Philadelphia, Phoenix, Washington
WN	Southwest Airlines	Atlanta, Washington, Chicago, Dallas, Los Angeles, Las Vegas, Houston, Phoenix, Oakland

Mazzeo (2003) finds interestingly that flights out of the hub have a longer than scheduled flight time on average, whereas flights into the hub do not. He partly attributes these differences to the logistical difficulties associated with turning around large banks of flights at busy hub airports. We were able to obtain similar results from an estimation not shown in this paper.

Since carriers often have hubs of different sizes, a particular airport might be a major hub for the airline while another airport might be a medium-size hub. However, the

[13] It is difficult to make a reliable welfare statement about the relationship between OTP and congestion in the absence of data on demand.

$INTOHUB$ variable does not capture the heterogeneity in hub sizes for a given carrier since it is a dummy variable. Thus, to capture this heterogeneity in carrier's hub sizes, we also include a continuous variable $DPRESCOST$ which counts the number of different cities that an airline serves using nonstop flight from the destination city of the market. Including $DPRESCOST$ controls for (dis)economies of scope and hubbing effects associated with offering multiple routes from the same destination airport. The coefficient estimate on $DPRESCOST$ is negative and statistically significant as expected. A carrier's arrival delay decreases with the size of its hub to which it transports passengers. The incentive for (hub) carriers to improve arrival OTP on flights into their hubs is stronger for larger hubs.

Table 2.10: *Arrival On-Time Performance Estimation Results*

Variables	Arrival Delay in Minutes (1)	Arrival Delay in Minutes (2)	% of Flights Arriving at Least 15 Minutes Late (3)	% of Flights Arriving at Least 15 Minutes Late (4)	% of Flights Arriving at Least 30 Minutes Late (5)	% of Flights Arriving at Least 30 Minutes Late (6)
$INTOHUB$	-1.3499***	-1.3478***	-1.1886***	-1.1787***	-0.7450***	-0.7502***
	(0.2065)	(0.2066)	(0.1585)	(0.1586)	(0.1079)	(0.1079)
$DPRESCOST$	-0.0208***	-0.0208***	0.0083***	0.0079***	0.0018	0.002
	(0.0037)	(0.0037)	(0.0029)	(0.0029)	(0.0019)	(0.0019)
$MKTSIZE$	20.6967***	21.0915***	17.8731***	18.0976***	12.2403***	12.4839***
	(5.4601)	(5.4639)	(4.1912)	(4.1936)	(2.8517)	(2.8538)
$DISTANCE$	-0.0022***	-0.0022***	-0.0001	-0.0001	-0.0006***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$RELSPEED$	-37.0368***	-37.3472***	4.3097	4.0099	3.8671**	3.7672**
	(3.4189)	(3.4205)	(2.6244)	(2.6253)	(1.7857)	(1.7866)
$MONOMKT$	0.6765***	0.6999***	6.1969***	6.2091***	3.2302***	3.2455***
	(0.1934)	(0.1938)	(0.1484)	(0.1488)	(0.1010)	(0.1012)
$NUMCOMP$	-0.0609	-0.0373	-3.0513***	-3.0253***	-1.7877***	-1.7826***
	(0.1188)	(0.1191)	(0.0912)	(0.0914)	(0.0620)	(0.0622)
DNC_{fmt}	1.4607***	1.3976***	0.6141***	0.5186**	-0.4826***	-0.4771***
	(0.2733)	(0.2755)	(0.2098)	(0.2115)	(0.1427)	(0.1439)
T_t^{dnc}	4.2784***	4.2674***	2.9316***	2.9217***	2.0867***	2.0827***
	(0.1695)	(0.1696)	(0.1301)	(0.1301)	(0.0885)	(0.0886)
$T_t^{dnc} \times DNC_{fmt}$	-1.4460***	-1.3132***	-0.4744**	-0.3517*	-0.6666***	-0.6198***
	(0.2507)	(0.2555)	(0.1925)	(0.1961)	(0.1310)	(0.1335)
MKT^{dnc}		0.5691		0.0625		0.5453**
		(0.5150)		(0.3953)		(0.2690)
$T_t^{dnc} \times DNC_{fmt} \times MKT^{dnc}$		-2.1015***		-2.0021***		-0.6964*
		(0.7669)		(0.5886)		(0.4005)
Constant	-226.7955***	-231.6940***	-224.3223***	-227.0041***	-155.5177***	-158.6174***
	(71.4461)	(71.4932)	(54.8431)	(54.8718)	(37.3152)	(37.3417)
No. of Obs.	31748	31748	31748	31748	31748	31748
R^2	0.23	0.23	0.41	0.41	0.35	0.35

The equations are estimated using ordinary least squares. Fixed effects are included in each specification but were not reported for brevity.
*Note: Standard errors are in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10*

Columns 3 through 6 of Table 2.10 re-estimate the model using different measures of OTP—the percentage of flights arriving at least 15 minutes late and the percentage of flights arriving at least 30 minutes late. These other measures look at delay over a certain threshold.

The coefficient estimate on $DPRESCOST$ is positive and statistically significant when the dependent variable is the percentage of flights arriving at least 15 minutes late. The coefficient estimate on $DPRESCOST$ in columns 3 and 4 of Table 2.10 indicates that for flights over a certain delay threshold (15 minutes and more), an airline's OTP worsens with increases in the number of distinct cities that an airline has nonstop flights to, going out of the destination airport. In other words, for flights into destination airport that are at least 15 minute late, carriers' arrival OTP worsens, the larger the scale of operations at the destination airport. This result is potentially driven by logistical difficulties associated with turning around large banks of flights. The same reasoning applies when we use the percentage of flights arriving at least 30 minutes late as the dependent variable, however the estimates on $DPRESCOST$ in columns 3 and 4 of Table 2.10 are not statistically significant.

In addition, we also control for market size ($MKTSIZE$), measured as the (logged) geometric mean of the populations at both market endpoints. The net impact of market size on OTP may either be negative or positive. On one hand, larger market sizes may be associated with higher demand for air travel and thus more airport congestion resulting in more delays. On the other hand, in larger markets airlines have more incentive to be on time because more people will be affected if they are not, resulting in future loss of business. Thus, in the latter case, arrival OTP may improve with increasing market size. Therefore, we argue that $MKTSIZE$ captures the net effect of these conflicting forces. The coefficient estimate on $MKTSIZE$ is positive and statistically significant, suggesting that larger markets are associated with worse arrival on-time performance. Thus, the airport congestion effect dominates.

On-time performance is also influenced by flight distance and the relative speed of the flight. The variable $DISTANCE$ represents the flight's distance in miles. The parameter estimate on $DISTANCE$ is negative and statistically significant, suggesting that carriers have some ability to "make time up in the air" on longer flights. This ability to "make time up in the air" improves arrival OTP.

We also include a measure for the carrier's relative speed ($RELSPEED$) defined as the average speed of a carrier's flights in the market divided by the average speed of all flights in the market. $RELSPEED$ captures how fast a carrier is, relative to the typical carrier's velocity in a market. The parameter estimate on $RELSPEED$ is negative and statistically significant, suggesting that airline carriers with above-average flying speed tend to have better arrival OTP.

Building on extant research exploring the relationship between service quality and competitive conditions, we investigate how route competition affects carriers' arrival OTP.[14] We control for route-level competition by including a measure of market structure ($MONOMKT$), which is a monopoly dummy variable that equals one if there is only one carrier serving a given market. The coefficient estimate on $MONOMKT$ is positive and statistically significant. This result is consistent with our expectations, suggesting that arrival delays are greater on less competitive routes. This result is also consistent with findings by Mazzeo (2003) and Rupp et al. (2006) who posit that airlines provide worse on-time performance on less competitive routes.

To go a step further, consider how the degree of market competitiveness, as measured by the number of competitors ($NUMCOMP$) in a given market, affects the arrival OTP. $NUMCOMP$ represents a more heterogeneous measure of market structure compared to the $MONOMKT$ dummy variable. As expected, arrival OTP improves with increasing

[14]Studies by Mazzeo (2003) and Rupp et al. (2006) examine this relationship.

number of competitors. Though the coefficient estimate on $NUMCOMP$ has the expected sign, it is not statistically significant in columns 1 and 2 of Table 2.10.

Codeshare Effects on Arrival On-Time Performance

The remaining rows of Table 2.10 contain the key variables of interest in evaluating the codeshare effects of a codeshare agreement on arrival OTP. We also focus on changes in arrival OTP in certain types of markets—markets where any two of the three alliance firms had competed prior to the alliance.

To examine persistent differences in OTP of flights operated by the alliance partners, we include a dummy variable DNC_{fmt} which equals unity for flights operated by any of the alliance carriers. The coefficient estimate on DNC_{fmt} is positive and statistically significant in columns 1–4 in Table 2.10, indicating that throughout the sample period the mean arrival delay of flights operated by Delta, Northwest and Continental is greater than the mean arrival delay of flights operated by other carriers in the sample.

We also define a dummy variable T_t^{dnc} to help identify the OTP effects of the codeshare alliance. T_t^{dnc} is a time period dummy variable, which equals unity in the post-alliance period. The positive coefficient estimate on T_t^{dnc} measures, on average, how arrival delay changes over the pre-post codeshare alliance period for flights that are not associated with Delta, Northwest or Continental Airlines. The positive coefficient estimate on T_t^{dnc} indicates that the mean arrival delay of flights operated by airlines other than Delta, Northwest and Continental airlines increased (OTP worsens) from pre- to post-alliance periods.

Finally, we include the interaction between the DNC_{fmt} and T_t^{dnc} variables. The coefficient estimate on this new variable $T_t^{dnc} \times DNC_{fmt}$ represents the difference-in-differences estimate that identifies whether arrival delay of flights operated by any of the alliance carriers changed differently relative to arrival delay of flights operated by other airlines over the pre- and post-alliance periods. It captures changes in arrival delay in DL/NW/CO flights (relative to non-DL/NW/CO flights) due to the alliance. The estimate is negative, suggesting that the alliance caused the mean arrival delay for DL/NW/CO flights to fall compared to the mean arrival delay for non-DL/NW/CO flights over the pre– and post–alliance periods. In a nutshell, the codeshare alliance is associated with improved arrival OTP for the alliance firms relative to other carriers.

This result is supported by Table A.1 in the Appendix. Table A.1 reports mean arrival (departure) delay minutes before and after the alliance for alliance partners versus other carriers. Table A.1 indicates that even though OTP worsens overall over the pre-post alliance periods for all carriers on average, the increase in delay minutes is smaller for the alliance partners' flights. We test for the difference in mean arrival (departure) delay minutes between alliance partners and other carriers. All tests of difference in means are statistically significant at 1% level.

Codeshare Effects on Arrival OTP based on Existence of Pre-alliance Competition between Alliance Firms

To examine whether changes in partner carriers' arrival OTP are explained by the existence of pre-alliance competition between alliance firms, we construct and include a market-specific dummy variable, MKT^{dnc} that equals to one for origin-destination markets in which any two of the three alliance partners competed prior to the alliance. Thus, we are able to examine whether the codeshare effects on OTP differ in markets where the alliance partners competed prior to the alliance. Columns 2, 4 and 6 in Table 2.10 reproduce the baseline arrival OTP regressions with the inclusion of the market dummy variable and some interactions with this dummy variable.

The effects of the DL/NW/CO codeshare alliance on OTP in markets where the alliance firms competed before the alliance is determined by summing the coefficients on the interaction variables $T_t^{dnc} \times DNC_{fmt}$ and $T_t^{dnc} \times DNC_{fmt} \times MKT^{dnc}$ in Specification 2 and doing the same for Specifications 4 and 6 (columns 2, 4 and 6 in Table 2.10). Summing the coefficients yields a negative estimate, indicating an improvement in arrival OTP of flights operated by the alliance firms in the markets where they competed with each other prior to their alliance.

The coefficient estimate on the interaction variable $T_t^{dnc} \times DNC_{fmt}$ in columns 2, 4 and 6 of Table 2.10, has a different interpretation. In fact, the coefficient estimate captures changes in arrival delay in DL/NW/CO flights due to the codeshare alliance in markets they did not compete prior to the alliance. The coefficient estimate on $T_t^{dnc} \times DNC_{fmt}$ in columns 2, 4 and 6 of Table 2.10, is negative and statistically significant at conventional levels of significance, suggesting that the codeshare alliance also improved arrival on-time performance in markets where the alliance firms did not compete prior to alliance. Thus, evidence shows that the alliance caused the alliance firms to improve arrival OTP regardless of whether they competed or not in markets prior to the alliance, but the partners' arrival OTP improvements are relatively larger in markets that the partners competed in prior to the alliance.

2.5.2 Estimates from Reduced-form Departure OTP Equation

To further isolate the source of delays, we investigate the effect of code-sharing on departure delay. Similar to arrival OTP, we consider three different measures of departure OTP. In Table 2.11, we report results for the three measures of departure delay in the data. We also control for flight and market structure characteristics as well as airline, month, year and airport-specific fixed effects.

Determinants of Departure OTP

We now analyze factors that influence airlines' departure OTP, with the ultimate goal of understanding how this OTP measure is influenced by a codeshare alliance. To control for

Table 2.11: *Departure On-Time Performance Estimation Results*

Variables	Departure Delay in Minutes (1)	Departure Delay in Minutes (2)	% of Flights Departing at Least 15 Minutes Late (3)	% of Flights Departing at Least 15 Minutes Late (4)	% of Flights Departing at Least 30 Minutes Late (5)	% of Flights Departing at Least 30 Minutes Late (6)
$OUTOFHUB$	0.8131***	0.8090***	1.2659***	1.2491***	0.8167***	0.8035***
	(0.1803)	(0.1803)	(0.1441)	(0.1442)	(0.1011)	(0.1011)
$OPRESCOST$	0.0238***	0.0240***	0.0287***	0.0294***	0.0127***	0.0132***
	(0.0032)	(0.0033)	(0.0026)	(0.0026)	(0.0018)	(0.0018)
$DISTANCE$	-2.98e-5	-2.83e-5	-0.0006***	-0.0006***	-0.0005***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$MKTSIZE$	18.5741***	18.7712***	25.8526***	26.4670***	13.7093***	14.1043***
	(4.7830)	(4.7869)	(3.8244)	(3.8262)	(2.6817)	(2.6829)
$MONOMKT$	0.4188**	0.4313**	4.9897***	5.0294***	2.8408***	2.8667***
	(0.1694)	(0.1698)	(0.1355)	(0.1358)	(0.0950)	(0.0952)
$NUMCOMP$	0.0438	0.0455	-2.4309***	-2.4319***	-1.4493***	-1.4535***
	(0.1041)	(0.1043)	(0.0832)	(0.0834)	(0.0583)	(0.0585)
DNC_{fmt}	-0.6325***	-0.6173**	-1.0298***	-0.9519***	-1.0913***	-1.0239***
	(0.2394)	(0.2413)	(0.1914)	(0.1929)	(0.1342)	(0.1353)
T_t^{dnc}	2.9635***	2.9608***	2.6752***	2.6689***	1.9002***	1.8973***
	(0.1485)	(0.1485)	(0.1187)	(0.1187)	(0.0832)	(0.0832)
$T_t^{dnc} \times DNC_{fmt}$	-1.3356***	-1.3065***	-0.7249***	-0.6581***	-0.6411***	-0.6118***
	(0.2197)	(0.2239)	(0.1756)	(0.1789)	(0.1232)	(0.1255)
MKT^{dnc}		0.486		1.6518***		1.1398***
		(0.4509)		(0.3604)		(0.2527)
$T_t^{dnc} \times DNC_{fmt} \times MKT^{dnc}$		-0.4129		-0.8777		-0.3321
		(0.6715)		(0.5367)		(0.3764)
Constant	-237.3860***	-239.9722***	-325.2973***	-333.3471***	-171.8417***	-177.0110***
	(62.4722)	(62.5240)	(49.9509)	(49.9755)	(35.0266)	(35.0426)
No. of Obs.	31748	31748	31748	31748	31748	31748
R^2	0.24	0.24	0.45	0.45	0.35	0.35

The equations are estimated using ordinary least squares. Fixed effects are included in each specification but were not reported for brevity.
*Note: Standard errors are in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10*

airport congestion, we include the $OUTOFHUB$ dummy variable that equals one if the origin airport is a hub for that carrier.[15] Similarly to $INTOHUB$ in Table 2.10, $OUTOFHUB$ captures the hubbing effect on departure OTP. For all three measures of departure OTP, the hubbing effect is positive and statistically significant, indicating that airlines produce poor departure OTP on flights originating from their hubs. Flights originating from an airline's hub are often spoke flights that are heading to passengers' final destination (spoke airport). At spoke airports, there are no interdependencies between airlines' aircrafts since few arrive or depart and passengers do not connect, hub carriers may have less incentive to improve

[15]See list of hub/airline combination in Table 2.9

OTP (Mayer and Sinai, 2003).

Given its binary nature, $OUTOFHUB$ fails to capture heterogeneity in airline's hub sizes. To solve this problem, we include a more reasonable measure of hubbing effects ($OPRESCOST$) in the departure delay regressions. $OPRESCOST$ counts the number of different cities that an airline offers flights from, going into the origin city of the market using a nonstop flight. The coefficient estimate on $OPRESCOST$ is positive and statistically significant for all measures of departure delay as expected. In particular, a carrier's departure delay increases with the size of its hub from which it departs.

The negative coefficient on $DISTANCE$ in the departure OTP regression in Table 2.11 suggests that longer flights tend to have shorter departure delays. On longer flights, carriers have an incentive to depart on time to minimize the likelihood of late arrival (or late departure for a subsequent connecting flight). Even though carriers departing late can "make time up" during a flight, there is a downside to that. "Making time up" means accelerating which end up burning substantially more fuel and adding thousands of dollars to the overall flight expense. Thus, carriers have an incentive to reduce departure delay so as to avoid additional costs in "making time up." Some studies show that pilots do try to make up time in the air, but only for delays that fall into a particular sweet spot.

Recall that market size is measured as the (logged) geometric mean of the populations at both market endpoints. The coefficient estimate on $MKTSIZE$ in the departure delay regression is positive and statistically significant suggesting that larger markets deteriorate departure OTP. Thus, the airport congestion argument prevails just like in the arrival delay results.

The market structure variables show similar results to arrival delay regressions. Once again, the coefficient estimate on the monopoly dummy variable $MONOMKT$ is positive and statistically significant, while the coefficient on the number of competitors in a given market $NUMCOMP$, is negative and statistically significant for two of the departure delay measures. These results are consistent with the premise that less competitive markets tend to have poor departure OTP because of less competitive pressure. Borenstein and Netz (1999) show that before airlines choose their departure time, they take into consideration the number of other non-stop competitors on a route.

Codeshare Effects on Departure OTP

The remaining rows of Table 2.11 display key variables of interest that examine the codeshare effects of the Delta/Northwest/Continental codeshare alliance on the partner carriers' departure OTP. Changes in departure OTP are investigated in markets where any two of the three alliance firms had competed prior to the alliance.

Similarly to the arrival OTP regressions, we include a dummy variable DNC_{fmt} which equals unity for flights operated by any of the alliance carriers to examine persistent differences in departure OTP of flights offered by the alliance partners. The coefficient estimate on DNC_{fmt} is negative and statistically significant across estimations, indicating that the mean departure delay of flights operated by Delta, Northwest and Continental airlines is less than the mean departure delay of flights operated by other carriers in the sample.

The time period dummy T_t^{dnc} has a positive coefficient estimate suggesting that the mean departure OTP of flights operated by airlines other than Delta, Northwest and Continental airlines increased (OTP worsens) from pre- to post-alliance periods.

The coefficient estimate on the interaction variable $T_t^{dnc} \times DNC_{fmt}$ represents the difference-in-differences estimate that identifies whether departure OTP of flights operated by any of the alliance carriers changed differently relative to departure OTP of flights operated by other airlines over the pre- and post-alliance periods. The coefficient estimate is negative and statistically significant across estimations, suggesting that the alliance caused the departure OTP for DL/NW/CO flights to increase relative to the mean departure OTP for non-DL/NW/CO flights over the pre- and post-alliance periods. In a nutshell, the codeshare alliance improved departure OTP for the alliance firms relative to other carriers.

Codeshare Effects on Departure OTP based on Existence of Pre-alliance Competition between Alliance Firms

Columns 2, 4 and 6 in Table 2.11 reproduce the baseline departure OTP regressions with the inclusion of the MKT^{dnc} dummy variable. The effects of the Delta/Northwest/Continental codeshare alliance on departure OTP in markets where the alliance firms competed before the alliance formation is determined by summing the coefficients on the interaction variables $T_t^{dnc} \times DNC_{fmt}$ and $T_t^{dnc} \times DNC_{fmt} \times MKT^{dnc}$ in Specification 2 and doing the same for Specifications 4 and 6 (columns 2, 4 and 6 in Table 2.11). Even though the coefficient estimates on $T_t^{dnc} \times DNC_{fmt} \times MKT^{dnc}$ have the same sign as in the arrival delay regression, they are not statistically significant.

The coefficient estimate on the interaction variable $T_t^{dnc} \times DNC_{fmt}$ in columns 2, 4 and 6 of Table 2.11, has a different interpretation. In fact, the coefficient estimate captures changes in departure OTP in DL/NW/CO flights due to the codeshare alliance in markets they did not compete prior to the alliance. The coefficient estimate is negative and statistically significant at conventional levels of significance, suggesting that the codeshare alliance improved departure OTP in markets where the alliance firms did not compete prior to alliance.

Thus, evidence shows that the alliance caused the alliance firms to improve departure OTP regardless of whether they competed or not in different markets prior to the alliance.

2.6 Conclusion

This study builds on the existing literature linking airline alliance and product quality, but is the first to empirically link airline codeshare alliance to OTP. Airline carriers typically coordinate to seamlessly integrate their route networks which potentially result in more travel-convenient route network connections across partner carriers. While not attempting to study the incentives to form an alliance, the question that this research intends to shed light on is whether the route network integration that comes with the alliance provides sufficient extra incentive to partner carriers to improve their OTP.

We made use of airline OTP data to measure service quality and examine the above relationship. After controlling for carrier, airport and market structure characteristics, we find strong evidence that the Delta/Northwest/Continental codeshare alliance improved both arrival and departure OTP for the alliance firms.

We then explore OTP effects of code-sharing based on the existence of pre-alliance competition between the alliance firms. We find that the alliance firms improved OTP in both markets where the partners competed prior to the alliance, and markets where they did not compete prior. However, the arrival OTP effects of code-sharing are larger in markets where the partners competed in prior to the alliance.

Chapter 3

Modelling the Impact of Airline Product Quality on Airlines' and Passengers' Choice Behavior

3.1 Introduction

Punctuality is certainly a key performance indicator in the airline industry and carriers with excellent on-time performance record use it as a marketing tool by prominently displaying it on their websites. Given the increased competition that followed the deregulation of the airline industry in 1978, many carriers have resorted to product quality differentiation as a key to long-term profitability. Although airlines generally compete based on pricing, flight on-time performance is a very important indicator of airline service quality which drives customer satisfaction and loyalty. For example in the 1990s American Airlines ran ads calling itself "The On-Time Machine."[1] Likewise, airlines that produce excessive flight delays receive a great deal of negative publicity.

[1] Boozer et al. (1990)

In 1987, the U.S. Congress passed the flight on-time disclosure rule amidst chronic air traffic delays that stirred public outcry and media coverage. The disclosure rule made it mandatory for airlines with at least one percent of all domestic traffic to publish flight-by-flight delay data. Airlines are required to track and report five segments of travel time for each of their flights to the Federal Aviation Administration (FAA): *i*) departure delay, *ii*) taxi-out, *iii*) air time, *iv*) taxi-in, and *v*) arrival delay.

Remarkably, even with the flight on-time disclosure rule, the industry's on-time performance is still far below satisfactory levels. A report from the U.S. Department of Transportation's (DOT) Office of Aviation Enforcement and Proceedings[2] revealed that the most prevailing consumer air travel complaint in the year 2000, stems from flight problems namely cancellations, delays and missed connections. In fact, 1 out of 4 flights was either delayed, canceled or diverted (Rupp et al., 2006). According to Mayer and Sinai (2003), in 2000, flights that arrived at their destination within 15 minutes of their scheduled arrival time and without being canceled or diverted, accounted for less than 70 percent. Even more recently, the Bureau of Transportation statistics (BTS) showed that 23.02% of U.S. domestic flights were delayed[3] in 2014, an increase from 14.69% in 2012. The BTS maintains an archive of monthly and yearly on-time performance data that is also accessible through the Internet.[4] Thus, passengers' most common source of frustration are flight delays.

In the midst of these delay statistics, airlines usually claim that air traffic delays are out of their control, placing the blame on adverse weather or air traffic control as the most common culprits.[5] A good portion of delay can be attributed to extreme weather, air traffic control and security checks (U.S. DOT, 2015). In June 2003, the Air Carrier On-Time

[2]U.S. Department of Transportation Office of Aviation Enforcement and Proceedings (USDTOAEP) Feb. 2001 p. 34

[3]A flight is considered delayed if it arrived at (or departed) the gate 15 minutes or more after the scheduled arrival (departure) time.

[4]The BTS archived data are located at http://www.transtats.bts.gov/homedrillchart.asp

[5]http://www.washingtonpost.com/lifestyle/travel/what-to-do-when-airlines-blame-flight-problems-on-circumstances-beyond-our-control/2015/02/12/7298b264-a57f-11e4-a7c2-03d37af98440_story.html

Reporting Advisory Committee defined five broad categories for the cause of any flight delay:

1. *Air Carrier:* The cause of the cancellation or delay was due to circumstances within the airline's control (e.g. maintenance or crew problems, aircraft cleaning, baggage loading, fueling, etc).

2. *Extreme Weather:* Significant meteorological conditions (actual or forecasted) that, in the judgment of the carrier, delay or prevent the operation of a flight (e.g. tornado, blizzard, hurricane, etc.). Weather delays are also included in the National Aviation System and late-arriving aircraft categories.

3. *National Aviation System (NAS):* Delays and cancellations attributable to the national aviation system that refer to a broad set of conditions—non-extreme weather conditions, airport operations, heavy traffic volume, air traffic control, etc.

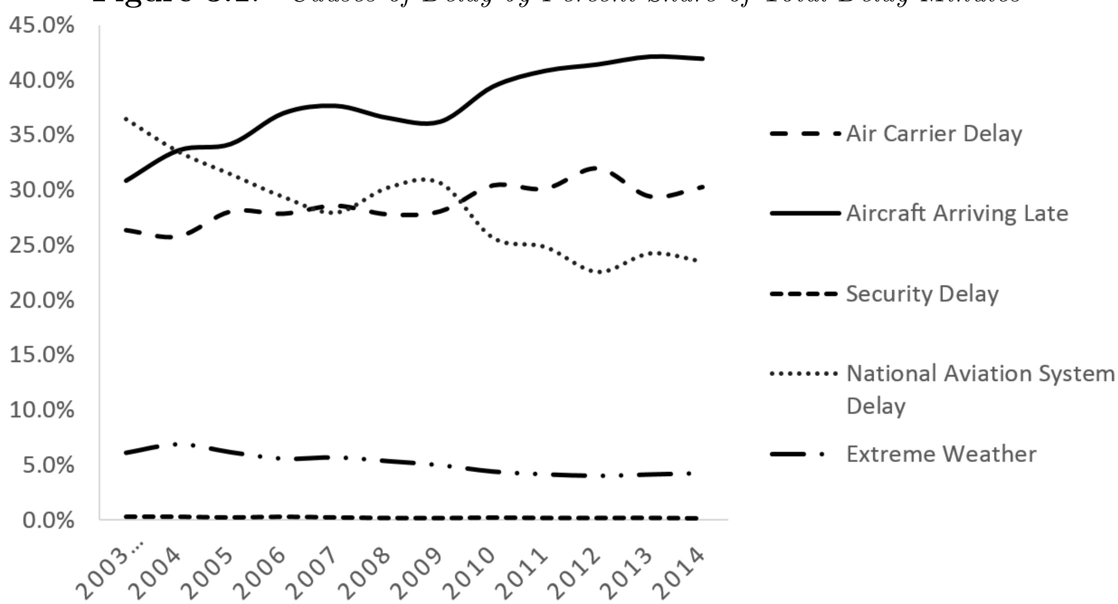
4. *Late-arriving Aircraft:* A previous flight with same aircraft arrived late, causing the present flight to depart late.

5. *Security:* Delays or cancellations caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach, inoperative screening equipment and/or long lines in excess of 29 minutes at screening areas.

Although some of these factors are uncontrollable, airlines still have a substantial level of control over their on-time performance. An airline can schedule a longer flight time to absorb potential delays on the taxiways or choose a longer layover on the ground to buffer against the risk of a late incoming aircraft (Mayer and Sinai, 2003). Figure 3.1 shows the declining shares of flight delay caused by weather and air traffic control (NAS) while at the same time the shares of delay caused by late-arriving aircraft and air carrier, continue to rise. Figures 3.1 and 3.2 indicate that on-time performance improvement potential within the reach of airlines is feasible.

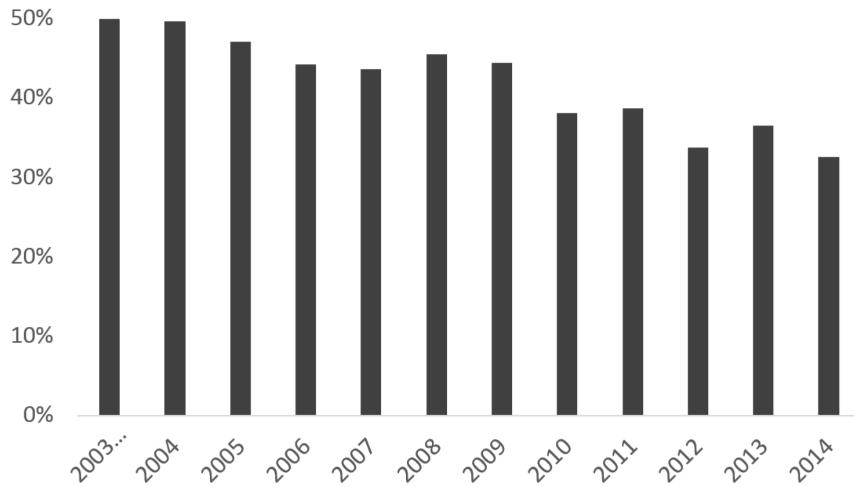
The objective of this paper is twofold. First, we examine the monetary value that consumers place on on-time performance. In order to make our case about consumers valuing improved OTP, we estimate a discrete choice demand model which allows us to quantify the opportunity cost of delays to consumers. Thus, incorporating on-time performance into our demand model affords us the advantage of measuring how much on-time performance matters to consumers. How much are they willing to pay for better on-time performance or for each minute of delay?

Figure 3.1: *Causes of Delay by Percent Share of Total Delay Minutes*



Second, if consumers do value on-time performance, to what extent are airlines willing to provide improved on-time performance? How does improved on-time performance affect airlines' markup in an oligopoly world, a strategic environment where firms are competing with each other? One way to answer these questions is by examining how airlines product markups respond to changes in on-time performance. We use the variation in product

Figure 3.2: *Weather's Share of Total Delay Minutes*



markups to measure the incentive a given airline has to improve on-time performance.

The rationale for using markups as a reasonable measure of airlines' incentive is that investing in on-time performance is costly but if the improvement can lead to prices sufficiently higher than the increase in costs, which means an increase in markup, then improving on-time performance might be a worthwhile proposition for airlines. Using markups allows us to analyze airlines incentive without directly estimating the cost of improving on-time performance in a sense—a unique feature that sets our methodology apart from others in the literature. Therefore, airlines only care about how the improvement will affect their markup, in other words, what are their returns for investing in on-time performance?

Over the last three decades, empirical studies on air travel have neglected to incorporate service quality into air travel demand estimation, specifically the incorporation of delay-based quality of service measures. The first model to incorporate service quality, proxied by flight frequency, in a demand model is from De Vany (1975). Anderson and Kraus (1981), Ippolito (1981), Abrahams (1983) and De Vany (1975) estimated air travel demand models with schedule delay[6] as a measure of service quality. We contribute to this literature.

[6]Defined as the sum of frequency delay and stochastic delay. Frequency delay is the gap between one's desired and the nearest offered departure time while stochastic delay is time lost due to the nearest offered

A novel feature of this study is that we model demand on a passenger origin-destination[7] demand rather than flight segment only. Previous demand studies, based on origin-destination data, have been unable to incorporate flight delay[8] and studies that have incorporated delay (Abrahams, 1983; Anderson and Kraus, 1981; De Vany, 1975; Douglas and Miller, 1974; Ippolito, 1981), model demand on a service segment rather than passenger origin-destination basis. But much air travel is done in several segments rather than non-stop. In fact, our dataset shows that only 17 percent of itineraries are non-stop flights. Travelers demand air transportation between a directional origin and destination pair and not segment-by-segment. Given the importance of on-time performance to consumers,[9] it is only reasonable that a demand model incorporates such information. This, not only help to predict passengers' behavioral intentions but provides a structure for the measurement of consumer welfare effects of flight delay.

After estimating the demand model, we specify the supply-side assuming that prices are set according to a static differentiated products Bertrand-Nash equilibrium with multiproduct firms. With the static Bertrand-Nash assumption, we derive product-specific markups and recover product-level marginal costs. With the estimated markups and marginal costs in hand, we are able to specify and estimate markup and marginal cost functions. Both functions allow us to measure on-time performance effects on markup and marginal cost.

Several conclusions emerge from the empirical analysis. First, other things equal, consumers value on-time performance and are willing to pay for it. Our demand estimates show that consumers are willing to pay \$0.78 per minute late to avoid delay. We also found that, from a strategic perspective, airlines do not have enough incentive to invest in on-time performance because the change in markup is small and statistically insignificant. Further-

departure being unavailable.

[7]Tickets are issued for the entire itinerary which may include intermediate airport.

[8]Origin-destination passenger data contain no information on routings' on-time performance.

[9]Our demand estimates show that passengers are willing to pay \$0.78 on average for each additional minute of flight delay to avoid delay.

more, since markup is a function of price and marginal cost, we decompose the effects of on-time performance on markup by separately estimating price and marginal cost functions. We found that on-time performance affects price and marginal cost similarly in terms of coefficient magnitudes. This suggests that a marginal improvement in on-time performance raises price and marginal cost by almost the same amount resulting in a zero net effect on markup.

3.2 Literature Review

Researchers have written extensively on airline flight delays. The literature on flight delays abounds in both operations management and economics. The operations management literature uses models that attempt to explain flight delays from an operational standpoint of running an airline. Shumsky (1995) contributed to the literature of airline scheduling performance analysis by examining US air carriers' response to the on-time disclosure rule of 1987. The rule creates incentives for the carriers to improve their on-time performance by either reducing the amount of time to complete a flight or lengthening the amount of time scheduled for a flight. Shumsky (1995) shows that although actual flight times have fluctuated, scheduled flight times have increased significantly. Ramdas and Williams (2006) investigate the tradeoff between aircraft utilization and on-time performance using queuing theory and found out that flight delays increase with increasing aircraft utilization and Sohoni et al. (2011) develop a stochastic integer programming model that achieves desired trade-off between service level and profitability. They use two service-level metrics for an airline schedule. The first one is similar to the on-time performance measure of the U.S. Department of Transportation and the second metric, called the network service level, is geared toward completion of passenger itineraries.

In the economics literature, researchers have tried to explain variations in flight delays by estimating how flight delay relates to airline hub size and airport concentration (Mayer and Sinai, 2003), competition (Mayer and Sinai, 2003; Rupp et al., 2006; Mazzeo, 2003), multimarket contact (Prince and Simon, 2009), prices (Forbes, 2008) and entry or threat of entry (Prince and Simon, 2014), among others. Mayer and Sinai (2003) found that as origin (destination) airport concentration increases, flight delays originating (arriving) from (to) that airport decrease.

On the other hand, for both origin and destination airports, flight delays increase with increasing airport hub size. Mazzeo (2003) found out that the prevalence and duration of flight delays are significantly greater on routes where only one airline provides direct service. Rupp and Holmes (2006) examined the determinants of flight cancellations such as revenue, competition, aircraft utilization, and airline network. Prince and Simon (2009) tested the mutual forbearance hypothesis (Edwards, 1955) using different measures of on-time performance. This hypothesis suggests that firms that meet in multiple markets compete less aggressively because they recognize that a competitive attack in any one market may call for response(s) in all jointly contested markets. They conclude that multimarket contact increases delays and that the effect is substantially larger in less competitive markets.

Forbes (2008) examines the effect of air traffic delays on airline fares and found out that prices fall by \$1.42 on average for each additional minute of flight delay, and that the price response is substantially larger the more competitive the markets are. Prince and Simon (2014) examine whether entry and entry threats by Southwest Airlines cause incumbent airlines to improve their on-time performance as a way to protect their market share. Surprisingly, their results show that incumbents' delays increase with entry and entry threats by Southwest Airlines. They provide two possible explanations for their findings: 1) incumbents worsen on-time performance in an effort to cut costs in order to compete against Southwest's low costs/prices; or 2) incumbents worsen on-time performance to differentiate away from Southwest, a top-performing airline in on-time performance.

3.3 Dataset Construction and Definitions

3.3.1 Dataset Construction

We construct our dataset using data from two sources that span from the first quarter of 2002 to the fourth quarter of 2012 for 20 U.S. carriers.[10] First, we use data from the Airline Origin and Destination Survey (DB1B) collected by the Office of Airline Information of the Bureau of Transportation Statistics. The data are quarterly and represent a 10 percent sample of airline tickets from reporting carriers. Each record or itinerary contains the following information; (*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. Regrettably, passenger-specific information, that would facilitate the estimation of a richer demand model than the one we use, is not available. Information on ticket restrictions such as advance-purchase and length-of-stay requirements are unavailable as well.

Second, we also use the U.S. Department of Transportation (DOT) Bureau of Transportation Statistics (BTS) On-Time Performance data set to construct product quality variables. All U.S. domestic carriers with revenues from domestic passenger flights of at least one percent of total industry revenues must report flight on-time performance data. The data frequency is monthly and covers scheduled-service flights between points within the United States. So, a record in this survey represents a flight. Each record or fight contains information on the operating carrier, the origin and destination airports, miles flown, flight times, and departure/arrival delay information. Previous demand studies, based on origin-destination data, have been unable to incorporate delay data because of the challenge

[10] See Table 3.1 for list of carriers in sample

of matching the data sources described above. The challenge is that origin-destination passenger data contain no information on routings' on-time performance. To construct product quality variables from the on-time performance data, we take the average departure (arrival) delay measure for each carrier at any given origin (destination) airport in a quarter for a given year. This aggregated on-time performance data is then matched to the DB1B dataset. The matching process is done at all airports of the passengers' itineraries. In this study, we only focus on on-time performance at the itinerary final destination. In order to construct our data set, we place some restrictions on the raw data:

(i) We confine our analysis to U.S. domestic flights operated by US domestic carriers.

(ii) We only focus on passengers purchasing round-trip, coach class tickets.

(iii) We exclude real airfares less than \$25 or greater than \$2,000. Dropping real airfares that are too low gets rid of discounted airfares from passengers using their frequent-flyer miles to offset the full price of the trip or employee travel tickets. Likewise, excluding real airfares that are too high gets rid of first-class or business-class tickets.

(iv) Our analysis is limited to air travel products possessing at least 9 passengers to exclude products that are not part of the regular offerings by an airline.

(v) Our analysis focuses on itineraries: (1) within the 48 states in US mainland; (2) no more than one intermediate stop; and (3) with a single ticketing carrier.

(vi) Following Aguirregabiria and Ho (2012), markets selection focuses on air travel amongst the 65 largest US cities. City size is based on the Census Bureau's Population Estimates Program (PEP), which publishes estimates of U.S. population. Data are drawn from the category "Cities and Towns." We use the size of population in the origin city as a proxy for potential market size. Unlike Aguirregabiria and Ho (2012), we do not group cities that belong to the same metropolitan areas and share the same airport since airport grouping will lessen the heterogeneity in on-time performance.

(vii) Given that there are often multiple records for the same itinerary because different passengers paid different prices, we construct the price and quantity variables by averaging the airfares and aggregating the number of passengers respectively based on our product definition and then collapse the data by product. So, in the collapsed data that we use for analyses, a product appears only once during a given time period.

Our final working dataset includes a total of 65 airports representing 1,346,384 air travel products bought across 156,750 different directional city-pair markets.

3.3.2 Definitions

A *market* is a directional, round-trip between an origin and destination city during a specific time period. By directional, we mean that a round-trip air travel from Chicago to Boston is a distinct market from a round-trip air travel from Boston to Chicago. This directional definition of a market controls for heterogeneity in demographics across origin cities that may affect air travel demand (Berry et al., 2006; Gayle, 2007).

An *itinerary* is a planned route from an origin city to a destination city. It entails one or more flight coupons, each coupon typically representing point-to-point travel between two airports that could be on a particular flight segment.

An air travel *product* is defined as a unique combination of ticketing carrier, operating carrier(s) and itinerary. Following Gayle (2007) and Ito and Lee (2007), we focus on three types of air travel products: pure online; traditional codeshare; and virtual codeshare.

For a pure online product, the same airline is the ticketing and operating carrier on all segments of the trip. For example, a two-segment ticket with both segments marketed by Delta Air Lines and both segments of the itinerary are also operated by Delta Air Lines. An

Table 3.1: *Airlines in Sample*

Code	Airline
AA	American Airlines
AQ	Aloha Airlines
AS	Alaska Airlines
B6	JetBlue Airways
CO	Continental Air Lines
DH	Independence Air
DL	Delta Air Lines
F9	Frontier Airlines
FL	AirTran Airways
HA	Hawaiian Airlines
HP	America West Airlines
NW	Northwest Airlines
OO	SkyWest
TZ	ATA Airlines
UA	United Air Lines
US	US Airways
VX	Virgin America Inc.
WN	Southwest Airlines
XE	ExpressJet Airlines
YX	Midwest Airlines

air travel product is said to be code-shared if the operating and ticketing carriers for that itinerary differ. We consider two types of codeshare products: (1) *Traditional Codeshare*; and (2) *Virtual Codeshare*.

A *traditional codeshare* product has a single ticketing carrier, but multiple operating carriers, one of which is the ticketing carrier. For example, a connecting itinerary operated by Delta Air Lines (DL) and Northwest Airlines (NW) but marketed solely by Delta Air Lines (DL) is a traditional codeshare product. A *virtual codeshare* air travel product has the same operating carrier for all segments of the itinerary, but the ticketing carrier is different from the operating carrier. For example, a connecting itinerary operated entirely by Northwest Airlines (NW) but marketed solely by Delta Air Lines (DL) is a virtual codeshare product

For proper identification of the different types of product—pure online, traditional codeshare, and virtual codeshare—we recode regional feeder carriers to have their major carriers' code.[11] For instance, a product that involves Delta Air Lines (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 Air Lines (DL). Without recoding, this product would mistakenly be considered a codeshare product because the ticketing and operating carriers are different.

3.4 Product Quality Variables

3.4.1 On-Time Performance Measures

Delay-based measures are obtained using on-time performance from the DOT BTS' dataset. According to the US DOT, flights that don't arrive at (depart from) the gate within 15 minutes of scheduled arrival (departure) time are late arrivals (departures). This represents performance measured against airlines' published schedules. For example, if your flight is scheduled to arrive at 3:30 p.m. and does not get in until 3:44 p.m., it is not late. With this measurement standard, 81.9 percent of flights arrived on time in April 2015.[12] However, if we count all flights that arrive after their scheduled arrival time including when they are one minute late, the industry's "true" on-time performance drops to about 60 percent. In this study, we focus on arrival on-time performance at destination. The three main measures are arrival minutes late, the percentage of flights arriving at least 15 minutes late and the percentage of flights arriving at least 30 minutes late. Table 3.2 summarizes on-time performance by carrier and Hawaiian Airlines (HA) tops all carriers across on-time performance measures. Figure 3.3 shows that overall, airlines performed the worst in 2007.

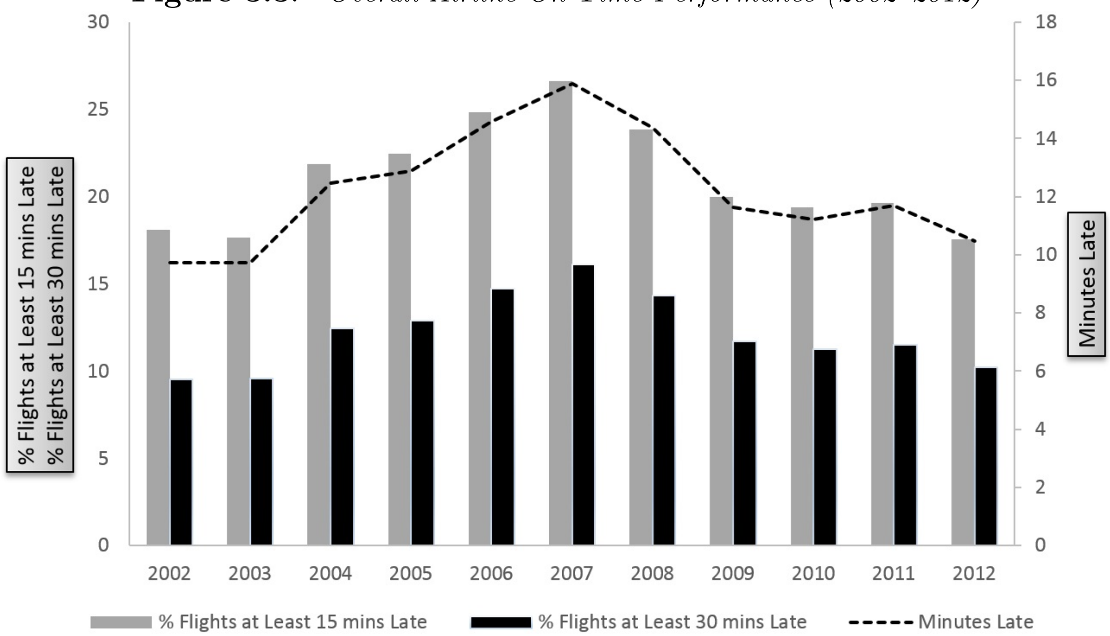
[11] The International Air Transport Association (IATA) uses two-character codes to identify all airlines; for example the code DL is assigned to Delta Airlines.

[12] U.S. Department of Transportation (2015)

Table 3.2: *Airlines' Mean Arrival Delay (2002:Q1—2012:Q4)*

Code	Airlines	Minutes Late	% Flights Arriving at Least 15 Minutes Late	% Flights Arriving at Least 30 Minutes Late
HA	Hawaiian Airlines	4.75	8.06	3.66
AQ	Aloha Airlines	9.23	17.30	8.10
VX	Virgin America Inc.	9.90	13.53	8.54
WN	Southwest Airlines	9.96	18.27	10.17
HP	America West Airlines	10.67	21.06	10.55
US	US Airways	11.09	19.72	11.21
AS	Alaska Airlines	11.84	19.96	11.41
F9	Frontier Airlines	12.02	23.08	11.70
DL	Delta Air Lines	12.15	21.17	11.93
CO	Continental Air Lines	12.90	21.72	12.41
NW	Northwest Airlines	12.92	24.20	13.06
FL	AirTran Airways	13.22	21.82	13.14
UA	United Air Lines	13.31	21.21	13.21
TZ	ATA Airlines	13.40	21.65	12.95
OO	SkyWest	13.42	20.32	13.39
XE	ExpressJet Airlines	13.48	24.34	14.16
AA	American Airlines	13.71	22.61	13.93
YX	Midwest Airlines	13.87	23.04	13.30
B6	JetBlue Airways	15.14	22.98	14.61
DH	Independence Air	15.49	25.16	15.59
Overall Mean		12.12	20.56	11.85

Figure 3.3: *Overall Airline On-Time Performance (2002–2012)*



3.4.2 Routing Quality Measure

We include the distance-based measure, *Routing Quality*, into our analysis following the literature.[13] *Routing Quality* is defined as the ratio of nonstop fight distance to the product's itinerary fight distance used to get passengers from the origin to destination. Based on our routing quality measure, a nonstop flight between the origin and destination will have the shortest itinerary flight distance. Hence, air travel products that require intermediate airport stop(s) that are not on a straight path between the origin and destination, will have an itinerary flight distance that is longer than the nonstop flight distance. Our rationale for choosing this measure is that the longer the itinerary flight distance of an intermediate-stop product relative to the nonstop flight distance, the lower the routing quality of the intermediate-stop product.

3.4.3 Creation of Other Variables

In the collapsed and matched dataset, we create more variables to include in the demand model. The observed product share variable is created by dividing quantity sold by the market size. Measured non-price product characteristic variables include: *Nonstop* and *Origin Presence*. *Nonstop* is an indicator variable that takes the value one if a product has no intermediate stop. This variable constitutes one measure of the travel inconvenience embodied in a product's itinerary since passengers would prefer a non-stop product to one with intermediate stop(s). The *Origin Presence* variable counts the number of different cities that an airline provides service to via a nonstop flight from the origin airport of the market.

We include dummy variables for quarter, year, origin, destination, and carrier to capture unobserved product characteristics that vary across time periods, origins, destinations, and

[13] Reiss and Spiller (1989); Borenstein (1989); Ito and Lee (2007); Färe et al. (2007) Gayle (2007, 2013). Chen and Gayle (2013) and Gayle and Yimga (2014) use routing quality as defined in this paper.

carriers that cannot be measured directly.

We create indicator variables for the different product types—pure online, traditional codeshare, and virtual codeshare. Table 3.3 presents summary statistics for variables used in our analysis.

Table 3.3: *Summary Statistics*

Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Price[a]	169.224	57.539	50.371	1679.103
Quantity	139.975	453.431	9	11266
Observed Product Share	0.00023	0.001	1.07E-06	0.095
Origin presence	17.510	23.281	0	142
Nonstop (dummy variable)	0.174	0.379	0	1
Itinerary distance flown (miles)[b]	1510.806	702.375	47	3982
Nonstop flight distance (miles)	1340.965	652.289	47	2724
Routing Quality[c]	0.890	0.129	0.337	1
Traditional Codeshare	0.016	0.124	0	1
Virtual Codeshare	0.029	0.167	0	1
Pure Online	0.955	0.206	0	1
Arrival On-Time Performance Variables:				
Minutes Late	12.30	4.88	0	68.43
% flights arriving at least 15 minutes late	21.15	7.25	0	100
% flights arriving at least 30 minutes late	12.27	5.21	0	100
Number of Products	1,346,384			
Number of Markets[d]	156,750			

[a] *Adjusted for inflation*

[b] *Reported as "market miles flown" in the DB1B database*

[c] *Defined as the ratio of non-stop distance to itinerary distance*

[d] *A market is an origin-destination-time period combination*

3.5 The Model

3.5.1 Demand

The nested logit model is used to specify air travel demand. A typical passenger i may either buy one of J products (air travel products), $j = 1, ..., J$, or otherwise choose the outside good 0 ($j = 0$) for example, driving or using another transportation means. Thus, passenger i makes a choice among $J_{mt} + 1$ alternatives in market m during time period t. The nested logit model classifies products into G groups, and one additional group for the outside good. Therefore, products are organized into $G + 1$ mutually exclusive groups. The passenger solves the following utility maximization problem:

$$\underset{j \in \{0,1,\cdots,J_{mt}\}}{Max} U_{ijmt} = \delta_{jmt} + \sigma \varsigma_{imtg} + (1 - \sigma)\varepsilon_{ijmt} \tag{3.1}$$

$$\delta_{jmt} = x_{jmt}\beta + \alpha p_{jmt} + \eta_j + \upsilon_t + origin_m + dest_m + \xi_{jmt} \tag{3.2}$$

where U_{ijmt} is passenger i's utility from choosing product j; δ_{jmt} is the mean level of utility across passengers that choose product j; ς_{imtg} represents a random component of utility common across all products within the same group; ε_{ijmt} is an independently and identically distributed (across products, consumers, markets and time) random error term assumed to have an extreme value distribution.

In Equation (3.2), x_{jmt} represents a vector of observed non-price product characteristics described below; p_{jmt} is the price; η_j captures airline-specific fixed effects; υ_t captures time period fixed effects; $origin_m$ and $dest_m$ are origin and destination city fixed effects and ξ_{jmt}, the unobserved (by the researcher) component of product characteristics that affects consumer utility.

The vector x_{jmt} includes *Routing Quality*[14], *Origin Presence* which is a measure of the size of an airlines airport presence, product-level zero-one codeshare dummy variables (*traditional and virtual codeshare*) and a zero-one dummy variable that equals to unity only if the product uses a nonstop flight to get passengers from the origin to destination. The origin city presence variable is measured by the number of different cities an airline provides

[14]Note that including *Routing Quality* in our demand model is paramount since a positive estimate on this variable would empirically validate that consumers' choice behavior is consistent with the fact that better routing quality is associated with a more desirable itinerary.

service to using nonstop flights from the relevant market origin to destination cities.

The vector β measures the passenger's marginal utilities associated with the product characteristics. The parameter α captures the marginal utility of price. The parameter σ lies between 0 and 1 and measures the correlation of consumer utility across products belonging to the same airline. The correlation of preferences increases as σ approaches 1. In the case where is 0, the model collapses to the standard logit model where products compete symmetrically. For notational convenience, we drop the market and time subscripts to complete the derivation of the model.

Let there be G_g products in group g. If product j is in group g, then the conditional probability of choosing product j given that group g is chosen, is given by:

$$S_{j/g} = \frac{e^{(1-\sigma)^{-1}\delta_j}}{D_g} \quad \text{where,} \quad D_g = \sum_{j \in G_g} e^{(1-\sigma)^{-1}\delta_j} \tag{3.3}$$

The probability of choosing group g or group g's predicted share is given by:

$$S_g = \frac{D_g^{1-\sigma}}{D_0^{1-\sigma} + \sum_{g=1}^{G} D_g^{1-\sigma}} \tag{3.4}$$

The outside good is the only good in group 0. Therefore, $D_0^{1-\sigma} = e^{\delta_0}$. We normalize the mean utility of the outside good to zero. This implies $D_0^{1-\sigma} = 1$. Equation (3.4) can be rewritten as:

$$S_g = \frac{D_g^{1-\sigma}}{1 + \sum_{g=1}^{G} D_g^{1-\sigma}} \tag{3.5}$$

The unconditional probability of choosing product j or the market share of product j is:

$$S_j = S_{j/g} \times S_g = \frac{e^{(1-\sigma)^{-1}\delta_j}}{D_g} \times \frac{D_g^{1-\sigma}}{1 + \sum_{g=1}^{G} D_g^{1-\sigma}} \quad \text{or} \quad S_j = \frac{e^{(1-\sigma)^{-1}\delta_j}}{D_g^{\sigma}\left[1 + \sum_{g=1}^{G} D_g^{1-\sigma}\right]} \tag{3.6}$$

Therefore, the demand for product j is given by:

$$d_j = M \times S_j(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \alpha, \beta, \sigma) \tag{3.7}$$

where M is a measure of market size—the population in the origin city. The predicted market share of product j is S_j while $\mathbf{x}$, $\mathbf{p}$ and $\boldsymbol{\xi}$ are vectors of observed non-price product characteristics, price, and the unobserved vector of product characteristics. α, β and σ are parameters to be estimated.

3.5.2 Product Markups and Product Marginal Costs

We assume that carriers simultaneously choose prices as in a static Bertrand-Nash model of differentiated products. Let each carrier f offer for sale a set F_{fm} of products in market m. Firm f's variable profit in market m is given by:

$$\pi_{fm} = \sum_{j \in F_{fm}} (p_{jm} - mc_{jm}) q_{jm} \tag{3.8}$$

where $q_{jm} = d_{jm}(\mathbf{p})$ in equilibrium, q_{jm} is the quantity of travel tickets for product j sold in market m, $d_{jm}(\mathbf{p})$ is the market demand for product j in equation (3.7), $\mathbf{p}$ is a vector of prices for the J products in market m, and mc_{jm} is the marginal cost of product j in market m. The corresponding first-order conditions are:

$$\sum_{r \in F_{fm}} (p_{rm} - mc_{rm}) \frac{\partial s_r}{\partial p_j} + s_{jm}(\mathbf{x}, \mathbf{p}, \xi; \alpha, \beta, \sigma) = 0 \quad \text{for all} \quad j = 1, ..., J \tag{3.9}$$

which can be rewritten in matrix notation as:

$$(\mathbf{p} - \mathbf{mc}) \times (\Omega * \Delta) + s(\mathbf{p}) = 0 \tag{3.10}$$

where $\mathbf{p}$, $\mathbf{mc}$ and $s(\cdot)$ are $J \times 1$ vectors of product prices, marginal costs, and predicted product shares respectively, while $\Omega * \Delta$ is an element-by-element multiplication of two matrices. Δ is a $J \times J$ matrix of first-order derivatives of model predicted product market shares with respect to prices, where element $\Delta_{jr} = \frac{\partial s_r(\cdot)}{\partial p_j}$. Ω is a $J \times J$ matrix which describes carriers ownership structure of the products. For example, let Ω_{jr} denote an element in Ω, where

$$\Omega_{jr} = \begin{cases} 1 & \text{if there exists } f : \{j, r\} \subset F_f \\ 0 & \text{otherwise} \end{cases}$$

That is, $\Omega_{jr} = 1$ if products j and r are offered for sale by the same carrier, otherwise $\Omega_{jr} = 0$. Based on equation (3.10), the markup equation can be obtained as:

$$markup = \mathbf{p} - \mathbf{mc} = -\left(\Omega * \Delta\right)^{-1} \times s(\mathbf{p}) \tag{3.11}$$

With computed product markups in hand, product marginal costs can be recovered simply by subtracting computed markup from price, i.e.

$$\mathbf{mc} = \mathbf{p} - markup \tag{3.12}$$

3.5.3 Estimation of Demand and Marginal Cost Functions

The estimation strategy of the demand parameters (α, β, σ) is such that the observed market shares $\mathbf{S}_{jmt}$ are equal to the market shares predicted by the model S_{jmt}. Empirical industrial organization shows that the model presented above results in a linear equation:

$$ln(\mathbf{S}_{jmt}) - ln(\mathbf{S}_{0mt}) = x_{jmt}\beta - \alpha p_{jmt} + \sigma ln(\mathbf{S}_{jmt/g}) + \eta_j + \upsilon_t + origin_m + dest_m + \xi_{jmt} \tag{3.13}$$

where $\mathbf{S}_{jmt}$ is the observed within group share of product j computed from the data by $\mathbf{S}_{jmt} = \frac{q_{jmt}}{M}$ where q_{jmt} is the quantity of air travel product j sold and M is the population of the origin city. $\mathbf{S}_{0mt} = 1 - \sum_{j \in J_m} S_{jmt}$ is the observed share of the outside good. $\mathbf{S}_{jmt/g}$ is the observed within-group share of product j and the other variables are described as in Equation (3.2). Equation (3.13) can be estimated using Two Stage Least Squares (2SLS) since price p_{jmt} and $\mathbf{S}_{jmt/g}$ are endogenous.

After recovering the product marginal cost using equation (3.12), we use the following linear specification for the marginal cost function:

$$\widehat{mc}_{jmt} = \tau_o + \tau_1 OTP_{jmt} + \tau_2 W_{jmt} + \psi_j + \mu_t + origin_m + dest_m + \varepsilon^{mc}_{jmt} \tag{3.14}$$

where OTP_{jmt} is the carrier's on-time performance, W_{jmt} is a vector of observed marginal cost-shifting variables, τ_1 and τ_2 are the associated vectors of parameters to be estimated. ψ_j is an airline-specific component of marginal cost captured by airline fixed effects. μ_t are time fixed effects captured by quarter and year dummy variables. $origin_m$ and $dest_m$ are sets of origin and destination dummy variables respectively. Finally, ε^{mc}_{jmt} is an unobserved random component of marginal cost. τ_1 would tell us by how much marginal cost would change if airlines improve arrival delay by one minute, ceteris paribus. Likewise, we specify markup and price equations and present the results in Tables 3.5 and 3.7.

3.5.4 Instruments for Endogenous Variables in Demand Equation

We exploit the fact that the set of product choices offered by airlines in a market is predetermined at the time of exogenous shocks to demand while the non-price characteristics of an airlines products are primarily determined by the route network structure of the airline.[15]

The instruments we use for the Two-stage Least Squares estimation are: (1) number of competitors products in the market; (2) number of competing products offered by other

[15] Unlike price and within group product share, airline route network structure is fixed in the short run, which mitigates the influence of demand shocks on the menu of products offered and their associated non-price characteristics (Gayle and Xie, 2014)

airlines with an equivalent number of intermediate stops; (3) number of other products offered by an airline in a market; and (4) average number of intermediate stops across products offered by an airline in a market. The rationale for using these instruments is discussed in Gayle (2007, 2013). Instruments (1)-(3) are motivated by supply theory, which predicts that a product's price and within-group product share are affected by changes in its markup.

Instruments (1) and (2) capture the degree of competition facing a product, which in turn affects the size of a product's markup. The use of instrument (3) is justified by the fact that, all else constant, as an airline offers more substitute products in a given market, the more capable the airline is to charge a higher markup on each of these products. The intuition for instrument (4) is as follows. Since we are using the nested logit demand model, we group products by airline. So, instrument (4) is likely to be correlated with the 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.

3.6 Empirical Results

3.6.1 Demand Results

We estimate the demand equation using both Ordinary Least Square (OLS) and Two-stage Least Squares (2SLS). Table 3.4 shows the demand regression results. As stated in section (3.5.3), price p_{jmt} and within-group product share $\mathbf{S}_{jmt/g}$ are endogenous variables in the demand equation. Thus, OLS estimation produces biased and inconsistent estimates of the price coefficient and σ. A Hausman test confirms by rejecting the exogeneity of price and within-group product share at conventional levels of statistical significance.

Table 3.4: *Demand Estimation Results*

Variables	**OLS** (1)	**2SLS** (2)	**2SLS** (3)	**2SLS** (4)
Price	0.0003***	-0.0260***	-0.0253***	-0.0254***
	(1.53e-5)	(0.0003)	(0.0003)	(0.0003)
$ln(\mathbf{S}_{jmt/g})$	0.4168***	0.0265***	0.0364***	0.0333***
	(0.0006)	(0.0028)	(0.0027)	(0.0027)
Origin Presence	0.0122***	0.0209***	0.0208***	0.0208***
	(4.34e-5)	(0.0002)	(0.0002)	(0.0002)
Nonstop	0.9815***	0.7979***	0.7943***	0.7958***
	(0.0025)	(0.0066)	(0.0065)	(0.0065)
Routing Quality	1.8128***	1.9659***	1.9604***	1.9714***
	(0.0071)	(0.0131)	(0.0128)	(0.0129)
Codeshare	-0.7206***	-1.0022***	-0.9915***	-1.0069***
	(0.0038)	(0.0074)	(0.0072)	(0.0073)
Arrival On-Time Performance				
Minutes late	-0.0113***	-0.0204***		
	(0.0002)	(0.0003)		
% flights late more than 15 minutes			-0.0204***	
			(0.0003)	
% flights late more than 30 minutes				-0.0333***
				(0.0004)
Constant	-10.6091***	-6.6820***	-6.5121***	-6.5424***
	(0.0117)	(0.0556)	(0.0558)	(0.0558)
Carrier Fixed Effects	YES	YES	YES	YES
Quarter and Year fixed effects	YES	YES	YES	YES
Market Origin fixed effects	YES	YES	YES	YES
Market Destination fixed effects	YES	YES	YES	YES
No. of Obs.	1,346,384	1,346,384	1,346,384	1,346,384
Endogeneity Test. H_0: *Price* and $ln(\mathbf{S}_{jmt/g})$ are exogenous		F(2, 1346218)= 43738.7***	F(2, 1346218)= 42988***	F(2,1346218)= 43449.3***
Wu-Hausman:		(p = 0.0000)	(p = 0.0000)	(p = 0.0000)

Note: Standard errors are in parentheses.

****p < 0.01; **p < 0.05; *p < 0.10*

To confirm the validity of instruments used in the 2SLS regression, we estimate first-stage reduced-form regressions for each of the endogenous variables. First-stage reduced-form regressions where we regress p_{jmt} and $\mathbf{S}_{jmt/g}$ against the instruments suggest that the instruments explain variations in the endogenous variables. R^2 measures for the regressions of price and within-group product share against the instruments are 0.0544 and 0.4202 respectively. Since the use of instruments is justified, we only discuss the 2SLS estimates.

The coefficient estimate on the price variable has the expected negative sign. All else equal, an increase in the product's price reduces the probability that a typical passenger will choose the product. The coefficient estimate on $ln(\mathbf{S}_{jmt/g})$, which is an estimate of σ should lie between zero and one. σ measures the correlation of consumers' preferences for products offered for sale by the same airline.

Given that we nest products by airlines and that σ is statistically significant, this suggests that passenger choice behavior shows some level of brand-loyalty to airlines. However, since the estimate of σ is closer to zero than it is to one, this brand-loyal behavior is not very strong. Even though airlines use customer loyalty programs to strengthen relationships with their customers loyalty program, such programs do not provide exceptional advantages mostly when any potential gain differential can be quickly eroded by competitive forces (Dowling and Uncles, 1997).

The coefficient estimate on *Origin presence* is positive. This result is consistent with our expectations and suggests that travelers prefer to fly with airlines, ceteris paribus, that offer services to more destinations from the travelers' origin city. Chen and Gayle (2013), Gayle and Le (2013) and Berry (1990) among others, obtained similar findings.

The positive coefficient estimate on the *Nonstop* variable suggests that direct flights are associated with higher levels of utility compared to connecting flights. Since we only consider nonstop products and products with one intermediate stop, passengers prefer products with nonstop flight itineraries to those with one intermediate stop when traveling from origin to destination. In fact, consumers are willing to pay up to $30.69 extra,[16] on average, to obtain a product with a nonstop itinerary in order to avoid products with intermediate stop.

The demand effects of code sharing are identified by interpreting the coefficient estimates on the Codeshare variable. The coefficient estimate on *Codeshare* measures utility differentials vis-à-vis the *Pure Online* product type and suggests that code-shared products are less preferred compared to pure online products. This may be the case because of the streamlined nature of pure online products. An airline offering such products tend to better organize its flights and schedules to minimize layover time, as well as efficiently organize its own gates at airports (Gayle and Xie, 2014). It is well documented that codeshare partners try to streamline flights across carriers to minimize layover times and facilitate smoother connections, however this result suggests that codeshare streamlining has not achieved parity with pure online products (Gayle, 2013). Consumers may perceive cooperation between two carriers less attractive than flying on a single airline.

The positive coefficient estimate on *Routing Quality* suggests that passengers prefer the most direct route to the destination. Consumers show preference for products with itinerary fight distance as close as possible to the nonstop flight distance between the origin and destination. So, consumer choice behavior is consistent with the premise that better routing quality is associated with a more passenger-desirable itinerary. In fact, consumers are willing to pay up to $75.60 extra,[17] on average, for each percentage point increase that the nonstop flight distance is of the actual itinerary flight distance.

The negative coefficient estimates on the on-time performance measures indicate that consumer choice behavior is consistent with our expectations that products with longer arrival delays at the destination airport are less desirable. The ratio of coefficient estimates of "Minutes Late" and price in column 2 of Table 3.4 suggests that consumers are willing to pay

[16] This is obtained by dividing the coefficient estimate on the *Nonstop* dummy variable by the coefficient estimate on Price from column 2 of Table 3.4.

[17] This is obtained by dividing the coefficient estimate on the Routing Quality variable by the coefficient estimate on Price from column 2 of Table 3.4

\$0.78 on average for each additional minute of flight arrival delay to avoid delay. This implies substantial welfare effects knowing that on average an airline carries about 140 passengers, is 12 minutes late and that our dataset consists of 1,346,384 products. So, extrapolating the consumer welfare effects due to arrival minutes late amounts to approximately \$1.76 billion.[18]

This extrapolation is very conservative since it only accounts for delay at the final destination. In reality, costs borne by passengers range from potential loss of business due to late arrival at a meeting; partial loss of social activity (Cook et al., 2009) including missed connections, cancelled flights, disrupted ground travel plans, forgone pre-paid hotel accommodations, and missed vacation times (Schumer and Maloney, 2008).

Studies that have examined consumers' reactions to product problems (Curren and Folkes, 1987; Folkes, 1984) show that passengers would be less willing to fly an airline again when delays are perceived to be controllable (caused by poor management for instance) than when they are perceived to be uncontrollable (due to bad weather for instance). Also, even when passengers may think that a delay may had arisen from an uncontrollable mechanical failure, they still nevertheless believe that the airline could take action to solve the problem (e.g., substitute another plane), and so refuse to fly that airline again (Folkes et al., 1987).

3.7 Markup, Marginal Cost and Price Results

3.7.1 Product Markup Regression Results

Table 3.5 shows the estimation results for a reduced-form product markup equation. Here, we examine the impact of arrival on-time performance on product markups. The sign and magnitude of the coefficient on "minutes late" suggests that arrival delay only marginally affects product markups and this effect is not statistically significant. This indicates that

[18] Welfare costs to consumers = $\$0.78 \times 12 \times 1,346,384 \times 140$

improving on-time performance has no effect on product markup. We find in Tables 3.6 and 3.7 that this result is driven by the fact that on-time performance improvement costs offset price increases, resulting in a zero net effect on product markups.

All other control variables in Table 3.5 have the expected sign and are statistically significant. First, we know from our demand results that passengers prefer airlines with large presence at the origin airport. Thus, we expect the coefficient estimate on the *Origin Presence* variable to be positive indicating that the size of an airline's presence at the origin airport of a market is positively related to markup. As suggested by Borenstein (1989), airlines have higher market power at their hub airports and are able to charge higher markups on flights out of their hub airports.

Second, markups are greater on nonstop products compared to products with intermediate stop all else constant, as indicated by the positive coefficient estimate on the *Nonstop* variable in Table 3.5.

The positive coefficient estimate for *RoutingQuality* indicates that the greater the routing quality of the itinerary, the higher the markup charged by the carrier, all else constant. This is consistent with our demand results showing that consumers prefer streamlined travel and are willing to pay more for travel that uses convenient routing.

Examining the effect of codesharing on markups, we find that the coefficient estimate for the codeshare variable is negative and statistically significant. Thus, all else constant, markups are lower on virtual and/or traditional codeshare products relative to pure online products. Overall, these results suggest that airlines charge lower markups on codeshare products compared to pure online products because consumers show a weaker preference for this type of products compared to pure online products.

Table 3.5: *Estimation Results for Reduced-form Markup Regression*

Variables	Coefficient Estimate	Robust Standard Errors
Minutes Late	-3.23e-05	4.39e-05
Origin Presence	0.001***	1.58e-05
Nonstop	0.046***	6.66e-04
Routing Quality	0.017***	7.43e-04
codeshare	-0.018***	3.47e-04
Constant	38.561***	1.14e-03
Operating carrier effects	YES	
Origin city effects	YES	
Destination city effects	YES	
Quarter and Year effects	YES	

****p < 0.01*

3.7.2 Marginal Cost Regression Results

We report the marginal cost equation estimation results in Table 3.6. As expected, arrival on-time performance is inversely related to marginal cost. A one-minute reduction in delay would cause marginal cost to increase by $0.30 since airline would have incur some costs in order to improve on-time performance

From an operating cost perspective, airlines desire shorter scheduled flights to keep wages of both flight attendants and pilots low (Mayer and Sinai, 2003). Thus, airlines have an incentive to reduce their scheduled flight times, and the tradeoff that comes with this decision is increased delays, higher customer waiting times and customer dissatisfaction. Mayer and Sinai (2003) argue that it is also conceivable that having more business customers dissatisfied due to delays could generate a higher goodwill cost.

The positive coefficient estimate for *Origin Presence_mc* suggests that larger origin presence increases the marginal cost. However, marginal cost increases at a diminishing rate—the squared term of *Origin Presence_mc* has a negative coefficient—all else constant. An airline's marginal cost increases initially with increases in the number of distinct cities

Table 3.6: *Estimation Results for Marginal Cost Regression*

Variables	Coefficient Estimate	Robust Standard Errors
Minutes Late	-0.303***	0.009
Distance	0.036***	8.32e-05
Origin Presence_mc	0.687***	0.008
(Origin Presence_mc)^2	-0.001***	8.01e-05
Destination Presence_mc	0.644***	0.007
(Destination Presence_mc)^2	-0.001***	6.94e-05
Constant	62.703***	0.450
Operating carrier effects	YES	
Origin city effects	YES	
Destination city effects	YES	
Quarter and Year effects	YES	

$^{***}p < 0.01$

that an airline has nonstop flights from, going into the origin airport, but eventually declines with further increases in the number of cities. Another interpretation of this result is that, cost efficiency gains due to economies of passenger-traffic density can be achieved when the size of an airline's airport presence exceeds some threshold level.

Similarly, the coefficient estimates on $DestinationPresence\_mc$ and $(OriginPresence\_mc)^2$ suggest that an airline's marginal cost increases initially with increases in the number of distinct cities that an airline has nonstop flights to, going out of the destination airport, but the marginal cost increases at a decreasing rate. As expected, marginal cost increases with distance flown, all else constant. A plausible explanation is that covering longer distances requires more fuel.

3.7.3 Price Regression Results

Table 3.7 presents the estimation results for a reduced-form price equation. We examine the impact of arrival on-time performance on airfares. The sign and magnitude of the coefficient on "minutes late" suggests that arrival delay is inversely related to prices (Forbes, 2008). This estimate implies that each additional minute of delay reduces the price for airline travel by \$0.31. In other words, airlines can charge \$0.31 for each additional minute reduction in arrival delay.

Table 3.7: *Estimation Results for Price Regression*

Variables	Coefficient Estimate	Robust Standard Errors
Minutes Late	-0.310***	0.009
Origin Presence_mc	0.685***	0.008
(Origin Presence_mc)^2	-0.001***	8.02e-05
Destination Presence_mc	0.642***	0.007
(Destination Presence_mc)^2	-0.001***	6.95e-05
Routing Quality	7.909***	0.412
Distance	0.037***	7.92e-05
Codeshare	-3.734***	0.247
Constant	94.294***	0.554
Operating carrier effects	YES	
Origin city effects	YES	
Destination city effects	YES	
Quarter and Year effects	YES	

$^{***}p < 0.01$

The coefficient estimates on the presence variables and their respective squared terms show that airlines charge higher prices the larger their presence at the origin and destination airports but these prices increase at a diminishing rate, all else constant. This is consistent with the presence of economies of passenger-traffic density that we found in the estimation of the marginal cost function previously discussed.

The routing quality variable is associated with higher price. This relationship is supported by our demand model estimation that shows that passengers prefer streamlined travel and are willing to pay more for travel that uses convenient routing. As expected, the estimated coefficient on the distance variable suggests price increases with longer itinerary distances. Not surprising given that we found that itinerary distance is positively related to marginal cost.

It appears that codeshare itineraries are associated with lower prices relative to pure online itineraries. Consumers may perceive cooperation between two carriers less attractive than flying on a single airline.

3.8 Conclusion

Researchers have long been interested in explaining why airlines are late. To answer this question, most researchers have resorted to a reduced form estimation approach where they explain variations in on-time performance through a set of explanatory variables. This approach yields a set of parameters that describes the marginal impact of an explanatory variable on on-time arrival performance. In contrast, we use a structural estimation approach.

The objective of this paper is twofold. First, using a demand model, we measure the cost of delay borne by consumers in terms of how much monetary value they are willing to pay to avoid delay. We find that consumers are willing to pay \$0.78 for every minute of arrival delay which after extrapolation amounts to consumer welfare effects of \$1.76 billion. Second, with consumers having a preference for flights that arrive at destination on time, we measure the incentive for airlines to provide on-time arrivals using a methodology that does not require cost data to draw inference on changes in cost associated with improvement in on-time performance. Our findings suggest that airlines have little to no incentive because their markups do not increase when they improve on-time performance. In fact, the marginal increase in price resulting from on-time performance improvement is offset by an increase in marginal cost.

Stronger conclusions may be drawn from future work about the underlying mechanisms through which product quality may impact product markups. On-time performance is one among other product quality dimensions such as mishandled baggage, oversales, consumer complaints, in-flight amenities etc. Examining changes in these other quality dimensions along with on-time performance may provide insights about how airlines engage in overall quality differentiation in a strategic environment where firms are competing with each other.

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Appendix A

Supplemental Materials for Chapter 2

Table A.1: *Mean On-time performance summary pre- and post-alliance*

	PRE		POST	
	All Carriers	Codeshare partners	All Carriers	Codeshare partners
Arrival Delay (in minutes)	8.5	9.3	12.4	11.5
Departure Delay (in minutes)	7.7	6.8	11.2	8.5

Note: All tests of difference in means are statistically significant at 1% level

Figure A.1: *Histogram of Departure Minutes Late*

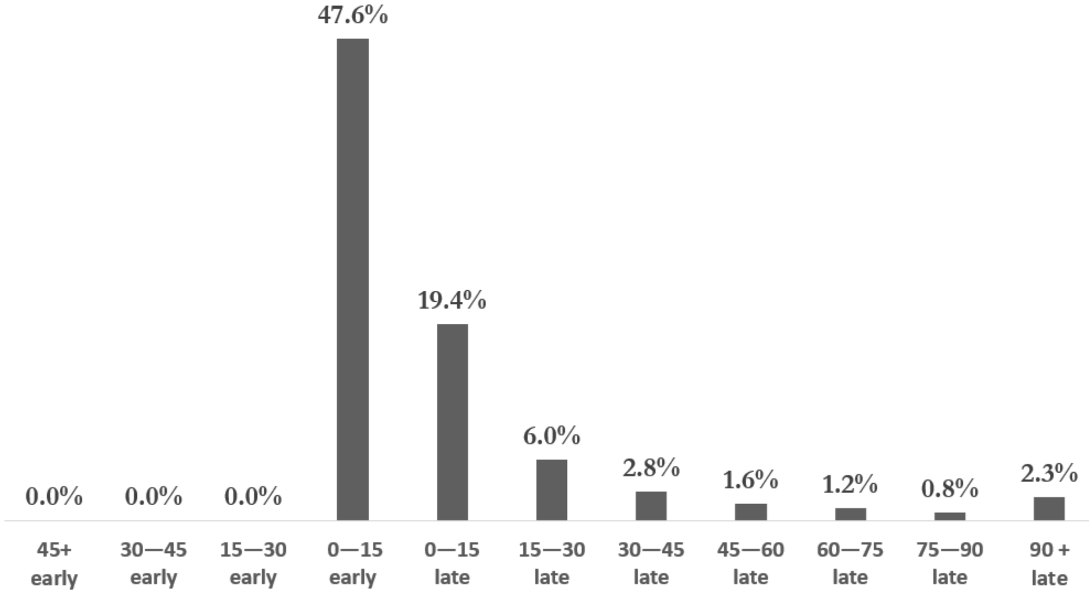

Figure A.2: *Histogram of Arrival Minutes Late*