Extracting Airline and Passenger Behavior from Online Distribution Channels: Applications using Online Pricing and Seat Map Data

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Stacey M. Mumbower

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Extracting Airline and Passenger Behavior from Online Distribution Channels: Applications using Online Pricing and Seat Map Data

Approved by:

Dr. Laurie A. Garrow, Advisor
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. John D. Leonard
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Jeffrey P. Newman
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Matthew J. Higgins
Ernest Scheller Jr. College of Business
Georgia Institute of Technology

Dr. Mark E. Ferguson
Darla Moore School of Business
University of South Carolina

Date Approved: June 5, 2013

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LIST OF SYMBOLS AND ABBREVIATIONS

2SLS	Two-Stage Least Squares
AA	American Airlines
AATF	U.S. Airport and Airways Trust Fund
AP	Advance Purchase
AS	Alaska Airlines
ASMs	Available Seat Miles
B6	JetBlue Airways
BTS	Bureau of Transportation Statistics
CO	Continental Airlines
CV	Coefficient of Variation
DB1A	Origin and Destination Data Bank 1A
DB1B	Origin and Destination Data Bank 1B
DFD	Days from Flight Departure
DL	Delta Air Lines
EMS	Even More™ Space
F9	Frontier Airlines
FAA	Federal Aviation Administration
FL	Air Tran Airways
GDS	Global Distribution System
IQR	Interquartile Range
IV	Instrumental Variable
LCC	Low Cost Carrier
MNL	Multinomial Logit
NK	Spirit Airlines
NW	Northwest Airlines
OLS	Ordinary Least Squares
OTA	Online Travel Agent
PD	Price Dispersion
QSI	Quality of Service Index
RM	Revenue Management
SD	Standard Deviation
UA	United Airlines
US	US Airways
U.S. DOT	United States Department of Transportation
VOT	Value of Time
WN	Southwest Airlines

Note: Airport codes are listed in Tables 2.2, 4.2, 6.2, and A.2.

SUMMARY

Although the airline industry has drastically changed since its deregulation in 1978, publically available sources of data have remained nearly the same. In the U.S., most researchers and decision-makers rely on government data that contains highly aggregated price information (e.g., average quarterly prices). However, aggregate data can hide important market behavior. With the emergence of online distribution channels, there is a new opportunity to model air travel demand using detailed price information.

This dissertation uses online prices and seat maps to build a dataset of daily prices and bookings at the flight-level. Several research contributions are made, all related to leveraging online data to better understand airline pricing and product strategies, and how these strategies impact customers, as well as the industry in general. One major contribution is the finding that the recent product debundling trend in the U.S. airline industry has diluted revenues to the U.S. Airport and Airways Trust Fund by at least five percent.

Additionally, several new behavioral insights are found for one debundling trend that has been widely adopted by U.S. airlines: seat reservation fees. Customers are found to be between 2 and 3.3 times more likely to purchase premium coach seats (with extra legroom and early boarding privileges) when there are no regular coach window or aisle seats that can be reserved for free, suggesting that the ability of airlines to charge seat fees is strongly tied to load factors. Model results are used to explore optimal seat fees and find that an optimal static fee could increase revenues by 8 percent, whereas optimal dynamic fees could increase revenues by 10.2 percent.

Another major contribution is in modeling daily bookings and estimating price elasticities using ordinary least squares (OLS) regression without correcting for price endogeneity and two-stage least squares (2SLS) regression, which corrects for endogeneity. Results highlight the importance of correcting for price endogeneity (which is not often done in air travel applications). In particular, models that do not correct for endogeneity find inelastic demand estimates whereas models that do correct for endogeneity find elastic demand estimates. This is important, as pricing recommendations differ for inelastic and elastic models. A set of instrumental variables are found to pass validity tests and can be used to correct for price endogeneity in future models of daily flight-level demand.

CHAPTER 1: INTRODUCTION

1.1. Background and Motivation

Since deregulation (which occurred in the United States in 1978), the airline industry has faced a large number of changes. Competition has been transformed by low cost carriers (LCCs) that typically offer lower prices than legacy carriers. Between 2000 and 2008, the number of domestic passengers served by LCCs grew at an average annual rate of 11 percent, whereas during this same time period many legacy carriers experienced declining figures. Also during this time period, LCCs increased their weekly flight departures and cities served by 60 percent. Traditionally, LCCs mainly targeted price-sensitive leisure passengers. However, LCCs are beginning to target business passengers by flying in heavily traveled business routes (Steenland, 2008).

In addition to increased competition from LCCs, the internet has also transformed the airline industry, leading to pricing transparency. Online travel agents such as Expedia®, Orbitz®, and Travelocity® make it easy for customers to search the prices of multiple airlines across multiple departure dates. Customers can quickly search for and purchase the lowest possible fare. In fact, 60 percent of leisure travelers report that they purchase the lowest fare they can find (Harteveldt et al., 2004; PhoCusWright, 2004). An increasing number of purchases are being made through the internet. For example, in 1998, approximately one percent of domestic leisure bookings were sold through the internet, but by 2005 the percentage of domestic leisure bookings made online had increased to 35 percent (Brunger and Perelli, 2008).

The growth of LCCs combined with the increased transparency of airfares has led, at least in part, to lower average prices in the airline industry. Airlines have not been able to increase fares at a rate that keeps up with inflation. In the first 30 years after passenger deregulation, domestic airline prices fell 41.2 percent in real terms (ATA, 2010).

In addition to increased competition from low cost carriers and increased use of the internet as a major distribution channel, airlines also faced a series of financial challenges in the first decade of the 21st century, including unprecedented fuel costs, continued security threats post 9/11, health outbreaks (SARS, H1N1), economic recessions, and the global financial crisis. Due to the numerous industry changes and financial challenges, airlines have struggled to remain profitable. Between 2000 and 2010, the seven largest U.S. network carriers[1] collectively lost $35.1 billion (U.S. DOT, 2010), and four of these carriers went into bankruptcy[2]. As a result, widespread industry consolidation has taken place, as five major mergers/acquisitions[3] involving nine carriers were initiated between 2005 and 2012.

In response to the financial challenges in the first decade of the 21st century, airlines began debundling services that were once included in the base price of a ticket, including new fees for checked baggage, seat reservations, and food. Additionally, the

[1] Alaska, American, Continental, Delta, Northwest, United, and US Airways.
[2] Delta, Northwest, United, and US Airways filed for bankruptcy.
[3] Mergers/acquisitions took place between America West and US Airways in 2005; Delta and Northwest in 2008; Continental and United in 2010; Southwest and AirTran in 2011; US Airways and American in 2012.

cost of existing ancillary services were increased, including fees for services such as redeeming mileage award tickets, exchanging tickets, and checking pets. Revenues from ancillary fees have rapidly increased in the past few years. From 2007-2011 ancillary revenues reported by U.S. carriers with operating revenues over $20 million grew from $3.6 billion to $9.8 billion (U.S. DOT, 2012), and similar trends are observed worldwide. Ancillary services provide an important revenue source that can help carriers achieve profitability. For example, in 2011 JetBlue reported a net profit of $86 million and seat fee revenues of more than $120 million (JetBlue Airways, 2011).

Although the airline industry has drastically changed since its deregulation, and especially within the last decade, publically available sources of data have not changed. Most researchers and decision-makers currently rely on government datasets to answer questions about airline pricing, demand and competition. These government data sources provide highly aggregated data. For example, the U.S. Department of Transportation's Origin and Destination Survey Databank 1A/1B (which contains a 10% random sample of tickets sold in the U.S.) provides information on average quarterly market-level prices by airline. However, airlines are constantly changing prices in response to demand, often many times per day.

The lack of disaggregate data sources has hindered the ability to fully understand or to even explore many relevant questions. For example, how do mergers (and/or the degree of competition) impact airline prices? What factors related to seat reservation fees impact customer purchasing behavior? Will the debundling trend dilute revenues to the U.S. Airport and Airways Trust Fund? How do daily flight prices (and competitor prices/promotions) influence daily demand?

With the emergence of online booking, there is a new opportunity to collect detailed data. Several firms, such as QL2® and Infare Solutions collect pricing data from online and from other channels and sell this data to airlines. In turn, airlines use this information to inform their day-to-day pricing and revenue management decisions. Airline websites can be used to compare airlines' product offerings and fee policies for ancillary services, which provides important insights into how different carriers are approaching ancillary revenues. Airline websites can also be used to track the prices of multiple airlines over the booking horizon, which provides insights into airlines' competitive pricing strategies across different market structures (such as monopolies versus more competitive markets). Airline websites can also provide insights into how different airlines respond when a competitor drops or increases prices. Further, airline websites can be used to track online seat maps. By looking at the daily changes of "reserved" vs. "available" seats displayed to customers on online seat maps, an estimate for daily flight-level bookings (a measure of demand) can be captured. By leveraging the internet, disaggregate databases can be used to explore research questions at a finer level of detail.

1.2. Research Objectives

There are four main research objectives of this dissertation. Each objective is related to leveraging online data to better understand airline pricing and product strategies, and how these strategies impact customers, as well as the industry in general.

The first research objective is to study the relationship between airline prices and competitive market structures (such as monopolies, duopolies, and oligopolies both with and without low cost carrier competition). With so much recent industry consolidation, it is important to understand how competition among air carriers impacts prices offered to customers, as this relationship will directly impact the formation of future policies associated with competition policy (anti-trust), deregulation, and mergers. As part of this objective, airline pricing is analyzed using a dataset of disaggregate online pricing data for 62 markets across a range of different market structure types.

The second objective is to identify and review product debundling trends that have recently occurred in the U.S. airline industry. Information pertaining to carriers' products is obtained from airline websites and implications of multiple sources of ancillary fees (related to ticketing refunds and exchanges, checked baggage, on-board pets, preferred and/or advanced seating assignments, frequent flyer ticket redemptions, and day of departure standby policies) are discussed. Part of this objective is to better understand how product offerings are changing, and to better understand how these trends may potentially impact the industry, such as diluting revenues to the U.S. Airport and Airways Trust Fund and impacting other system performance objectives (such as minimizing the number of misconnecting passengers).

The third objective focuses on one debundling trend that has been widely adopted by U.S. airlines: seat reservation fees. The objective is to investigate factors that influence airline customers' premium coach seat purchases and to estimate revenue impacts of different seat pricing strategies. Using a database of online prices and seat map displays collected from JetBlue's website, a binary logit model is used to estimate the probability of purchasing a premium coach seat with extra legroom, given that a ticket was purchased. Variables included in the analysis include the amount of the seat fee, how far in advance the ticket is purchased, the number of passengers traveling together, and load factors (as revealed through seat map displays). The model results are used to estimate revenue impacts associated with different pricing structures, such as dynamically pricing seats as a function of time until flight departure.

The fourth, and final, objective has two interrelated parts. The first piece of the objective is to determine whether it is possible to use online prices and seat maps to build detailed flight-level models of daily bookings. However, within the airline industry, most demand studies have failed to address price endogeneity and have assumed that prices are exogenous, which contradicts basic economic theory of supply and demand[4]. Failing to address price endogeneity can lead to models with biased coefficient estimates, which can be misleading when making policy decisions. Therefore, price endogeneity is an important methodological consideration that must be addressed. The second piece of the objective is to correct for price endogeneity in the demand model by finding a valid set of instrumental variables that can be used with instrumental variable estimation methods, such as two-stage least squares regression. Instrumented variable methods allow for consistent parameter estimation when an endogenous variable is present. Price elasticities can then be estimated across different dimensions of the data, including advanced purchase ranges.

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[4] Price endogeneity will be discussed in more detail later in Chapter 5. Basically, price is endogenous when price influences demand, but demand also influences price. We know that airlines use revenue management strategies that set prices in response to changes in demand, indicating that prices should be endogenous. Assuming that price is exogenous assumes that demand does not influence price, which is not the case in most economic models of supply and demand.

1.3. Major Contributions

There are several major contributions of this dissertation. Perhaps most importantly from a public policy perspective, this dissertation demonstrates the importance of disaggregate data that describe individual airline behavior and prices. Much public policy discussion and analysis relies on average market values that can hide important market behavior. With the advent of internet-based ticketing, a powerful tool now exists that can be used to understand some of the finer detail of airline markets and competition. This enhances the ability of regulators, government officials, academics and airlines to better understand issues related to fares and customer service and to make more informed decisions and/or policies.

Another major contribution is in respect to the recent product debundling trends that have occurred in the U.S. airline industry. Specifically, we estimate that the debundling phenomenon has diluted revenues to the U.S. Airport and Airways Trust Fund (AATF) by at least five percent. This is important as the AATF finances investments in the airport and airway system. The AATF was established as a source of funding that would increase concurrently with the use of the system, and assure timely and long-term commitments to capacity increases. The finding that debundling has diluted revenues to the AATF means that policy-makers may need to consider taxing ancillary fees in the future in order to maintain the viability of the fund.

Another major contribution provides several new behavioral insights into seat reservation fees. Seat fees are currently causing tensions among customers, regulatory agencies, and airlines. Customers and regulatory agencies are focusing on the importance of fee transparency and fairness, but airlines want to add complexity to further differentiate fees across customer groups (e.g., by blocking premium seats for preferred customers) so as to capture more of the consumer surplus. We find that customers are between 2 and 3.3 times more likely to purchase premium coach seats (with extra legroom and early boarding privileges) when there are no regular coach window or aisle seats that can be reserved for free, suggesting that the ability of airlines to charge seat fees is strongly tied to load factors. In an environment in which load factors are high, the airlines' ability to generate revenues from seat fees is strong. However, in the future if load factors decrease, we would expect that the incremental revenues generated from seat fee reservations would also decrease, which is something that airlines should consider before investing in reconfigurations of airplane seats. We also find that customers who purchase tickets closer to the departure date are willing to pay higher seat fees. We use these model results to show that JetBlue's seat fees are currently underpriced in many markets; an optimal static fee would increase revenues by 8 percent whereas optimal dynamic fees would increase revenues by 10.2 percent. In addition, if JetBlue were to leave their seat fees unchanged and instead blocked certain rows of seats for premier customers, they could potentially increase revenues by 12.8%. This finding underscores the importance of ensuring customers are not inadvertently misled into purchasing premium seats by seat map displays that block seats for premier customers.

Another major contribution is in modeling daily bookings and estimating airfare price elasticities using daily online prices and seat maps from airline websites. Using this data, we estimate airfare price elasticity using ordinary least squares (OLS) regression without correcting for price endogeneity and two-stage least squares (2SLS) regression which corrects for endogeneity. Results show the importance of correcting for price endogeneity. In particular, models that do not correct for endogeneity find inelastic demand estimates whereas models that do correct for endogeneity find elastic demand estimates. This is important, as pricing recommendations differ for inelastic and elastic models. Further, a set of instruments are found to pass validity tests and can be used in future models of daily flight-level demand. To our knowledge, this is the first time online seat maps have been used to estimate price elasticities, and this is also one of the first studies to correct for price endogeneity in models of airline demand.

1.4. Dissertation Structure

The chapters of this dissertation are written in journal format. Each chapter begins with an abstract, followed by background and motivation for the research, a discussion of methodologies used, and main findings. Each chapter concludes with a discussion of implications (for public policy, customers, and/or airlines), future research directions, and a list of referenced literature.

Chapter 2 explores competitive airline pricing policies in markets with different types of competitive market structures using a dataset of online prices from 2007. This chapter was published in *Transportation Research Record* as part of the Airport Cooperative Research Program's Graduate Research Award Program on Public-Sector Aviation Issues (Mumbower and Garrow, 2010).

Chapter 3 reviews product debundling trends that were quickly being implemented in the airline industry in 2009-2010 (Garrow, Hotle and Mumbower, 2012). Chapter 4 focuses on one popular debundling trend, seat reservation fees, and models airline customers' premium coach seat purchases using a database of online prices and seat maps collected from JetBlue's website in 2010. Revenue implications for optimal pricing strategies are further explored (Mumbower, Garrow and Newman, 2013).

Chapter 5 reviews the concept of price endogeneity in demand models, discusses endogeneity bias, and explains how instrumental variable methods can be used to correct for price endogeneity. Chapter 6 uses the methods discussed in Chapter 5 to correct for price endogeneity in linear models of disaggregate flight-level demand. Price elasticities are then estimated across several dimensions of the data, including different advance purchase ranges.

This dissertation also includes Appendix A, which provides more detailed information about an online dataset of competitor prices that was compiled using automated web client robots. This dataset was used to formulate the set of instrumental variables used to correct for endogeneity in the demand models of Chapter 6. We hope to address research gaps by making this dataset publically available for other researchers to use (Mumbower and Garrow, 2013). The dataset contains pricing information over a four week booking horizon for 42 U.S. markets and 21 departure dates in September of 2010, which amounts to over 228,000 price observations.

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CHAPTER 2: COMPETITIVE AIRLINE PRICING POLICIES

Mumbower, S. and Garrow, L.A. (2010) Using online data to explore competitive airline pricing policies: A case study approach. *Transportation Research Record: Journal of the Transportation Research Board*, 2184, 1-12.

2.1. Abstract

Since the mid 2000's, the airline industry has seen volatile fuel prices, a record number of carriers ending service, and a merger between two major airlines. In a time of such turmoil in the industry it is increasingly important to understand the relationship between airline consolidation and competitive pricing policies, as this relationship will directly impact the formation of future airline policies associated with competition policy (anti-trust), deregulation, and mergers. However, there is a lack of consensus about market concentration and its influence on airfares, mainly due to data limitations of past research. Given the emergence of online booking engines, there is a new opportunity to collect detailed fare data. This project uses disaggregate, online airfare data to study the relationship between market concentration and pricing policies. The dataset includes 62 markets that cover a broad range of market structures. A case study approach is used to analyze the data. Using disaggregate fare data, this study finds low price dispersion can be associated with both low and high levels of market concentration. As the day of departure approaches, price dispersion is seen to either increase or decrease, depending on the specific market. Additionally, peak and off-peak periods demonstrate differing pricing strategies. Also, markets with codeshares are shown to sometimes exhibit unusually high price dispersion.

2.2. Background

Since its deregulation in 1978, the airline industry has seen a large number of changes. Low cost carriers (LCCs) have penetrated the market and generally offer lower prices than legacy carriers, mainly due to their significantly lower operating costs[5]. Between 2000 and 2008, the number of domestic passengers served by LCCs grew at an average annual rate of 11 percent, while during this same time period many legacy carriers experienced declining figures. Also during this time period, LCCs increased their weekly departures and cities served by 60 percent. In the third quarter of 2007, Southwest Airlines (the largest LCC) alone carried more domestic passengers than any other airline. Although LCCs traditionally target leisure passengers, this has even begun to change. More and more, LCCs are starting to target business passengers by flying in heavily traveled business routes. It is apparent that competition in the airline industry has been transformed by LCCs. (Steenland, 2008)

In addition to LCCs, the internet has also transformed the airline industry. On-line travel agents such as Expedia®, Orbitz®, and Travelocity® make it convenient for customers to search the prices of multiple airlines across multiple departure dates. Customers can find and purchase the lowest possible fare in a matter of minutes. In fact, 60 percent of leisure travelers purchase the lowest fare they can find (Harteveldt et al., 2004; PhoCusWright, 2004). In a May 2008 testimony to the House Committee on

[5] See a book by Cento (2000) for detailed information about the differences between the business models of legacy carriers and LCCs.

Transportation and Infrastructure (Subcommittee on Aviation) about the impact of the Delta and Northwest merger, Former President and CEO of Northwest Airlines, Doug Steenland, refers to the internet as a “transparency revolution” and goes on to state that online travel agencies “…have provided enormous benefits to consumers and have increased the price-competitiveness of the airline industry. In fact, there are few businesses in which there is as much pricing transparency.” (Steenland, 2008)

The growth of LCCs combined with the increased transparency of airfares has led, at least in part, to lower average prices in the airline industry. Between 1995 and 2004, the prices that passengers paid for tickets declined by more than 20 percent after adjusting for inflation[6] (Borenstein, 2005). While decreased prices are good for consumers, its implications on airlines are quite the opposite. Airline operating costs have increased dramatically over the last few years, but airlines have not been able to increase fares to match rising costs. In the first quarter of 2009, U.S. network carriers reported a total operating loss of $867 million, which was the sixth consecutive quarterly loss (Bureau of Transportation Statistics, 2009). Between 2002 and 2008, four major carriers filed for bankruptcy protection (Delta Air Lines, Northwest Airlines, United Airlines, and US Airways). In addition, ATA Airlines, Skybus Airlines, and Aloha Airlines filed for bankruptcy and ended service. Frontier Airlines has also filed for bankruptcy but has not

[6] It should be noted that during this time period, the airline industry faced an economic slowdown in 2000, along with the terrorist attacks of September 11, 2001.

ended service, and in 2008 Delta and Northwest merged in an effort to become more financially stable.

2.3. Price Dispersion Literature

With the current state of the airline industry, it is not surprising that there has been a great deal of interest in studying the effect of airline consolidation on airfares. In the past, many researchers have studied how market structure affects the dispersion of airfares, often called price dispersion. Price dispersion has been defined in many ways by different researchers and is specific to the unit of observation of analysis. However, price dispersion can generally be thought of as the difference between an airline's highest and lowest fares in a market. The interest in price dispersion of airfares was sparked when Borenstein (1989) used government data sources to show that there is a negative relationship between market concentration and price dispersion, meaning that as a route becomes more dominated by one airline and moves closer towards monopoly the price dispersion decreases . More specifically, he found that as a route moves closer towards a monopoly, an air carrier's low-end fares increase while high-end fares decrease, thus decreasing the overall dispersion of prices (while increasing average prices). Over the next several years, other researchers also used U.S. government data sources to study this relationship empirically, with findings that supported the negative relationship between market concentration and price dispersion (Borenstein and Rose, 1994; Hayes and Ross, 1998; Verlinda and Lane, 2004). A theoretical model also supported this relationship by Dana (1999). These researchers also found many other factors that influence the dispersion of prices. For instance, it has been shown that price dispersion increases with increased airport dominance (Borenstein and Rose, 1994), airport congestion (Borenstein and Rose, 1994), and internet search for airfares (Verlinda and Lane, 2004). These researchers also found that price dispersion decreases with increased frequency of flights on a route (Borenstein and Rose, 1994), higher levels of tourist traffic (Borenstein and Rose, 1994), and competition from Southwest (Hayes and Ross, 1998).

The negative relationship between market concentration and price dispersion has been contradicted, however, in at least two more recent studies that use the same government data sources and analyze the data differently. In past studies, the modeling approach was to take millions of available records and aggregate them into one unique observation by carrier-route for each quarter. In doing this, these records would be aggregated to a few thousand records that were used for analysis. However, Verlinda (2005) used one quarter of the government data to demonstrate that the data could be analyzed disaggregately without collapsing the data into average carrier-route observations. In doing so, a positive relationship between market concentration and price dispersion is found. Another study using government data also finds a positive relationship between market concentration and price dispersion, although the change in relation is attributed not to the aggregated method of analysis, but to omitted-variable bias present in other studies, which the authors correct for using an instrumental variables approach (Gerardi and Shapiro; 2007).

Yet another conflicting finding is that the relationship between market concentration and price dispersion is not strictly positive or negative, but is non-monotonic, inverse U-shaped (Liu and Serfes, 2006). The authors of this study provide a theoretical model, as well as an empirical model using government data sources, to demonstrate the non-monotonic relationship. In this model, an increase in market concentration when the market is already competitive will result in higher price dispersion while an increase in market concentration when the market is already concentrated enough will result in lower price dispersion.

As seen from this literature, there are many conflicting theories related to airline price dispersion, and the method of analysis greatly influences the findings. One reason why there are so many conflicting theories of price dispersion is the data that is being used. Government data sources for airfares are considered aggregate data in that they summarize and/or randomly sample a small portion of all tickets sold. However, with the widespread use of the internet for booking tickets, there is an opportunity to collect much more detailed and disaggregate data. The use of disaggregate data can be used to resolve some of these conflicting theories. To date, there have been three studies of price dispersion using disaggregate data. However, two of these studies are for international markets that are not comparable to U.S. domestic markets (Bilotkach, 2005; Giaume and Guillou, 2004). The other study was analyzed on 12 routes and found a negative relationship between market concentration and price dispersion (Stavins, 2001). It is also important to point out that ticket observations used in the price dispersion literature differ across studies; some studies observe actual ticket purchases, while other studies observe offered tickets that may or may not have actually been purchased.

Table 2.1 provides a summary of the price dispersion literature and includes information about: the relationship between market concentration and price dispersion, whether the data used was aggregate or disaggregate, the data source and time period, the number of airlines and routes, the total number of observations, and other relevant notes about the data. As seen in the table, there have been few studies that use disaggregate data to study price dispersion, and these disaggregate studies are limited in the sense that they observe a small number of markets with a limited number of observations. There remains a research need to model the relationship between price dispersion and market concentration in a broad range of U.S. markets by using disaggregate data.

Table 2.1: Summary of Data Used in Price Dispersion Literature

Study	Market Concentration & Price Dispersion	Disagg Data?	Data Source and Time Period	Num Air-lines	Num Routes	Total Observ-ations	Data Notes and/or Limitations
Borenstein (*1989)*	Negative	No	DB1A:1987Q3, SSD	9	1,508	---	Airline-route observations
Borenstein & Rose (*1994)*	Negative	No	DB1A:1986Q2, OAG®	11	521	1,020	Airline-route observations
Hayes & Ross *(1998)*	Negative	No	DB1A:1990Q1-1992Q4, T100	15	973	14,652	Airline-route-year-quarter obs.
Stavins *(2001)*	Negative	**Yes**	OAG® (electronic version): 9/28/1995	---	12	5,804	Offered tickets observations
Giaune & Guillou *(2004)*	Negative	**Yes**	Amadeus System (a Global CRS)	17	20	2,592	Ticket observations; Nice, France to Europe markets; LCCs not included; 1 Departure Date: 10/16/02; 4 DFD: 22, 14, 7, 1 day(s)
Verlinda & Lane *(2004)*	Negative	No	DB1B:1998Q1-2002Q2, OAG®	---	25	---	Average fare by market-year-quarter-restriction type obs; do not observe fares by airline or airport, but by city market
Bilotkach *(2005)*	N/A - *fares aimed at business are more dispersed than leisure*	**Yes**	Travelocity® website: 3/5/2002- 4/ 23/2002	7	3	499	Offered tickets observations; London-New York market; 2 DFD/2 Day Stay; 2 DFD/10 Day Stay; 30 DFD/10 Day Stay
Verlinda *(2005)*	Positive	No	DB1A/B:2000Q1, T100, OAG®	14	1,428	773,811	Ticket observations; LCCs and Southwest included; Disaggregate analysis approach
Liu & Serfes *(2006)*	Non-monotonic (inverse U)	No	DB1A: Q2 of odd years 1991-1999, T100	---	946	7,104	Airline-route-year-quarter obs.
Gerardi & Shapiro *(2007)*	Positive	No	DB1B:1993Q1-2006Q3, T100	9	2,752	82,855	Airline-route-year-quarter obs. LCCs not included
This study *(2009)*		**Yes**	Airlines' websites: 11/15/2007-12/15/2007	12	62	108,632	LCCs and Southwest included; Codeshares represented

CRS = Computer Reservation System; DB1A/1B = U.S. DOT's Origin and Destination Survey Databank 1A/1B, a 10% random sample of all tickets sold in the U.S., includes market and pricing data; DFD = days from flight departure; LCC = Low Cost Carrier; OAG® = Official Airline Guide; Q = Quarter; T100 = Domestic Segment Data, gives information on capacity and frequency of service, published monthly; SSD = U.S. DOT's Service Segment Data, data on airline flight operations, submittal is required for airlines that operated before deregulation; "---" = information not available in the referenced report.

2.4. Methodology

Given the data limitations of past studies that used disaggregate data to study airfares, the goal of this paper is to study how certain characteristics of a market affect airfares by using a larger sample of U.S. domestic markets that cover a broad range of market structures. To the best of the authors' knowledge, the dataset used in this study represents the largest and most comprehensive disaggregate airline pricing database used to research airfares thus far.

2.4.1. Data

The data was collected in the fall of 2007 in collaboration with QL2® Software, one of the major U.S. companies that collects competitive pricing and product information from websites. In order to obtain data for Southwest Airlines, additional webbots were written by an academic team at Georgia Tech in order to supplement the data provided by QL2®. The data collected consists of prices for more than 100 U.S. markets for one month of departure dates, which were selected to represent periods of peak and off-peak demands (*i.e.*, Thanksgiving and early December 2007, respectively). Round-trip and one-way fares were recorded daily for at least 30 days prior to flight departure. Nonstop fares were obtained from each airline's website, while nonstop and connecting fares were obtained from at least one major online travel agency (Orbitz®, Travelocity® or Expedia®). For an especially detailed explanation of the data collection methodology and compilation, as well as a more specific account of the dataset, the reader is referred to (Pope, Garrow, et al., 2009).

A subset of the aforementioned dataset was chosen for data analysis in order to represent a wide variety of interesting market competition structures and airline competition effects, such as monopolies, duopolies, and competitive markets broken down into subcategories representing whether the markets have multi-airport effects and/or LCC presence. In defining these categories of market structures, only airlines that fly nonstop in a market were considered, thus all observations for connecting flights were eliminated. This is in following with the methodology of a number of other researchers (for example, Borenstein and Rose, 1994; Bilotkach, 2005; Bilotkach et al., 2006; Gerardi and Shapiro, 2007; Giaume and Guillou, 2004; Liu and Serfes, 2006; Verlinda, 2005; Verlinda and Lane, 2004) and is done for two reasons. Firstly, this ensures that the analysis is somewhat comparable to those of past studies. Secondly, eliminating connecting tickets makes the analysis far less complicated. This is due to the fact that connecting tickets represent significantly different qualities of service than direct tickets and controlling for the cost differences would be more complex. Additionally, only the lowest fares are included in the observations, which is also comparable to the methodology of other researchers (Bilotkach and Pejcinovska, 2007; Mentzer, 2000; Pels and Rietveld, 2004). Using the lowest observed fare controls for vertical price differentiation. Vertical price differentiation is the difference in prices due to the differing qualities of tickets (such as restricted vs. non-restricted tickets). By controlling for vertical differentiation, the analysis focuses on horizontal price differentiation, which is defined as the difference in prices due to the varying tastes of customers (such as brand preference, aircraft preference, etc). By focusing on the horizontal price differentiation, the analysis can capture the competitive impacts associated with price dispersion.

The final dataset that was used in this study consists of 108,632 observations for 62 airport-to-airport markets and 12 airlines. Each observation represents the lowest nonstop, round-trip fare that was offered by each airline flying nonstop in the market on the date that the website was queried and for each specific day of flight departure, assuming a one night stay. The major[7] airlines (with airline code) included are: American Airlines (AA), Alaska Airlines (AS), Continental Airlines (CO), Delta Air Lines (DL), Northwest Airlines (NW), United Airlines (UA), and US Airways (US), and the LCCs included are: Air Tran Airways (FL), Frontier Airlines (F9), JetBlue Airways (B6), Spirit Airlines (NK) and Southwest Airlines (WN). In addition, several codeshares are also represented and are denoted by the code of the marketing carrier followed by the code of the operating carrier in parenthesis. The codeshares represented include: AA (AS), AS (AA), NW (AS), UA (US), and US (UA). Table 2.2 lists the airports included in the dataset, along with the airport codes used throughout this paper.

[7] These airlines are network carriers, which are referred to as "major" carriers throughout the rest of the paper.

Table 2.2: Airport Codes and Names

Airport Code	Name of Airport, City and State
ATL	Hartsfield-Jackson International Airport, Atlanta, Georgia
BOS	Logan International Airport, Boston, Massachusetts
BWI	Baltimore-Washington International Thurgood Marshall Airport, Baltimore, Maryland
COS	City of Colorado Springs Municipal Airport, Colorado Springs, Colorado
DAL	Dallas Love Field Airport, Dallas, Texas
DCA	Ronald Regan Washington National Airport, Washington D.C.
DEN	Denver International Airport, Denver, Colorado
DFW	Dallas/Fort Worth International Airport, Dallas-Fort Worth, Texas
DSM	Des Moines International Airport, Des Moines, Iowa
DTW	Detroit Metropolitan Wayne County Airport, Detroit, Michigan
EWR	Newark Liberty International Airport, Newark, New Jersey
FLL	Fort Lauderdale Hollywood International Airport, Fort Lauderdale, Florida
FNT	Bishop International Airport, Flint, Michigan
GSO	Piedmont Triad International Airport, Greensboro, North Carolina
GTF	Great Falls International Airport, Great Falls, Montana
HOU	William P. Hobby Airport, Houston, Texas
IAD	Washington Dulles International Airport, Washington D.C.
IAH	George Bush Intercontinental Airport, Houston, Texas
ICT	Wichita Mid-Continent Airport, Wichita, Kansas
IND	Indianapolis International Airport, Indianapolis, Indiana
JFK	John F. Kennedy International, New York City, New York
LAS	McCarran International Airport, Las Vegas, Nevada
LAX	Los Angeles International Airport, Los Angeles, California
LGA	La Guardia Airport, New York City, New York
MCO	Orlando International Airport, Orlando, Florida
MDW	Chicago Midway International Airport, Chicago, Illinois
MEM	Memphis International Airport, Memphis, Tennessee
MHT	Manchester-Boston Regional Airport, Manchester, New Hampshire
MIA	Miami International Airport, Miami, Florida
MSP	Minneapolis-Saint Paul International Airport, Minneapolis, Minnesota
OAK	Oakland International, Oakland, California
OMA	Eppley Airfield Airport, Omaha, Nebraska
ORD	Chicago O'Hare International Airport, Chicago, Illinois
PDX	Portland International Airport, Portland, Oregon
PHL	Philadelphia International Airport, Philadelphia, Pennsylvania
PVD	Theodore Francis Green State Airport, Providence, Rhode Island
SFO	San Francisco International Airport, San Francisco, California
STL	Lambert-St. Louis International Airport, St. Louis, Missouri

2.4.2. Analysis of Data

When analyzing the data, it was apparent that any level of aggregation only served to hide some of the most interesting observations in the dataset. Airline pricing policies in the dataset vary greatly by airline, market, peak/off peak time periods, and the number of days from departure. Thus, it was inappropriate to analyze the data in a way that would aggregate some of these important variables. Because of this, a case study approach was taken instead of a regression type approach.

An additional challenge that was encountered was determining which measure to use for price dispersion. Four measures of price dispersion were investigated. These included the standard deviation of fares, the coefficient of variation (standard deviation normalized by the mean), the range of fares (the difference between the highest and lowest fares), and the interquartile range (the difference between the 75^{th} and 25^{th} percentile fares). Each price dispersion measure gave different results about the magnitude of price dispersion in the market. Table 2.3 lists the 62 markets (denoted by the three letters of the origin airport followed by the three letters of the destination airport) used in this analysis, along with the airlines that fly nonstop in each market. Table 2.3 also includes the mean, standard deviation (SD), interquartile range (IQR), coefficient of variation (CV), and range for each market as reference.

Table 2.3: Markets, Airlines, and Summary Statistics

Market	Airlines	Mean	SD	IQR	CV	Range	Roundtrip Miles
ATLEWR	CO, DL, FL	$299	$117	$128	0.39	$526	1,490
ATLICT	DL, FL	$294	$115	$164	0.39	$682	1,554
ATLJFK	DL	$332	$138	$147	0.42	$546	1,520
ATLLGA	AA, DL, FL	$309	$122	$135	0.39	$576	1,522
ATLOMA	DL	$1,046	$308	$100	0.29	$1,240	1,640
BOSBWI	DL, FL	$225	$125	$216	0.56	$682	736
BOSDCA	AA, DL, US, UA (US)	$417	$186	$273	0.45	$1,093	796
BOSIAD	UA, B6, US (UA)	$261	$83	$100	0.32	$1,100	822
BOSMCO	DL, FL, B6	$310	$136	$174	0.44	$830	2,240
BWIDFW	AA	$375	$168	$140	0.45	$944	2,420
BWIPVD	WN	$126	$32	$15	0.25	$130	652
DALHOU	WN	$128	$33	$43	0.26	$136	478
DCADFW	AA, US	$379	$180	$167	0.47	$1,110	2,380
DENGTF	UA	$723	$168	$88	0.23	$995	1,246
DENOAK	UA, WN	$288	$118	$226	0.41	$597	1,908
DENSFO	UA, F9, US (UA)	$377	$121	$172	0.32	$525	1,930
DFWCOS	AA	$307	$87	$118	0.28	$426	1,184
DFWHOU	AA	$192	$51	$53	0.27	$344	496
DFWIAH	AA,CO	$159	$48	$62	0.3	$206	450
DTWBWI	NW, WN	$159	$68	$51	0.43	$465	816
DTWDCA	NW, US	$224	$118	$79	0.53	$866	810
DTWIAD	NW, UA	$243	$116	$52	0.48	$840	766
EWRDFW	AA, CO	$560	$366	$333	0.65	$1,390	2,740
EWRDTW	CO, NW	$666	$219	$341	0.33	$860	972
EWRFLL	CO, B6	$223	$99	$130	0.44	$465	2,140
EWRMCO	CO, B6	$235	$101	$160	0.43	$440	1,876
FNTLAS	FL	$266	$72	$79	0.27	$350	3,460
IADDFW	UA, AA	$430	$204	$224	0.47	$1,076	2,340
IAHDSM	CO	$921	$257	$284	0.28	$930	1,606
INDEWR	CO	$628	$201	$361	0.32	$681	1,282
INDJFK	DL	$440	$203	$270	0.46	$886	1,324
INDLGA	NW, US	$362	$157	$147	0.43	$920	1,314
JFKDFW	AA, DL	$538	$357	$339	0.66	$1,497	2,780
JFKDTW	DL, NW	$348	$150	$110	0.43	$900	1,014
JFKFLL	DL, B6	$253	$96	$80	0.38	$625	2,140
JFKMCO	DL, B6	$252	$96	$80	0.38	$1,180	1,890

Table 2.3: Markets, Airlines, and Summary Statistics (Continued)

Market	Airlines	Mean	SD	IQR	CV	Range	Roundtrip Miles
LASLAX	AA, AS (AA), DL, NW, UA, US, WN	$180	$76	$80	0.42	$636	472
LAXDEN	AA, F9, AS (AA), UA, DL, US (UA)	$333	$104	$67	0.31	$1,042	1,720
LGADFW	AA	$537	$370	$309	0.69	$1,518	2,780
LGADTW	AA, NW, NK	$302	$144	$106	0.48	$1,016	1,000
LGAFLL	AA, DL, NK, B6	$290	$177	$150	0.61	$1,329	2,160
MDWDTW	NW, WN	$146	$42	$56	0.29	$302	454
MDWEWR	CO	$324	$128	$140	0.4	$651	1,416
MDWMIA	FL	$253	$114	$120	0.45	$610	2,360
MEMGSO	NW	$675	$296	$622	0.44	$1,052	1,136
MHTBWI	WN	$144	$37	$50	0.26	$130	752
MIADCA	AA	$338	$208	$115	0.62	$1,108	1,842
MIAIAD	AA, UA	$411	$248	$378	0.6	$1,268	1,846
MSPMDW	NW, FL	$143	$45	$40	0.31	$268	696
MSPORD	AA, NW, UA, US (UA)	$166	$105	$50	0.63	$1,409	666
ORDDTW	UA, NW, AA, US (UA)	$167	$48	$55	0.29	$292	468
ORDEWR	AA, UA, CO	$306	$98	$84	0.32	$557	1,434
ORDJFK	AA, DL, B6	$264	$114	$75	0.43	$810	1,474
ORDLGA	AA, UA	$273	$95	$110	0.35	$628	1,462
ORDMIA	AA, UA, US (UA)	$362	$198	$210	0.55	$1,041	2,400
PDXSFO	AA (AS), AS, NW(AS), UA, US (UA)	$276	$89	$92	0.32	$1,056	1,102
PHLMCO	FL, US, UA (US), WN	$250	$101	$83	0.4	$788	1,726
PHLMHT	UA (US), WN, US	$197	$138	$83	0.7	$961	576
PHLPVD	UA (US), WN, US	$210	$154	$99	0.73	$664	472
STLEWR	AA, CO	$521	$320	$337	0.61	$1,284	1,738
STLJFK	AA, DL	$562	$334	$400	0.59	$1,466	1,778
STLLGA	AA	$412	$210	$99	0.51	$1,333	1,770

2.5. Case Studies

In order to investigate the effect of market structure on airfares, the sample of 62 markets was grouped according to the specific type of market structure that was observed on the route. Table 2.4 lists each of the market types (monopoly, duopoly and competitive), along with subcategories for each. The table discusses some of the results that were found for each market structure with respect to the general pricing strategies observed in the market, the specific carrier pricing strategies that seemed to stand out, and the degree of price dispersion observed. The table shows that pricing within a market is greatly influenced by many different characteristics of the market, including the presence of a LCC, the presence of multi-airport effects, leisure and business mix of passengers, temporal effects as the day of departure approaches, advance purchase (AP) restrictions, and the influence of demand (as exemplified in differences in pricing strategies between peak and non-peak periods). For space considerations, only the most interesting market structures and characteristics are chosen for detailed analysis. These sections are discussed in detail below.

Table 2.4: The Effect of Market Structure on Pricing Strategies and Price Dispersion

Markets and Structure	General Pricing Strategies	Carrier Strategies	Price Dispersion (PD)
1. Monopoly Markets (Only One Carrier Flies Nonstop)			
1a. One Major Carrier Only (without multi-airport effects): ATLOMA, DENGTF, DFWCOS, IAHDSM, MEMGSO	Generally exhibit the highest mean fares of all 62 markets. Mean fares have drastic increase as departure approaches for most markets.	PD differs by carrier: increases for some markets and decreases for others as departure approaches.	Has some of the highest standard deviations and lowest CV out of all markets (except DFWCOS, a leisure market with low PD).
1b. One Major Carrier Only (with multi-airport effects): ATLJFK, BWIDFW, INDEWR, INDJFK, LGADFW, MDWEWR, MIADCA, STLLGA, DFWHOU	Lower mean fares than major carrier monopolies without multi-airport effects. Mean fares similar to mean fares of duopolies with no LCC and similar round-trip distance.	AP restrictions apparent for most markets and carriers. AA's pricing out of LGADFW demonstrates the clearest AP restrictions.	Mid to high PD out of the 62 markets (except DFWHOU, which is short-haul with low PD, and LGADFW, which has highest PD out of all markets). Peak/off-peak trends vary greatly.
1c. One LCC Only: FNTLAS, BWIPVD, MDWMIA, MHTBWI, DALHOU	Flat prices as departure approaches. Mean fares tend to be lowest out of 62 markets, even for long-haul markets FNTLAS and MDWMIA.	WN pricing curves are flat as departure approaches. FL pricing curves are more dynamic.	PD tends to be the lowest out of the 62 markets and stays relatively constant or decreases slightly as departure approaches.
2. Duopolies (Two Carriers Fly Nonstop)			
2a. Two Major Carriers (No LCC): DCADFW, DFWIAH, DTWDCA, DTWIAD, EWRDFW, EWRDTW, IADDFW, INDLGA, JFKDFW, JFKDTW, MIAIAD, ORDLGA, ORDMIA, PDXSFO, STLEWR, STLJFK	Has some of the lowest and highest means out of the 62 markets. Round-trip mileage seems to play a role, but not always: EWRDTW has highest mean of this group, but has one of the lower round-trip mileages.	AP restrictions apparent. AA and CO have most clear AP restrictions, UA and US have flatter pricing. DL exhibits dynamic pricing, but AP not as apparent.	PD varies significantly by market, ranging from especially low (DFWIAH, PDXSFO, ORDLGA) to especially high (STLEWR, STLJFK, JFKDFW, EWRDFW).
2b. One Major Carrier, One LCC: ATLICT, BOSBWI, BOSIAD, DENOAK, DENSFO, DTWBWI, EWRFLL, EWRMCO, JFKFLL, JFKMCO, MDWDTW, MSPMDW, PHLMHT, PHLPVD	Mean fares tend to be lower than mean fares of duopolies without LCC competition.	AP restrictions apparent in almost every market, for every carrier, including LCCs WN, B6, FL and F9.	Mid to low PD. PD trend seems to correspond with AP restrictions. PD trends vary greatly in peak/off-peak for BOSIAD, JFKMCO, and PHLMHT.

Notes: AP=Advance Purchase; CV=Coefficient of Variation; PD =Price Dispersion

Table 2.4: The Effect of Market Structure on Pricing Strategies and Price Dispersion (Continued)

Markets and Structure	General Pricing Strategies	Carrier Strategies	Price Dispersion (PD)
3. Competitive Markets (Two or More Carriers Fly Nonstop)			
3a. Three Major Carriers (No LCC): BOSDCA, MSPORD, ORDDTW, ORDEWR	Flat pricing as departure approaches for most markets. Low mean fares in MSPORD and ORDDTW. Mid to high mean fares for other markets.	Pricing strategies are similar across airlines within each market, with the exception of US (UA) codeshare in MSPORD.	PD low for most markets, except MSPORD. The US (UA) codeshare in MSPORD has an especially high PD.
3b. Two or More Major Carriers, One LCC: ATLEWR, ATLLGA, LAXDEN, LASLAX, LGAFLL, ORDJFK, LGADTW	Mid to low mean fares out of 62 markets.	Similar pricing strategies across airlines within a market. DL has dynamic pricing in LAXDEN.	Mid PD for most markets, except LASLAX which is a short-haul market with low PD.
3c. One Major Carrier, Two LCCs: BOSMCO, PHLMCO	Mid mean fares out of the 62 markets.	Similar pricing strategies across airlines within each market. DL is more dynamic.	Mid PD. PD trends are similar for peak/off-peak periods and are rather flat as departure approaches.

Notes: AP=Advance Purchase; CV=Coefficient of Variation; PD =Price Dispersion

2.5.1. The Case of Advance Purchase Restrictions

Evidence of advance purchase price restrictions was found in several markets in the sample. Here we compare two markets that both originate at Lambert-St. Louis International Airport in St. Louis, Missouri. The market from St. Louis to Newark Liberty International Airport in Newark, New Jersey (STLEWR) has a step-like trend as the day of departure approaches, indicating that prices change in increments as the day of the flight departure nears. Figure 2.1 demonstrates price dispersion for each airline as the range of fares (defined as the difference between the maximum and minimum lowest daily nonstop airfares observed for each carrier for the set of departure dates) as the day of departure approaches[8]. The peak and off-peak periods have been separated to illustrate how demand influences price dispersion. For this market, the off-peak period for both AA and CO have a step-like trend, indicating the presence of advance purchase restrictions. This implies that the airlines are trying to distinguish between business and leisure customers. However, a step-like movement of prices is less obvious for the peak period in this market, as the movement of prices is more dynamic. On the other hand, the market from St. Louis to John F. Kennedy International Airport in New York City (STLJFK) has advance purchase requirements that are not as obvious in either the peak or off-peak periods.

[8] In all of the following figures, price dispersion is defined in the same way: as the range of fares (i.e., the difference between the maximum and minimum lowest daily nonstop airfares observed for each carrier for the set of departure dates) as the day of flight departure approaches.

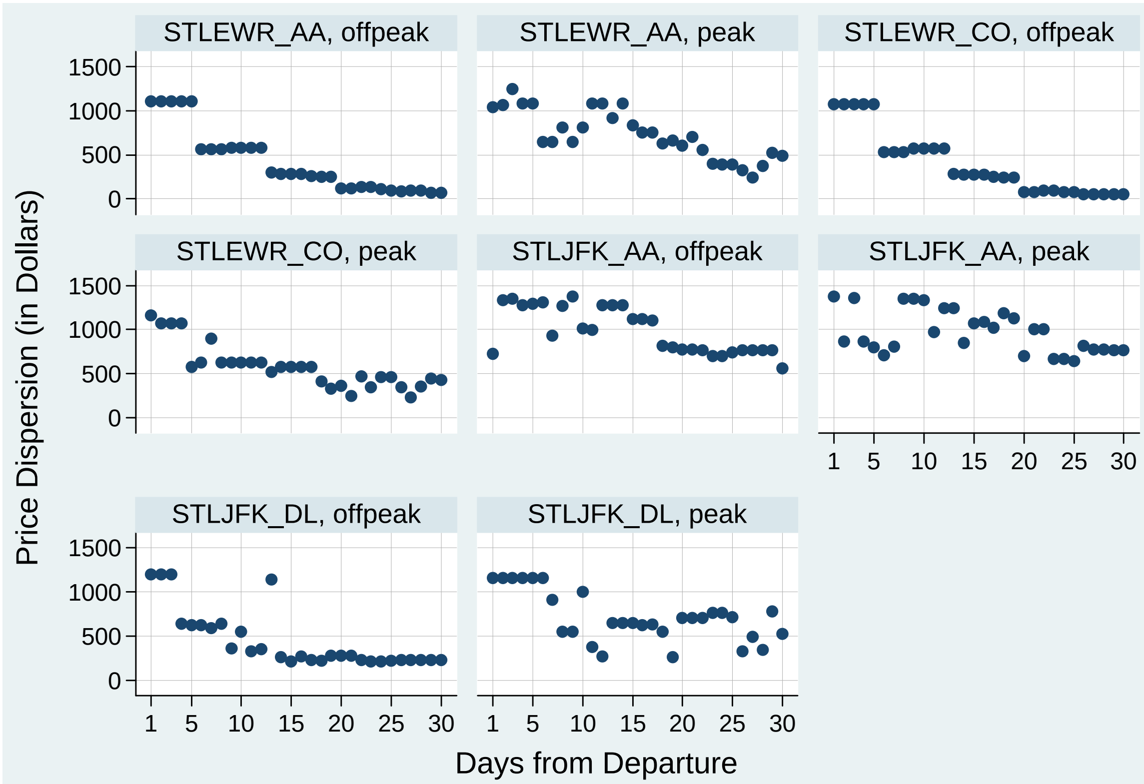

Figure 2.1: Price Dispersion by Market, Airline, Peak/Off-Peak for Two Markets with Advance Purchase Trends

2.5.2. The Case of Business vs. Leisure Markets

Differences between pricing in business and leisure markets were observed in the data. Chicago to New York markets represent a predominately business route and includes ORDEWR, ORDJFK, and ORDLGA. New York to Florida markets represent predominately leisure routes and include EWRFLL, EWRMCO, JFKFLL, and JFKMCO. The Chicago to New York and New York to Florida markets were chosen for analysis due to the similar round-trip distances across the markets, as well as the presence of a LCC (JetBlue) in the markets. In comparing the business and leisure routes, the overall means of each market are similar, with the business routes exhibiting slightly higher average prices (as shown in the "Mean" column of Table 2.3). The overall price dispersions of both the business and leisure routes are also quite similar (as shown in the SD, IQR, CV, And Range columns of Table 2.3). The main difference between the business and leisure routes is the different pricing trends observed during the peak and off-peak periods, which is demonstrated in Figures 2.2 and 2.3 (note that both figures have the same Y-axis scale for comparison purposes). Figure 2.2 shows that in the business markets, the peak pricing is dynamic and is different than the flatter pricing observed in the off-peak period. On the other hand, Figure 2.3 shows that in the leisure markets, the peak pricing is less dynamic and is similar to the flat pricing observed during the off-peak period. An additional observation is that when looking at the carrier-level effects, JetBlue seems to demonstrate less dynamic pricing than the major carriers (AA, CO, UA, DL).

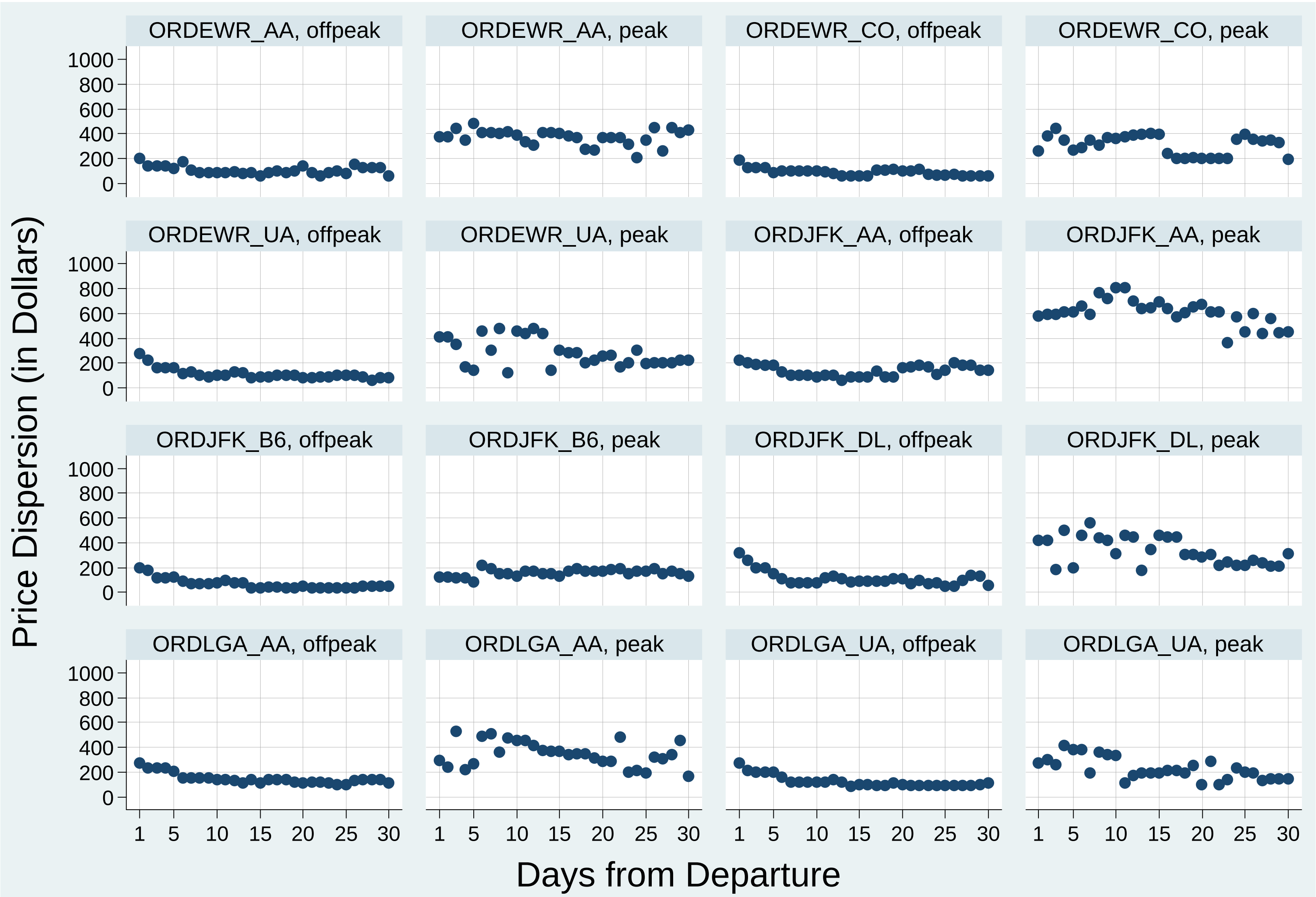

Figure 2.2: Price Dispersion by Market, Airline, Peak/Off-Peak for Chicago to New York Markets (Business Markets)

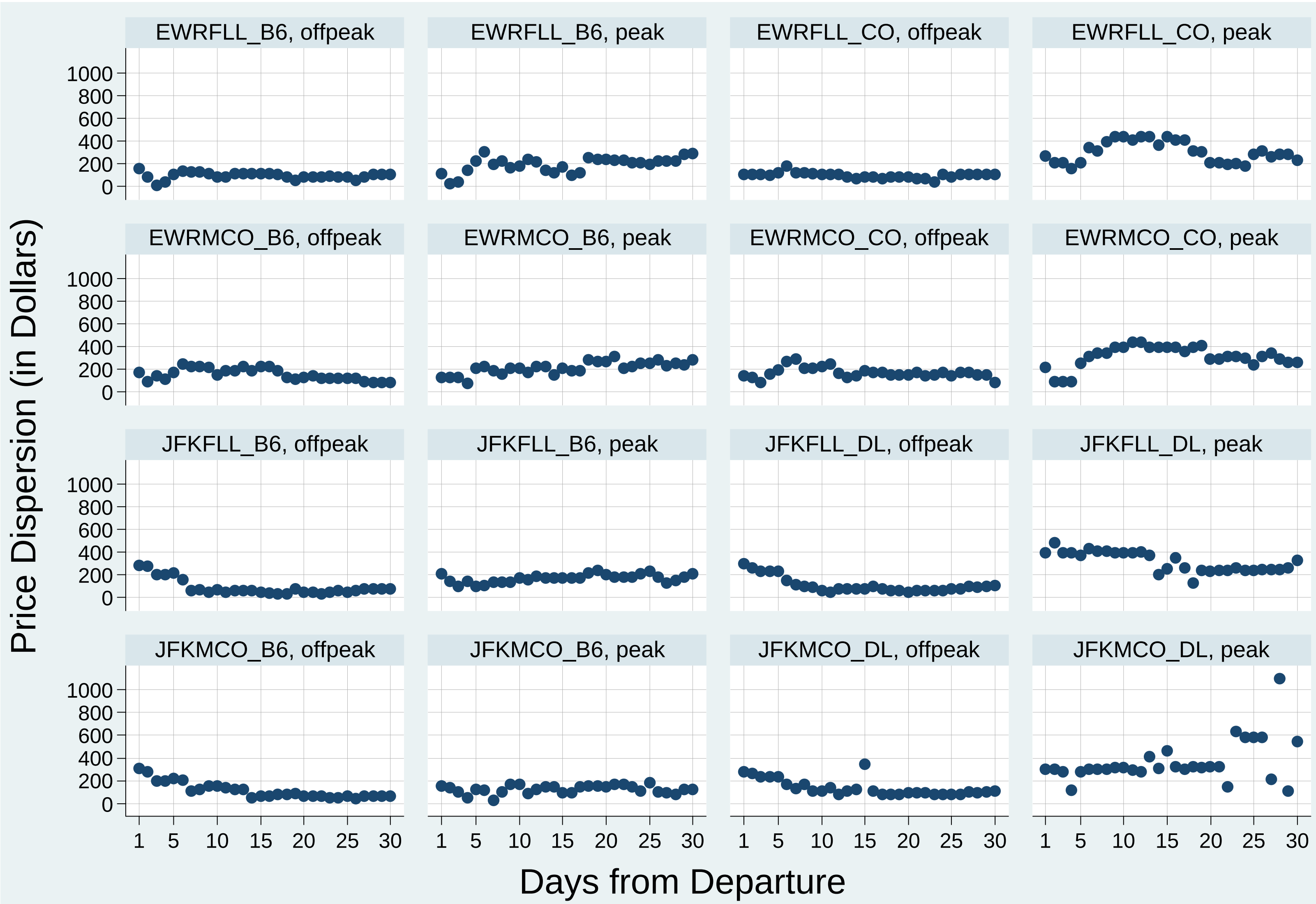

Figure 2.3: Price Dispersion by Market, Airline, Peak/Off-Peak for New York to Florida Markets (Leisure Markets)

2.5.3. The Case of Codeshare Markets

In the sample of 62 markets, codeshares were represented for 12 markets. In some of these markets, the marketing carrier seemed to mimic the pricing strategies of the operating carrier. However, there were two extreme cases where this was not the case. When comparing MSPORD and ORDDTW, the markets look similar. Both markets have the same nonstop competitors (AA, NW, and UA) and also have the same codesharing airline (US sells fares on flights that UA operates). Additionally, they are both hub-to-hub, short-haul flights with similar round-trip mileage. Further, mean prices in these markets are almost identical ($166 and $167, as shown in Table 2.3). However, the level of price dispersion for these two markets differs dramatically, where MSPORD has low price dispersion and ORDDTW has high price dispersion. Upon further investigation of these markets, it is apparent that the codeshare in MSPORD is driving the high price dispersion. Figure 2.4 demonstrates the price dispersion of each airline as the day of departure approaches. All airlines exhibit flat pricing with low price dispersion, except the codeshare in MSPORD, which is significantly higher than the other airlines.

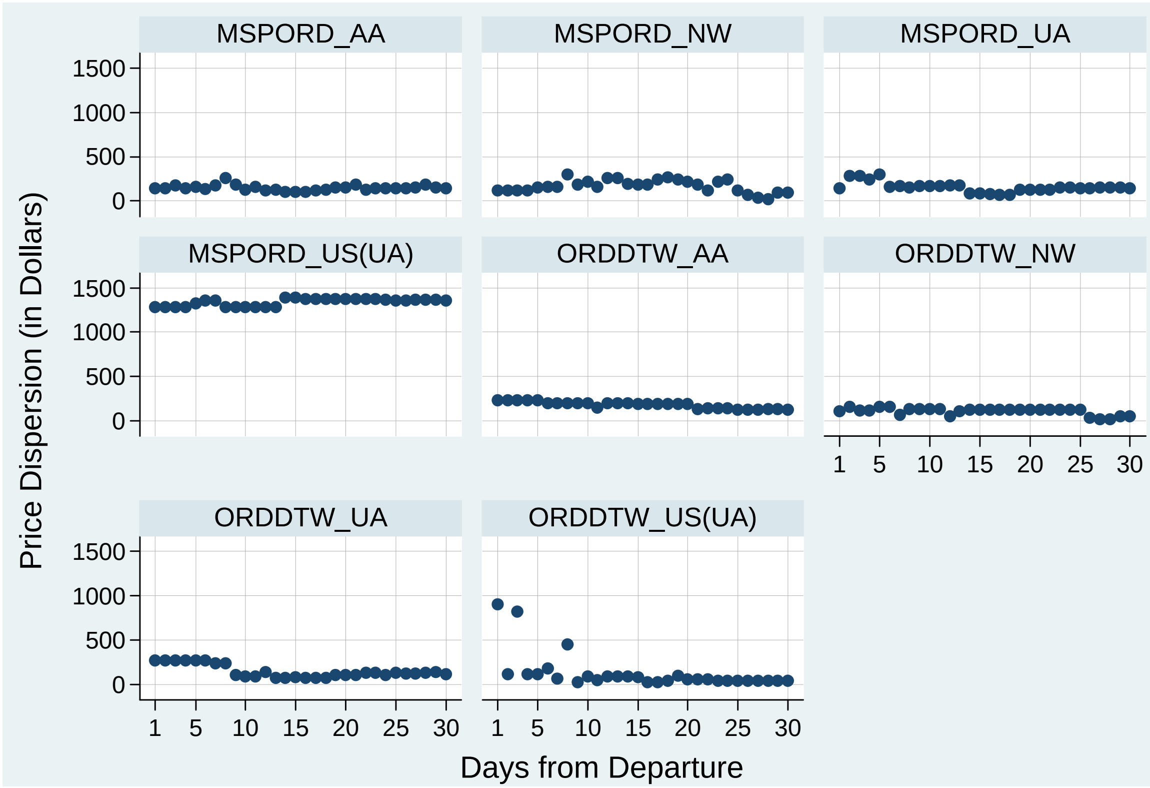

Figure 2.4: Price Dispersion by Market and Airline for Two Markets with Codeshares

A similar phenomenon is also found in the PDXSFO market. In this market the pricing strategies of AS and its codeshares with both AA and NW (AA and NW sell fares on flights that AS operates) all exhibit similar pricing and means. However, UA and its codeshare with US (US sells fares on flights that UA operates) exhibit extremely different pricing strategies. The mean prices for the US/UA codeshare are four times higher than the mean prices for all other flights in the market, including the UA flights. One reason for this high price could be due to the underlying revenue management system. That is, instead of showing “no availability” for a codeshare partner, the system displays a fare that is significantly higher than the fares of the operating carrier, effectively shutting off codeshare sales.

2.5.4. The Case of Monopoly Markets

In the sample of 62 markets, three types of monopoly markets existed:

1a. One major carrier flies nonstop in the market with no apparent multi-airport effects,

1b. One major carrier flies nonstop in the market with observable multi-airport effects,

1c. One LCC flies nonstop in the market.

Each type of monopoly exhibits different price dispersions, average prices, and carrier pricing strategies. What is interesting is that out of all of the different market structures, the two most extreme cases on both sides of the spectrum are both monopoly cases. More specifically, monopolies with one major carrier and no multi-airport effects exhibit the highest fares and highest price dispersion out of the entire sample, while monopolies with a LCC exhibit the lowest prices and lowest price dispersion out of the entire sample.

Figures 2.5, 2.6, and 2.7 demonstrate price dispersion as the day of departure approaches for each type of monopoly (holding the scale of the Y-axis the same across the three figures for comparison). In these figures, the peak and off-peak periods have been separated in order to demonstrate how demand influences price dispersion. In monopolies with one major carrier and no multi-airport effects, price dispersion is often different for the peak and off-peak periods. For example, price dispersion in the ATLOMA market for the off-peak period increases as the day of departure approaches, but in the peak period the price dispersion decreases down to zero for the last two days before flight departure, so that there is only one price offered. This could be the influence of advance purchase restrictions. On the other hand, the price dispersion in the DENGTF market for the off-peak period decreases to nearly zero as the day of departure approaches, but in the peak period the price dispersion increases as the day of departure approaches.

In monopolies with one major carrier and multi-airport effects (type 1a), the mean fares are often lower than those of major carrier monopolies without multi-airport effects (type 1b), as seen in Table 2.3. The price dispersions of these types of monopolies can also be different for the peak and off-peak periods, as exemplified in BWIDFW, INDEWR, and especially STLLGA. One interesting observation is the extremely low and flat price dispersion of DFWHOU as the day of departure approaches. One thing that could influence this is the fact that DFWHOU is a short-haul market with a round-trip distance much shorter that the other markets in this category of monopoly; DFW is a hub for Southwest, and it is also one of Southwest's original routes. Another interesting market is LGADFW which actually has the highest price dispersion out of all 62 markets in the dataset. In this market, advance purchase requirements are apparent for both peak and off-peak periods.

Finally, in monopolies with a LCC as the only nonstop competitor (type 1c), both price dispersion and the average fares are significantly lower than the major carrier monopolies, and are also lower than most of the other markets in the sample of 62 markets. For the most part, the price dispersion as the day of departure approaches stays flat or decreases slightly for both peak and off-peak periods. This type of pricing seems to be an anomaly for a monopoly market where higher average prices could be charged. BWIPVD, DALHOU, MHTBWI are all short-haul markets flown by Southwest and exhibit extremely flat pricing. The flat pricing on these markets could be due to Southwest's business model, or could also be due to the fact that they are all short-haul markets. FNTLAS and MDWMIA are long-haul markets flown by Air Tran. In these two markets, the average prices are higher and the price dispersion is more dynamic as the day of departure approaches.

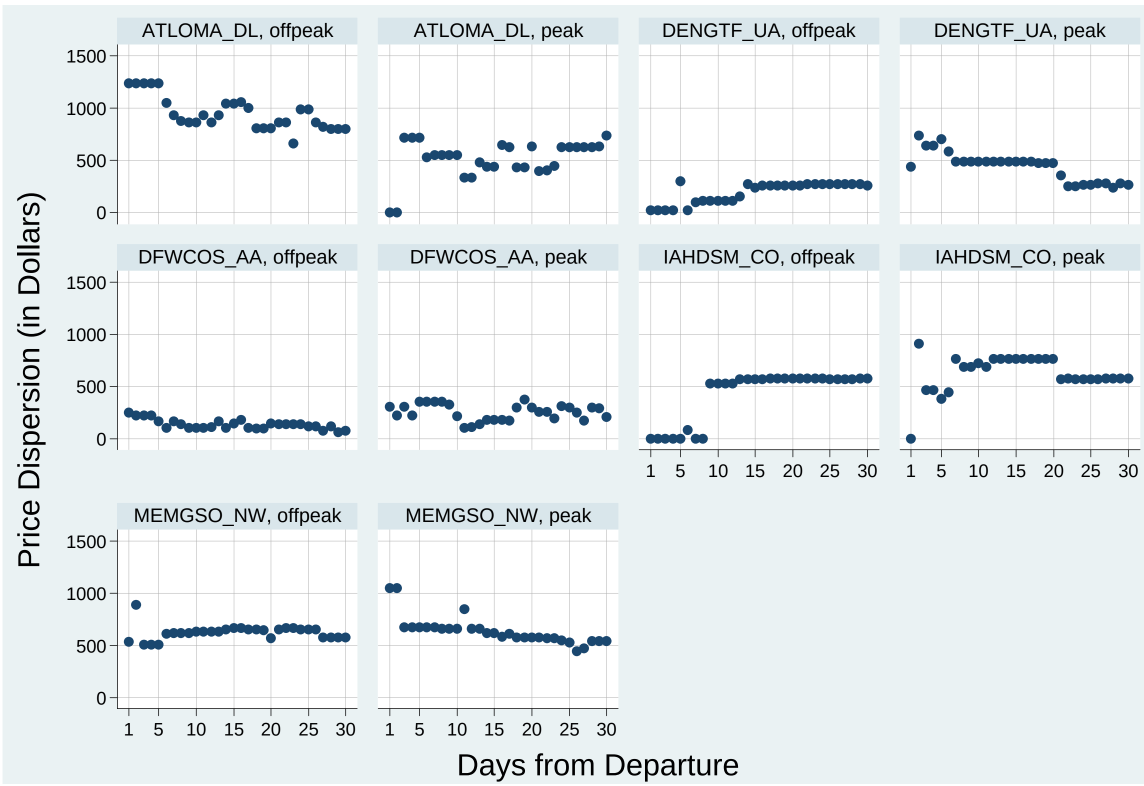

Figure 2.5: Price Dispersion by Market, Airline, Peak/Off-Peak for Major Carrier Monopolies without Multi-Airport Effects (Type 1a)

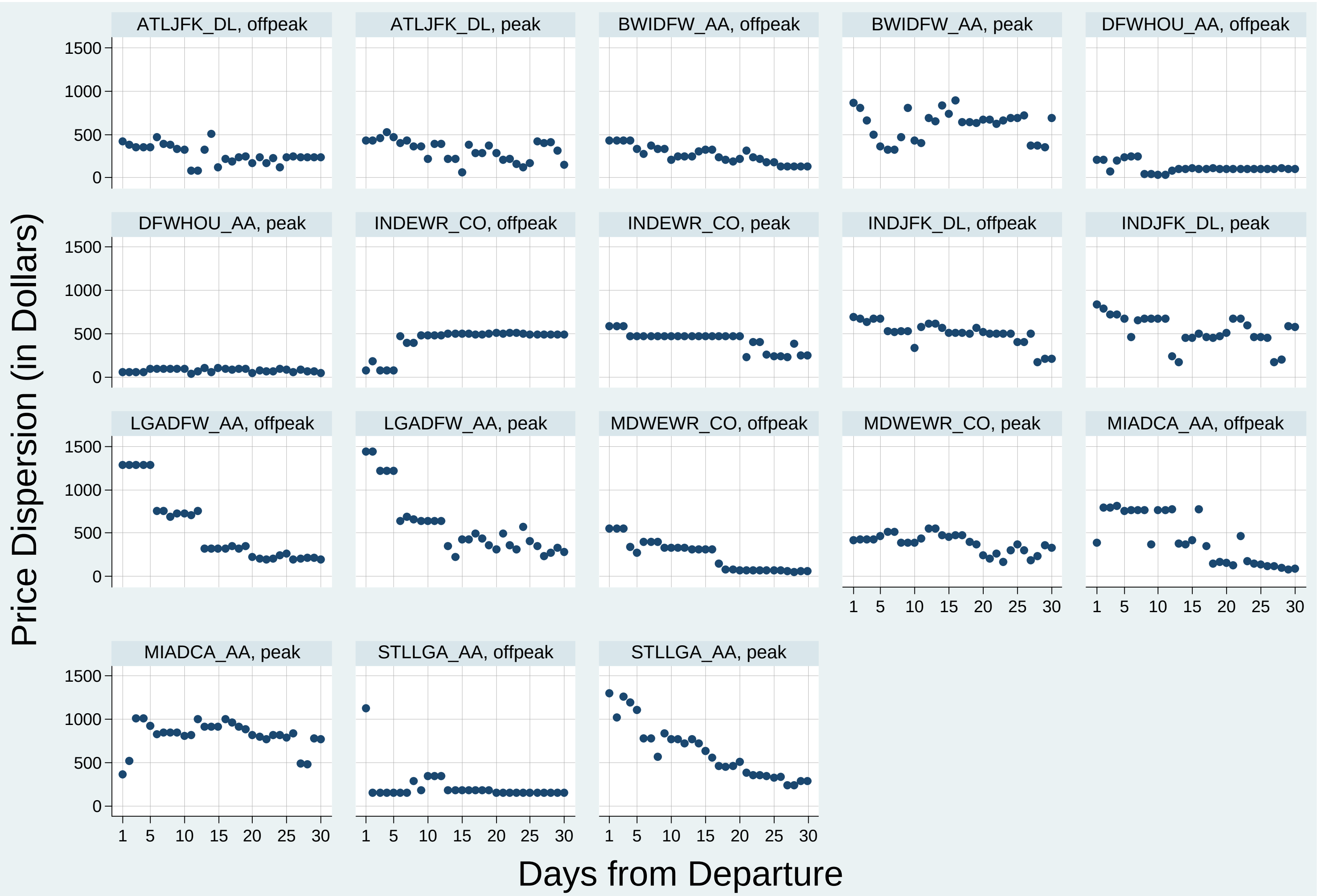

Figure 2.6: Price Dispersion by Market, Airline, Peak/Off-Peak for Major Carrier Monopolies with Multi-Airport Effects (Type 1b)

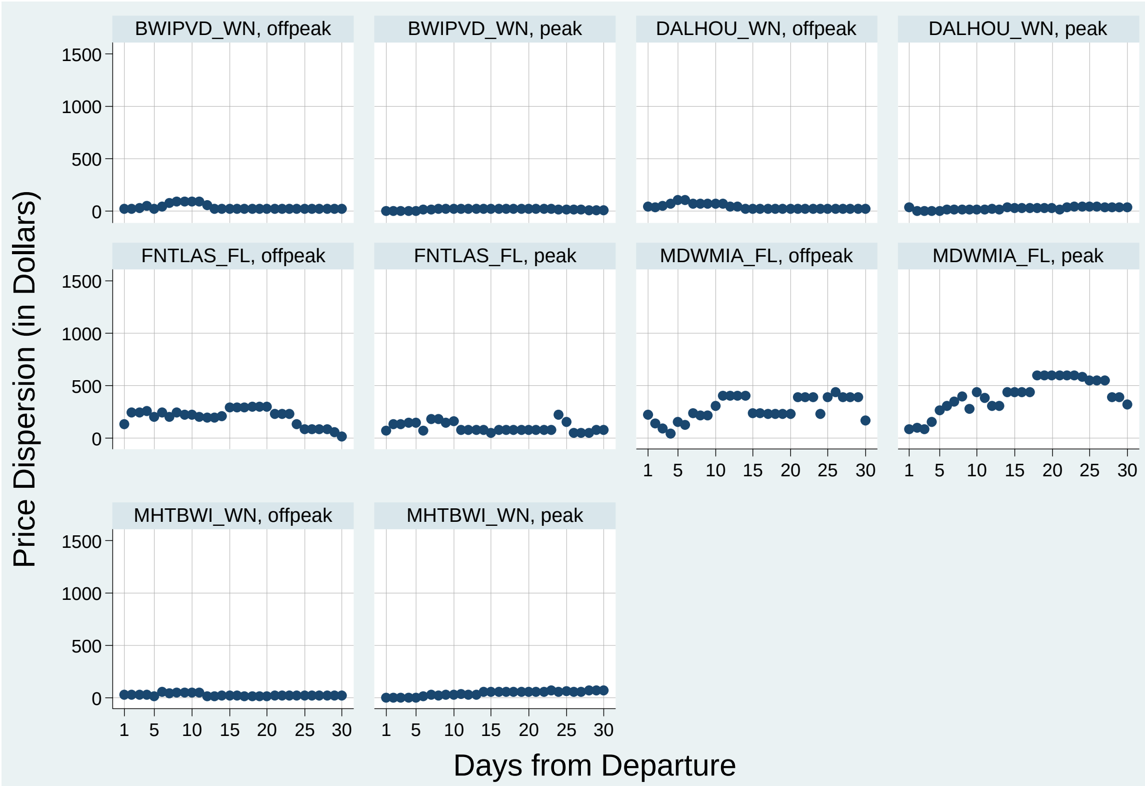

Figure 2.7: Price Dispersion by Market, Airline, Peak/Off-Peak for Low Cost Carrier Monopolies (Type 1c)

2.5.5. The Case of Competitive Markets with Two Low Cost Carriers

Head-to-head competition by two nonstop LCCs within a market occurs rarely in the U.S. and primarily occurs in leisure markets (mainly to Florida destinations). Data was collected for BOSMCO and PHLMCO, which are both leisure markets to Orlando. When comparing these two markets to all of the other markets in the sample, the overall price dispersion tends to be towards the middle of the sample. The price dispersion and means of these two markets are similar to those of competitive markets with two or more major carriers and one LCC. Figure 2.8 illustrates that as the day of departure approaches, the price dispersion tends to be rather flat for both the peak and off-peak periods, especially for the LCCs. The pricing trends are more dynamic for the major carriers, DL and US. In these two markets, the peak and off-peak periods exhibit similar pricing trends. This observation is similar to the findings of the business vs. leisure case study, which found that in the leisure market the peak pricing was less dynamic and was similar to the pricing during the off-peak period.

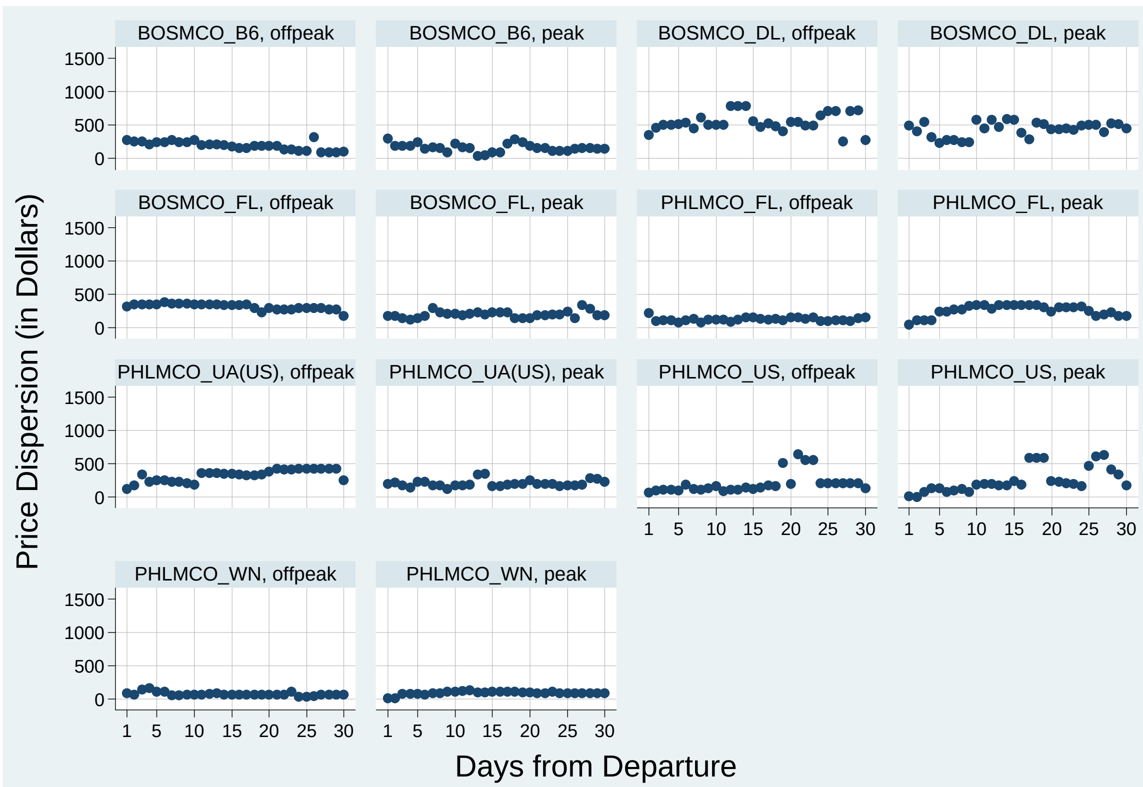

Figure 2.8: Price Dispersion by Market, Airline, Peak/Off-Peak for Markets with Two Low Cost Carriers

2.6. Implications for Public Policy

In this study, observations were made using disaggregate data on a sample of 62 markets that cover a broad range of market structures. Some of the most important points that were shown include the following:

- Low price dispersion can be associated with both low and high market concentration, depending on the characteristics of the market. This finding contrasts with the findings of past research on price dispersion.
- When a low cost carrier is the only airline competing nonstop on a route, the monopoly route functions differently than a monopoly with a major carrier. Even in a monopoly situation, low cost carriers (especially Southwest) demonstrate flat pricing and price dispersion as the day of departure approaches.
- As the day of departure approaches, price dispersion can either increase or decrease.
- Peak and off-peak periods often demonstrate different pricing strategies, highlighting the importance of jointly examining price and demand.
- Major carriers tend to exhibit more dynamic pricing strategies than those of low cost carriers, suggesting the former are targeting both business and leisure customers.
- Markets with codeshares (specifically codeshares between US and UA) sometimes exhibit unusually high price dispersion on the airline that is selling tickets for a flight operated by another airline.

The results of this study could be used to support analysis of mergers and acquisitions, allocation of gate slots for new entrants, and other policies that relate to airline competition and the assessment of consumer welfare benefits. For example, this paper has shown that there are certain instances when monopoly routes exhibit lower price dispersion and lower average prices than competitive routes, as is the case of monopoly routes with one nonstop low cost carrier. These differences in monopoly routes highlight the importance of understanding price dispersion at the detailed, disaggregate level when analyzing the impact of future mergers and acquisitions.

Perhaps most importantly from a public policy perspective, this paper shows the importance of disaggregate data that describe individual airline behavior. Much public policy discussion and analysis relies on average market values that can hide important market behavior. With the advent of internet-based ticketing, a powerful tool now exists that can be used to understand some of the finer detail of airline markets and competition.

2.7. Future Research

In future research efforts, there is a need for disaggregate demand data in order to link pricing strategies with demand as the day of departure approaches. This could be accomplished by pulling seat maps off of the internet while collecting airfares online. There is also an obvious need for more research, at the disaggregate level, on how codesharing affects pricing within a market. As more and more airlines begin to use codeshares, understanding the impacts on the market will become more important. There is also a need to link price dispersion to individual revenue management practices of airlines, as there appears to be evidence of more price dispersion in airlines with complex revenue management systems. Additionally, in future research efforts, it would be helpful to compare the offered ticket observations with an actual ticket sample to see which fares were actually purchased. In doing this, market sizes, carrier shares and average fares for each carrier could also be obtained from the ticket sample.

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CHAPTER 3: PRODUCT DEBUNDLING

Garrow, L.A., Hotle, S. and Mumbower, S. (2012) Assessment of product debundling trends in the U.S. airline industry: Customer service and public policy implications. *Transportation Research Part A: Policy and Practice*, 46 (2), 255-268.

3.1. Abstract

This paper reviews product debundling trends that have occurred in the U.S. airline industry. Multiple sources of ancillary fees related to ticketing refunds and exchanges, checked baggage, on-board pets, preferred and/or advanced seating assignments, frequent flyer ticket redemptions, and day of departure standby policies are reviewed. Despite the fact that both low cost and network carriers stress the importance of future ancillary fees in their investor reports, our assessment suggests that these fees will be more broadly adopted by low cost carriers. We anticipate that many network carriers will eliminate ancillary fees, particularly as they begin to recognize how these fees can impact other system performance objectives such as minimizing the number of misconnecting passengers. We estimate that the debundling phenomenon has diluted revenues to the U.S. Airport and Airways Trust Fund by at least five percent.

3.2. Introduction

The airline industry is fiercely competitive. Since deregulation (which in the United States occurred in 1978), the airline industry has faced a series of financial challenges and has struggled to maintain profitability. For example, according to the Air Transport Association, in the first 30 years after passenger deregulation, domestic airline prices fell 41.2 percent in real terms (2010). Numerous factors have contributed to this decrease, most notably the increased market penetration of low cost carriers combined with the increased use of the internet as a major distribution channel (which makes it easier for customers to find the lowest fares). For example, in 1998, approximately one percent of domestic leisure flight tickets were sold through the internet. In 2005, this number was 35 percent (Brunger and Perelli, 2008).

The first decade of the 21st century was especially challenging for major U.S. airlines. Faced with increased market penetration of low cost carriers, unprecedented fuel costs, continued security threats post 9/11, health outbreaks (SARS, H1N1), economic recessions, and the global financial crisis, it is no surprise that in the first decade of the 21st century, the seven largest U.S. network carriers (Alaska, American, Continental, Delta, Northwest, United, and US Airways) collectively lost $35.1 billion (U.S. DOT, 2010). We define largest using total number of passengers carried in 2006. However, the seven largest low cost carriers (AirTran, American West, ATA, Frontier, JetBlue, Southwest, and Spirit) earned $4.9 billion; and the seven largest regional carriers (American Eagle, Atlantic Southeast, Comair, ExpressJet, Mesa, Pinnacle, and SkyWest) earned $5.3 billion during this time period. This decade also saw customer satisfaction levels plummet, as passengers faced reduced flight schedules, higher load factors, and long security lines (Carpenter, 2008). From 2001-2005, four out of the seven largest network carriers went into bankruptcy (Delta, Northwest, United, and US Airways); and from 2005-2011, eight major U.S. carriers went through mergers/acquisitions (America West and US Airways in 2005; Delta and Northwest in 2008; Continental and United in 2010; Southwest and AirTran in 2011).

These statistics need to be viewed with some caution, however, as they only paint a portion of the full story of the structural market changes that have happened over the past decade. That is, although it is true that from 2000-2009, the total domestic available seat miles (ASMs) by U.S. passenger carriers dropped by 2.7 percent, it is important to recognize that domestic ASMs fell by 7.2 percent whereas international ASMs grew by 12.1 percent (U.S. DOT, 2010). Further, network carriers – Alaska, American, Continental, Delta, Northwest, United, and US Airways – moved much of their capacity from domestic to international markets, reducing their domestic capacity by 23.8 percent and increasing their international capacity by 7.4 percent. In contrast, low cost carriers – AirTran, Frontier, JetBlue, Southwest, and Spirit – increased their domestic capacity by 103 percent and began to provide international service[9] (U.S. DOT, 2010). As of 2009, the major network carriers concentrated 62.8 percent of their ASMs in domestic markets (compared to 70.4 percent in 2000), whereas the low cost carriers concentrated 96.5 percent of their ASMs in domestic markets (compared to 99.1 percent in 2000) (U.S.

[9] The other two major low cost carriers noted earlier – ATA Airlines and America West – are not included in this comparison as ATA Airlines ceased service in 2008 and America West merged with US Airways.

DOT, 2010). Consequently, as of 2009, Southwest became the largest domestic U.S. carrier in terms of total passengers (Southwest Airlines, 2009a).

The last decade in particular has been one of the most dynamic periods in airline history, with 2008 being especially challenging due to major economic events occurring outside the airline industry that raised costs and reduced demand. During 2008, oil prices soared to more than $130/barrel (CNN, 2010); and the global economic crisis hit, dropping the Dow Jones market value by 33.8 percent, the third worst calendar year performance on record (2002, the fifteenth worst calendar year performance on record, experienced a loss of approximately 18 percent) (Seeking Alpha, 2009). Further, major airlines had implemented many cost-cutting and revenue-generating measures during the early 2000s as part of their bankruptcy restructuring and merger processes. However, the large market penetration of the internet, combined with low cost carrier competition, hindered the ability to raise fares to a level that could overcome the “perfect storm” that emerged in 2008: soaring fuel costs followed immediately by plummeting demand. Consequently, “2009 proved to be the worst year on record for U.S. airlines, in terms of year-over-year revenue declines” (Southwest Airlines, 2009b).

In times of crisis, though, innovation often occurs. In the authors’ opinion, 2009 represents one of the fastest and most wide-spread (and bumpiest) implementations of new ancillary revenue streams in airline history. That is, new ancillary revenue sources, including checked baggage, seat reservation fees, and food for sale were introduced in the late 2000s. In addition, many existing ancillary fees, including fees for redeeming mileage award tickets, day of departure standby fees, agent-assisted ticketing fees, domestic and international ticketing exchange fees, on-board checked pet fees, and unaccompanied minor fees were increased.

This paper reviews the debundling trends that are occurring in the U.S. airline market and discusses potential policy and customer service implications.

3.3. Methodology

Several sources of data were used for this analysis. Information pertaining to carriers' products was obtained from airline websites, carriers' contracts of carriage, and reservation agents during the last two weeks of May, 2010. All mainline carriers serving destinations predominately in the continental United States with annual operating revenues exceeding $1 billion were included in the analysis. Using these criteria, Hawaiian Airlines as well as American Eagle and SkyWest were excluded from the analysis. An additional low cost carrier, Virgin America, was also included in the analysis in order to examine the product differentiation strategies of a relatively new carrier operating under the low cost model[10].

In gathering information, discrepancies were found within the same airline website. When these discrepancies were identified, they were resolved by calling airline ticketing agents. In several cases, we were able to further clarify the underlying motivations driving the debundling trends through interviews with airline managers.

[10] Spirit Airlines is another smaller low cost carrier that was considered for analysis, but was ultimately excluded because approximately half of their destinations are in the Caribbean and Latin America.

These interviews underscored the importance of examining current and historic debundling trends in the context of prevailing market conditions. Thus, when interpreting these trends, it was often helpful to include information pertaining to carriers not included in the detailed product assessment analysis.

Due to the many changes carriers are making to their fee structures, it is possible that some of the information obtained from the websites will change rapidly. Nonetheless, a comparative analysis based on this information provides important insights into how different carriers are approaching ancillary revenues and, consequently, enables one to infer likely policy and customer service implications.

3.4. U.S. Airline Market Characteristics

Before describing how carriers have debundled their products, it is useful to review the current structure of the U.S. airline industry, particularly as it relates to airlines' customer segmentation strategies. Table 3.1 illustrates key differences among major and low cost carriers. The first six airlines in the table represent major legacy network carriers (sorted by size) that serve a wide range of both domestic and international destinations. All of these carriers participate in well-established alliances that enable them to further increase the number of destinations they can serve. These major carriers also tend to have a moderate number of other airline partners that further enhance their networks. Due to the fact that these partnerships frequently change, it is difficult to pinpoint a precise estimate of the number of non-alliance partners from information provided on the carriers' websites, and thus an approximation is provided.

It is important to note that the four largest network carriers use a round-trip pricing strategy whereas the two smallest network carriers use a one-way pricing strategy. Round-trip pricing enables carriers to segment the market through offering lower prices to (predominately price-sensitive leisure) customers who travel over a Saturday and/or spend more than two days at a destination. Travelers who do not meet these criteria are more likely to be time-sensitive business travelers who are willing to pay more for their airline tickets. One-way pricing occurs when customers receive separate price quotes for their departing and returning itineraries. It is interesting to observe that the two smallest network carriers, US Airways and Alaska Airlines, despite their "legacy" characteristics, use one-way prices. It is also clear that when the United-Continental merger is complete, US Airways will be in a unique (and possibly difficult) position – substantially smaller than the network carriers with a pricing structure that mimics low cost carriers (which is better for targeting leisure customers), yet with a strong international presence (which is better for targeting business customers).

Table 3.1: U.S. Airline Characteristics

	# Cities Served	# Countries Served	# Daily Flights	Alliance (# Carriers)	Non-Alliance (# Partners)	Pricing
Network Carriers						
Delta	368	66	6206	SkyTeam (10+)	5+	Round-trip
American	250	40	3400	Oneworld (10+)	10+	Round-trip
United	230	25	3300	Star (25+)	5+	Round-trip
Continental	269	55	2700	Star (25+)	5++	Round-trip
US Airways	205	31	3134	Star (25+)	5+	One-way
Alaska	61	1	297	None	10+	One-way
Low Cost Carriers						
Southwest	69	1	3300	None	1[a]	One-way
AirTran	71	5	700	None	1[b]	One-way
JetBlue	61	11	650	None	<5	One-way
Frontier	73	3	350	None	<5	One-way
Virgin America	8	2	94	None	<5	One-way

[a] Southwest is finalizing an agreement with Volaris to serve Mexican markets in 2010.
[b] AirTran and Frontier are ending their partnership on 7/16/2010.

The next four carriers in the table (Southwest, AirTran, JetBlue, and Frontier) represent large low cost carriers. A smaller low cost carrier, Virgin America, is also included to illustrate how some new entry carriers operating under the low cost model are attempting to differentiate themselves from Southwest Airlines. The first thing to notice is that Southwest Airlines dominates the low cost carrier market, and in fact has a greater number of daily flights than US Airways and Alaska Airlines. None of the low cost carriers are part of international alliances, and the number of international destinations served is small. This is because the equipment types typically operated by the low cost carriers can only fly short distances without refueling, which effectively limits the international markets that can be served to destinations in Canada, Central America, and the Caribbean. Interestingly, the number of destinations served by the four largest low cost carriers is approximately the same, which implies the key difference among these carriers is flight frequency. The low cost carriers differ in the number of non-alliance partners, with the two largest – Southwest and AirTran – leaning towards being independent (although partners within Canada and Mexico are seen as highly valuable).

The different mix of business and leisure customers served by these airlines is also clearly observed by comparing their frequent flyer programs. Table 3.2 summarizes the different flyer categories among those carriers in Table 3.1 that provide one or more elite levels (those carriers not shown have only one flyer category). The number of tiers, yearly qualification criteria (expressed as a minimum number of flight segments and/or qualification miles), and bonus mileage percentages are shown. Clearly, network carriers are targeting business customers and are designing their programs such that the most elite members feel particularly valued. On United and Continental, for example, the highest level of memberships is by invitation only, and the specific qualification criteria are not public. The top elite level among the low cost carriers is equivalent to the second elite tier of the network carriers.

In the context of the recent debundling phenomena, the design of elite tiers is particularly relevant, as higher elite levels represent customers who travel more frequently (and typically generate a large percentage of a carrier's revenues). Further, network carriers that serve a large number of domestic and international destinations are better able to attract these frequent travelers. This is often accomplished through corporate volume agreements in which a carrier offers a discount to a corporation in exchange for the corporation directing a minimum number of trips to the carrier. Due to the presence of these high-valued customers and the ability of network carriers to attract a larger proportion of these customers, network and low cost carriers have adopted different debundling strategies. Specifically, as seen in the next section, many of these elite customers are exempted from paying fees.

Table 3.2: Frequent Flyer Elite Membership Tiers, Yearly Qualifications, and Bonus Miles Percentages

	Tier 1	Seg	Miles	Bonus	Tier 2	Seg	Miles	Bonus	Tier 3	Seg	Miles	Bonus	Tier 4	Seg	Miles	Bonus
United[d]	Premier	30	25K	25%	Premier Executive	60	50K	100%	1K	100	100K	100%	Global Services	Not public		
Continental	Silver	30	25K	25%	Gold	60	50K	100%	Platinum	90	75K	100%	Presidential Platinum	Not available[c]		
Delta	Silver	30	25K	25%	Gold	60	50K	100%	Platinum	100	75K	100%	Diamond	140	125K	125%
US Airways	Silver	30	25K	25%	Gold	60	50K	50%	Platinum	90	75K	75%	Chairman	120	100K	100%
American	Gold	30	25K	25%	Platinum	60	50K	100%	Executive Platinum	100	100K	100%				
Alaska	MVP	30	20K	50%	MVP Gold	60	40K	100%								
Frontier	Ascent	20	15K	25%[a]	Summit	30	25K	50%								
AirTran	A+ Rewards	25[b]	--	None												

[a] Bonus is also driven by fare class; 150% of miles for Classic Plus fares, 125% of miles for Classic fares and 100% of miles flown for Summit members.
[b] Can also qualify by flying 10 segments in 90 days.
[c] Program for Presidential Platinum Elites on Continental announced on 1/1/10 and appears to include minimum travel spend criteria in addition to Platinum status. No additional benefits for Presidential noted on website.
[d] United also has a lower Premier level called "Premier Associate" that can be designated or nominated through marketing, promotions, etc. The benefits of this are priority check-in/boarding and access to Economy Plus.

3.5. Rapid Debundling

This section reviews how airlines have created ancillary sources of revenue through debundling their products. Before reviewing these ancillary sources of revenue, it is helpful to distinguish between new and established fees and look at the definition of “new” in the context of a specific carrier, Southwest.

Table 3.3 summarizes major sources of ancillary revenues that have been collected through fees. The fees are organized into three main categories. The first category includes those fees that are the most established (and that customers typically expect to pay for). Some of these fees, most notably ticket exchange fees, are well established and existed before deregulation. On-board pet fees, unaccompanied minor fees, and day of departure standby fees are other examples of fees that are well-established within the U.S. airline industry.

The second category represents fees for services that used to be free to consumers. These include fees for making ticket changes through an agent, fees for redeeming mileage award tickets, checked baggage fees, seat reservation fees, and food for sale. Given these fees were once “free” to customers (in the sense that they were bundled into the ticket price), one would expect these fees to generate the majority of customer complaints. These are also the fees that would likely have the most difficulty surviving in the long-term.

The final category represents those fees that were imposed on newly introduced services such as live TV, personal movies, and on-board amenity packs. On-board food purchases can also be grouped into this category, as they represent the introduction of new product offerings distinct from the free meals that were eliminated for the majority of domestic flights. Given these fees were introduced at the same time as the new services, airlines did not set customers' expectations that these services would be free. Thus, we would expect that customer reactions to these fees would not be as negative as the reaction to the fees imposed on services that used to be free.

Table 3.3: Overview of Major Fees and Southwest's Approach to "New" Fees

Fee	Southwest's Implementation
Most established	
Ticket exchange	
Day of departure standby	Established fee: difference between fare purchased and fare available on the day of departure
On-board pets	New fee
Unaccompanied minor	New fee
Fees for services that used to be free	
Agent-assisted ticketing	
Mileage redemption	
Baggage	
Seat reservation	New – early check-in/first boarding zone
Food-for-sale	
Fees on newly introduced services	
In-flight entertainment	
On-board amenity packages	

It is interesting to examine these fees in the context of Southwest's approach to establishing "new" sources of ancillary revenues. A clear pattern emerges when looking at where and how Southwest has introduced "new" fees – namely, all fees introduced have been implemented at the same time as a new service is introduced. In the context of on-board pets and unaccompanied minors, these fees were already well-established within the industry, which made it more likely Southwest customers would be willing to accept these fees when it rolled out these "new" services to its customers. In the context of seat reservation fees, Southwest also introduced a new service –online early check-in– and charged passengers to board the aircraft in the first boarding zone. Given Southwest does not have assigned seating, this fee essentially provides customers with the ability to secure premium aisle and window seats.

The importance of these new revenue streams introduced in 2009 by Southwest Airlines is obvious. Southeast posted a net income of $99 million in 2009 (Southwest Airlines, 2009b). To put this in context, Southwest's Early Bird Check-in generated $15 million in four months and P.A.W.S. (Pets Are Welcome on Southwest) transported 60,000 pets in the first seven months, generating $5 million (Southwest Airlines, 2009b). An Unaccompanied Minor program was also implemented in 2009 (Southwest Airlines, 2010a).

These examples highlight the breadth of "old" and "new" fees that airlines have looked to as a potential source of increasing revenues. The examination of Southwest's introduction on new fees also sheds light on the strategy it has used to introduce fees without distancing its customers – explicitly tying the introduction of a fee to a new service offering. The remainder of this section examines three of the key sources of ancillary revenue in depth: ticket exchange fees, baggage fees, and seat reservation fees.

3.5.1. Ticket Exchange Fees

Since 2008, there has been a rapid debundling of products and services that used to be included in the base fare (defined as the portion of the fare that ties directly to airlines' operating revenues, i.e., the base fare excludes taxes and fees imposed by the government). One of the most well-recognized and established fees involves ticket exchanges. Table 3.4 summarizes current domestic exchange fees. In some cases, exchange fees depend on whether the customer requests the exchange online or uses a call center, airport agent, or city ticket office. For example, in the case of Alaska Airlines and Virgin America, the domestic exchange fee is $75 if the exchange is made online, $100 otherwise. The $25 additional surcharge is higher than the $15 "standard" fee for booking a ticket through a call center, which may be due to the added complexity and time that is typically associated with processing an exchange.

Table 3.4 also highlights a trend that will be seen across most implementations of ancillary fees: the predominant use of waivers for elite members and/or those customers purchasing higher fares. We will return to this point in our discussion of a U.S. Department of Transportation (DOT) *Proposed Ruling* that seeks to have carriers customize websites to perform "all inclusive" searches, as fee exemptions linked to fares and/or status may create substantial implementation difficulties.

Table 3.4: Ticketing/Agent Assisted Fees and Exchange Fees

	Ticketing/Agent Assisted Fees	Waivers for Ticketing/Agent Assisted Fees	Domestic Exchange Fee
Network Carriers			
Delta	$20 ($35)	Diamond, Platinum, Gold	$150
American	$20 ($30)	Executive Platinum	$150
United	$25 ($30)	1K, Global Services	$150
Continental	$25	Platinum	$150
US Airways	$25 ($35)	Preferred	$150
Alaska	$15 ($25)	None	$75/$100[b]
Low Cost Carriers			
Southwest	N/A	N/A	N/A
AirTran	$15	Elites	$75[a]
JetBlue	$15	None	$100
Frontier	$25	Elites	$50 Classic fares
		Classic/Classic Plus fares	$100 Economy fares
Virgin Am.	$15	None	$75/$100[c]

KEY: Call center fee (airport agent/city ticket office fee).
[a]Only business fares are refundable. Elites purchasing Y, B, M fares receive free exchanges/refunds.
[b]Some web tickets may not be exchanged. If fee applies, charge is $75 online, $100 otherwise.
[c]If fee applies (based on ticketing class) fee is $75 online, $100 otherwise.

Although carriers were not required to report exchange and cancellation fees until the late 2000s, three major network carriers (Alaska, United, and Northwest) and two low cost carriers (Frontier and JetBlue) have reported these revenues annually from 2000-2009. The trends in exchange and cancellation fees for these network and low cost carriers are shown in Figure 3.1. In general, ticketing fees expressed as a percent of total operating revenue have increased during the last decade across (non-Southwest) LCC carriers and network carriers (U.S. DOT, 2010).

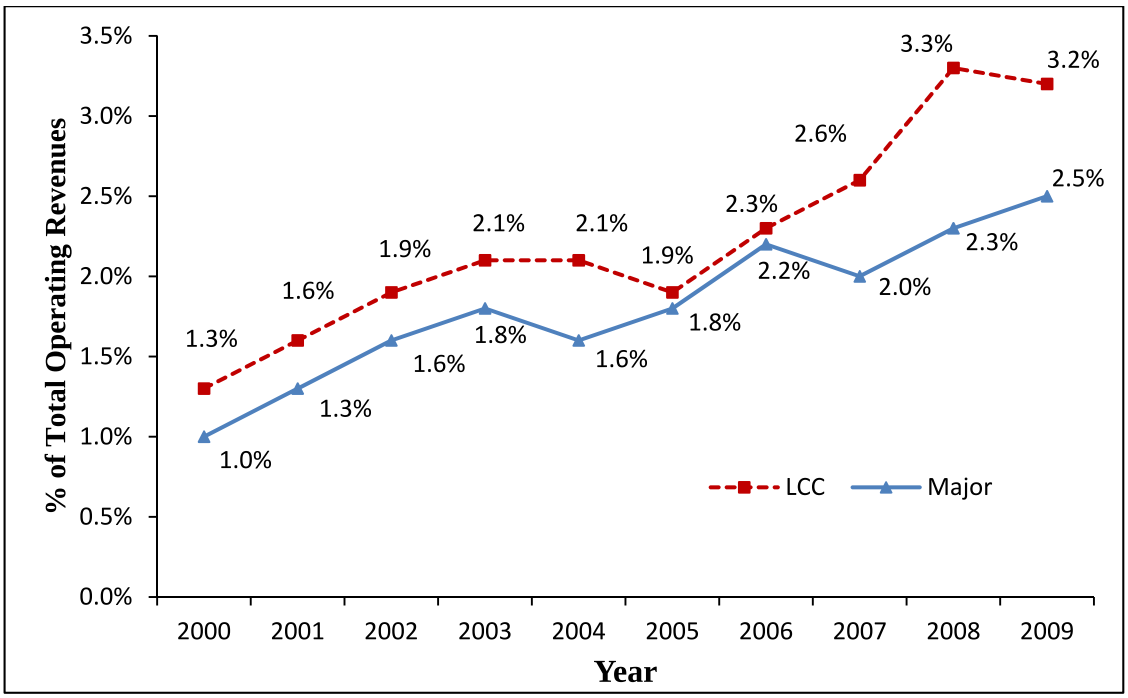

Figure 3.1: Exchange and Cancellation Revenues as Percentage of Total Operating Revenue

Historically, Southwest Airlines has not charged customers fees to exchange their tickets; i.e., customers who desire to make a change pay only the applicable difference in fares. To illustrate what this fare difference means, consider the one-way pricing curve for Southwest shown in Figure 3.2 (the fares shown represent the lowest one-way fares Southwest offered for flights departing on Monday, November 19, 2007, from Las Vegas to Los Angeles). For ease of interpretation, assume this price curve applies to all flights and departure dates Southwest offers from Las Vegas to Los Angeles. Next, assume a customer purchases a departing flight 21 days in advance of flight departure (for $54), but the day the flight departs becomes ill and cannot travel. The customer rebooks the outbound flight for the next day, but is now purchasing a ticket one day in advance of departure when the prevailing fare is $104. The customer does not pay a "fee" to exchange the ticket for the different departure date but must pay the difference between the 21-day advance purchase fare and the one-day advance purchase fare ($104-$54 = $50). Thus, although Southwest does not charge a fee for the ability to change a ticket (as many U.S. carriers do for their low-yield coach tickets), Southwest is likely to gain additional revenues when passengers need to change their tickets near the flight departure. However, U.S. carriers do not explicitly report the additional revenue generated due to these "fare differences" to the U.S. DOT, making it impossible to compare how this source of ticketing revenue differs across carriers.

The discussion of ticketing exchange and cancellation fees is an example of how U.S. carriers have looked to increase ancillary revenues through increasing established fees. Further, given Southwest has historically not charged fees for customers to exchange tickets, we would not expect Southwest to introduce these fees in the near-term future.

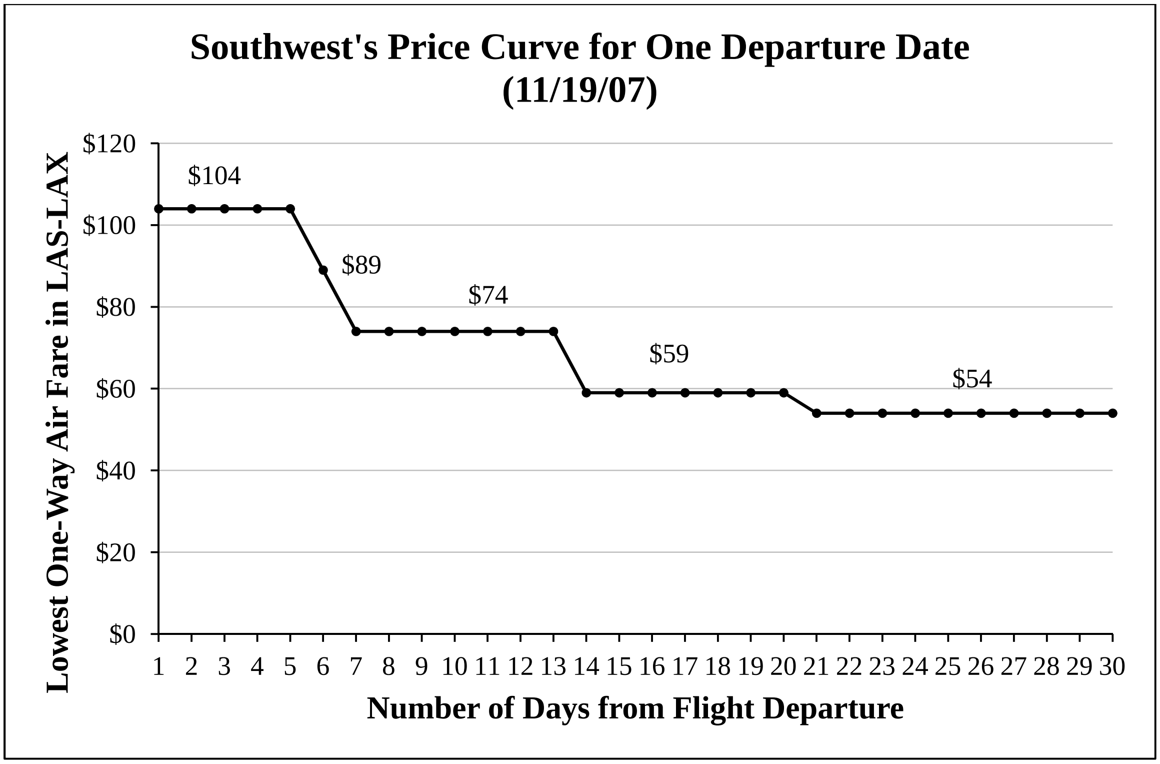

Figure 3.2: Southwest's One-Way Pricing from Las Vegas to Los Angeles

3.5.2. Baggage Fees

Whereas ticketing exchange and refund fees represent a more established source of ancillary revenues, in the past 24 to 36 months many new ancillary fees were also implemented. One of the largest sources of revenue was derived from the implementation of checked-baggage fees.

Although the majority of U.S. airlines implemented fees for the first checked bag in 2008, two major low cost airlines – Southwest and JetBlue – elected not to charge fees. Specifically, as of June, 2010, Southwest did not charge for the first two checked bags of standard size and weight, and JetBlue did not charge for the first checked bag of standard size and weight.

Expressed as a percentage of operating income, baggage fees for overweight, oversized, and/or extra bags remained relatively constant on Southwest, modestly increasing from 0.21 percent to 0.26 percent from 2007 to 2009. However, among all U.S. passenger airlines, baggage fees more than quadrupled, from 0.55 percent to 2.4 percent of operating income, over this same time period. The reliance on baggage fees as a source of revenue is particularly striking among the low cost carriers (excluding Southwest and JetBlue). For example, in 2009, baggage fees represented an equivalent of between 5.0 percent - 6.7 percent of the operating revenues for AirTran, Frontier, Spirit, and Sun Country. In contrast, among the major U.S. airlines (Alaska, American, Continental, Delta, Northwest, and United), baggage fees grew from a baseline of 0.3-0.6 percent of operating revenue in 2007 to 1.6-2.4 percent in 2009. JetBlue, which implemented a one-free bag checked policy, falls more in line with the growth seen among the major carriers, showing a growth from 0.5 percent of operating revenue in 2007 to 2.0 percent in 2009. US Airways also experienced faster-than-usual growth compared to the major airlines, growing from 0.3 percent of operating revenue in 2007 to 4.0 percent in 2009 (U.S. DOT, 2010).

Although it is relatively easy to quantify revenue gained by those carriers who introduced baggage fees, it is not easy to quantify revenue and market share shifts due to the customers' decision to travel on Southwest and/or JetBlue, which did not implement fees for the first checked bag. Southwest Airlines noted that in 2009, that "we launched an aggressive television advertising campaign to affirm that Bags Fly Free only on Southwest [and] experienced a domestic market share shift worth close to a billion dollars" (Southwest, 2009c). It is difficult – if not impossible – to verify Southwest's analysis from independent data sources. However, if we believe Southwest Airlines' analysis, then debundling baggage fees from the price of the ticket may have created value for the industry as a whole. That is, unlike many other product implementations, such as "wifi" service where one carrier may see a short-lived first-mover market share advantage before all other carriers match service, the way in which carriers implemented baggage fees reflect a unique market segmentation. Whereas Southwest Airlines reported that it may have shifted an equivalent of $1 billion in passenger revenues from the other carriers in 2009, other U.S. carriers collectively generated $2 billion in incremental baggage revenues (U.S. DOT, 2010); i.e., a net benefit of approximately $1 billion appears to have been generated through baggage fees for the U.S. airline industry as a whole. Even if Southwest's analysis is overstated, what is clear is that it has not been willing to charge customers fees for services that at one time were offered for free or bundled in the ticket price. In the case of baggage fees, Southwest would likely be able to generate additional short-term revenues in excess of $1 billion a year by matching other carriers' baggage fee policies. However, it does not appear willing to implement a baggage fee due to longer-term revenue impacts associated with losing repeat customers to other airlines and/or of losing its unique brand identity.

There is another point that is particularly interesting in the context of baggage fees, namely how quickly these fees were rolled out – and how quickly they were increased and matched by competitors as airlines began to recognize their potential for revenue generation. Table 3.5 shows one-way checked baggage and pet fees for several major U.S. carriers as of June 1, 2010, and Table 3.6 shows changes that occurred from 2008 to 2009 across these carriers. A quick scan of Table 3.5 shows that major network carriers (Delta, American, United, Continental, US Airways) have aligned their first and second checked baggage fees; whereas there is variability among the low cost carriers (in terms of how they position themselves in the market; that is most likely to compete against the generous baggage policies of JetBlue and Southwest). What is most interesting in Table 3.6 (and can be seen throughout other implementations of ancillary fees) is that due to the speed in which these fees were rolled out to the market, it appears that technology and/or human resource constraints were encountered and limited pre-market testing was conducted. For example, in the case of checked baggage fees, it appears that Continental initially charged for checked-bags when customers checked in online, but not at the airport; note the $0 fare for airport check-in in Table 3.6 (Continental, 2010b).

Table 3.5: One-Way Checked Baggage and Pet Fees as of June 1, 2010

Checked bag	1st	2nd	3rd	4th-5th	6th-10th	On-board Pet	Checked Pet
Network Carriers							
Delta	\$25 (\$23)	\$35 (\$32)	\$125	\$200	\$200	\$125	\$200
American	\$25	\$35	\$100	\$100	\$200	\$100	\$150
United	\$25 (\$23)	\$35 (\$32)	\$100	\$100	\$200	\$150	\$250
Continental	\$25 (\$23)	\$35 (\$32)	\$100	\$100	\$100	\$125	\$149+
US Airways	\$25 (\$23)	\$35 (\$32)	\$100	\$100	\$100	\$100	N/A
Alaska	\$15	\$25	\$50	\$100	\$100	\$100	\$100
Low Cost Carriers							
Southwest[a]	None	None	\$50	\$50	\$50	\$75	N/A
AirTran	\$15	\$25	\$50	\$50	\$50	\$69	N/A
JetBlue	None	\$30	\$75	\$75	\$75	\$100	N/A
Frontier	\$20	\$30	\$50	\$50	\$50	\$75	\$150
Virgin America	\$25	\$15	\$25	\$25	\$25	\$100	N/A

KEY: Airport check-in fee (online check-in fee/discount, if applicable).
[a] Baggage fees of \$110 apply for 11th+ bag.

Table 3.6: Representative Changes to Checked Baggage Fees

	Time Period	1st bag	2nd bag
Delta	Ticketed after 1/5/10 for travel on/after 1/12/10	\$25 (\$23)	\$35 (\$32)
	Ticketed 7/15/10-1/4/10	\$20 (\$15)	\$30 (\$25)
	Travel after 12/5/08 (to ticketing 7/14/10)	\$15	\$25
	Ticketing prior to 11/5/08 for travel on/after 12/5/08	\$0	\$50
American	Ticketed after 2/1/10	\$25	\$35
	Ticketed 8/14/09-1/31/10	\$20	\$30
	Ticketed before 8/14/09	\$15	\$25
Continental	Ticketed after 1/9/10	\$25 (\$23)	\$35 (\$32)
	Ticketed 10/2/09 – 1/8/10	\$10 (\$18)	\$25 (\$23)
	Ticketed 7/21/09 – 10/1/09	\$0 (\$15)	\$0 (\$25)
US Airways	Ticketed after 1/18/10	\$25 (\$23)	\$35 (\$32)
	Ticketed 8/26/09 – 1/17/10	\$25 (\$20)	\$35 (\$30)
	Ticketed before 8/26/09	\$20 (\$15)	\$30 (\$25)
Virgin America	Ticketed after 2/12/10 for travel on/after 3/1/10	\$25	\$25
	Ticketed 8/21/09-2/11/10	\$20	\$20
	Ticketed prior to 8/20/09	\$15	\$15

KEY: Airport check-in fee (online check-in fee/discount, if applicable).

3.5.3. Seat Fees

Although the implementation of baggage fees and associated alignment of fees across carriers was relatively simple, the same is not true for seat reservation fees. Table 3.7 summarizes U.S. carriers' seat fees and characteristics associated with seats that are sold to a broad customer base and/or set aside for premium customers. All low cost carriers and the majority of network carriers have some form of seat pricing, although it is interesting to examine how airlines distinguish among coach seats and create a "unique" product for which they can charge additional fees. Historically, seats with extra leg room were used to create a unique coach product that was offered to customers for a premium price. However, as of June 2010, only one network carrier (United) offered extra legroom in coach, and only three low cost carriers (JetBlue, Frontier, and Virgin America) differentiated coach products using available leg room. However, all low cost carriers charged seat fees (or a variant of seat fees, in the case of Southwest) as did three of the six major network carriers. In many cases, product differentiation is accomplished through defining preferred seating areas. These areas typically include exit rows, bulkhead rows, and aisle and window seats near the front of the aircraft. These preferred seating areas often have early boarding privileges. Ironically, by imposing checked-baggage fees, airlines were able to create a more valuable coach product linked to boarding zones, i.e., those customers who board the aircraft earlier have better access to overhead space for securing their carry-on luggage.

Table 3.7: Overview of Seat Reservation Fees and Access to Preferred Seating

	Seat pricing	Extra legroom	Seats for sale	Preferred seats	Preferred seat Access[c]
Network Carriers					
Delta	No[a]	No	No	Yes	Elites
American	No	No	No	Yes	Elites Y,B, Fares
United	Yes ($9-$49)	Yes	Yes	Yes	Elites All others at check-in ($)
Continental	Yes (varies)	No	Yes	Yes	Elites All at check-in ($)
US Airways	Yes ($5-$15)	No	Yes	Yes	General frequent flyers All at check-in ($)
Alaska	No	No	No	Yes	Elites
Low Cost Carriers					
Southwest	$10 early check-in[b]	No	Yes[b]	N/A	N/A
AirTran	Yes (6-$20)	No	Yes	Yes	All ($)
JetBlue	Yes ($9-$75)	Yes	Yes	Yes	All ($)
Frontier	Yes ($15-$25)	Yes	Yes	Yes	Elites Higher yield coach fares ($) All others at check-in ($)
Virgin Am	Yes ($35-$110)	Yes	Yes	Yes	All ($)

[a] Delta implemented seat pricing in 10/08 as part of the Northwest-Delta merger, but discontinued the practice shortly thereafter.

[b] Southwest charges $10 for early check-in (up to 36 hours in advance of flight) which has a high probability of boarding with first group.

[c] ($) indicates that a seat reservation/seat selection fee applies; if missing then exemption applies for that group/fare.

Unlike baggage fees, there is more variability across carriers' implementation of seat fees. Although all network and low cost carriers have preferred seating areas, they differ in which customers they make these seats available to, and which customers they charge to access these seats. For network carriers serving a large loyal elite customer base, such as Delta and American, it may not be advantageous to charge for these preferred seats. In addition, unlike low cost carriers that typically have one or two fleet types, network carriers typically have many fleet types. As a result, many network carriers have developed demand-driven dispatch policies to swap aircraft close to departure in order to better match unexpected fluctuations in demand. Implementation of seat pricing policies in which the number of seats for sale differs across aircraft may reduce network carriers' flexibility in reassigning customers to different seats as part of demand-driven dispatch policies.

Seat fees, reflected in the "seats for sale" column of Table 3.7, are often dependent on the purchased fare and/or the customer's status in the carrier's frequent flyer program. For some airlines, the seats for sale do not represent physical differences from other seats in coach (namely extra leg room) but rather are tied to boarding privileges or the ability to reserve a seat prior to check-in. For example, AirTran charges a $6 seat reservation fee for any "non-preferred" seat that customers purchase in a discount fare class; "preferred" exit and seats in the front of coach are sold for $13-$20, and no differentiation is made for fare class or membership status. Three of the remaining low cost carriers in the table – Southwest, JetBlue, and Virgin America – charge for preferred seating (or the equivalent preferred boarding in the case of Southwest); only Southwest differentiates based on membership status (elite members receive preferred boarding privileges). The remaining carrier in the table, Frontier, has a distinct preferred seating plan compared to the other low cost carriers. Unlike AirTran, it does not allow advance seat reservations for a fee at the time of booking on economy fares; that is, these customers have no option but to wait until check-in for their seat assignments. Similar to JetBlue and Virgin America, Frontier does sell preferred seats, but it differentiates by fare, status, and time of booking: elites receive these seats free of charge, customers purchasing higher-yield coach fares may purchase these seats at the time of booking, and all other customers may purchase these seats at check-in. Among the network carriers, more variability in seat fees can be observed. Delta, American, and Alaska Airlines do not charge seat fees but do provide preferred seating access to elite members and/or premium coach fare customers at no charge. In contrast, United, Continental, and US Airways charge seat fees and differentiate these fees by fare class, customer status, and/or time until departure.

3.6. Discussion of Policy and Customer Service Implications

New ancillary fees may result in a decrease in customer satisfaction. Although no surveys are available that measure customer responses to these new fees, it would not be surprising to find that customer satisfaction levels have dropped since these new fees were introduced – particularly those fees related to baggage fees and seat reservation fees that represent add-on charges to customers that used to be “free” or bundled in the base fare. The fact that the U.S. DOT has issued a *Proposed Ruling* discussing these fees is a clear indication that their long-term adoption may be influenced by customer backlash and possible regulatory intervention. This section reviews three main policy and customer service implications associated with the debundling phenomena.

3.6.1. Enhancing Customer Protections

The comparison of baggage and seat reservation fees in Section 4 illustrates the complexity of pricing that is emerging in the market, and underscores the fact that the choices facing air travelers today are much different than the choices they faced 30 years ago after deregulation. Looking ahead, the U.S. federal government may also play a large role in shaping the future of the airline industry, particularly as it relates to the distribution and presentation of “choices” to consumers. Specifically, on June 8, 2010, the U.S. DOT issued a *Notice of Proposed Rulemaking* on enhancing airline passenger protections; one of these proposed rules would require carriers to notify consumers of optional fees related to air transportation and of increased baggage fees (Federal Register, 2010). Specifically, the U.S. DOT states:

> We also seek comment on the costs and benefits of requiring that two prices be provided in certain airfare advertising – the full fare, including all mandatory charges, as well as that full fare plus the cost of baggage charges that traditionally have been included in the price of the ticket, if these prices differ. … Should the Department require carriers to include in the second price all services that traditionally have been included in the price of the ticket such as obtaining seat assignments in advance? … In the alternative, the Department is considering requiring sellers of air transportation to display on their Web sites information regarding a full price including optional fees selected by the

> passenger when a prospective passenger conducts a query for a particular itinerary. In other words, passengers would be able to conduct queries for their specific needs (e.g., airfare and two checked bags, airfare, one checked bag and extra leg room). … Proposed section 399.85(c) would require carriers that have a Web site accessible to the general public to disclose all fees for optional service to consumers through a prominent link on their homepage that leads directly to a listing of those fees. Optional services include but are not limited to the cost of a carry-on bag, checking baggage, advance seat assignments, in-flight food and beverage service, in-flight entertainment, blankets, pillows, or other comfort items, and fees for seat upgrades.

What is most interesting about the *Proposed Ruling* is the focus on regulating how information is displayed to consumers, and even how consumers should be able to interact with the website. Given that ancillary fees paid by a consumer are often tied to different fares and/or frequent flyer status, providing a customized search option will be challenging for airlines to implement as suggested in the *Proposed Ruling*. One implementation model that may be viable is that used by United in the context of its preferred Economy Plus seating. The ability to reserve an Economy Plus seat on United can only be done online if customers first log in to the website using their frequent flyer account. Through logging on, United is basically able to tailor seat selections to each customer. However, United also indirectly benefits from encouraging customers to log in at the beginning of the search process (versus when a ticket is ultimately purchased) in the sense that it can unobtrusively observe the sequence of screens across a single or multiple website session. As shown by many authors (e.g., see Hoffman and Novak, 1996; Moe and Fader, 2004; Montgomery et al., 2004; Lee et al., 2010), this can provide valuable marketing information. Thus, the *Proposed Ruling* and expressed desire by the DOT to dictate how customers can search for information needs to be viewed in a broader context, one that examines the potential benefits and disadvantages associated with: (1) customizing information to each individual; while, (2) providing new opportunities for carriers to customize marketing information. The ability to track individuals during their online search process may also raise new privacy concerns that need to be addressed.

From a research perspective, the impact of menu display and search options on customer choice is not a well understood area. It is an area that major carriers are just now beginning to investigate – particularly the trade-off between making low fares "transparent" for price-sensitive customers to stimulate demand without cannibalizing revenues for time-sensitive customers[11]. For example, Delta was recently testing the placement of its low fare search option, a "my dates are flexible" option on its home webpage. In one design, the "my dates are flexible" option appears prominently on its webpage; while in a second design, this option was still on the homepage, but was hidden in the sense it could be accessed only by first clicking the "more booking options" tab. In late 2009, Continental Airlines completely revamped its website, making low cost fare comparisons from the home page and default returns less obvious. Continental has

[11] See Brunger (2010) for a discussion that challenges one of the commonly-held beliefs in the industry related to internet transparency and revenues. Brunger offers that increase fare transparency has not decreased revenue.

recently implemented an advanced low fare search option, which is unique from other search engines in that it is customized to Continental's round-trip pricing philosophy (which imposes minimum stay requirements on fares for certain days of the week); but this feature is not prominently displayed on its home page and can only be accessed by performing an "advanced search option" query and clicking on the "my dates are flexible" option. This example further highlights the dynamic nature of the U.S. airline market, and the many open research questions that remain to be investigated in this area. It also brings to light another issue: the need to understand how seemingly isolated changes (such as website displays) may cause unintended consequences for other decision support systems (in this case, revenue management and demand predictions).

3.6.2. Airport and Airway Trust Fund

The debundling trend also has potential implications for government revenue sources, most notably the Airport and Airway Trust Fund (AATF). The tax structure associated with the AATF has undergone several major changes since deregulation. Karlsson (2006) provides a historical review of these changes. Today, the current aviation excise tax structure is based on the Taxpayer Relief Act of 1997, Public Law 105-35. The three largest components of the AATF are a domestic passenger ticket tax (7.5 percent of the ticket price), a domestic flight segment tax (set at $3.70 for 2010), and an international arrival and departure tax (set at $16.10 for 2010). According to a Federal Aviation Administration (FAA) presentation, in FY 2004, 51.5 percent of the excise taxes were levied through the passenger tax, 18.2 percent from the passenger segment tax, and 16.1 percent from the international passenger tax. The remaining excise taxes were collected from other passenger and fuel taxes (Federal Aviation Administration, 2005; Federal Aviation Administration, 2010a). These percentages have remained relatively constant across the years, i.e., the total receipts for the AATF from these three excise taxes has ranged from 72 percent in 1999 to 69 percent in 2006 (Federal Aviation Administration, 2010b). It is interesting to note that these funds have remained relatively constant despite the underlying structural changes in the U.S. airline market. Part of the reason is likely due to the mix of fees from domestic and international passengers, which helped the AATF protect itself against the shift towards international markets seen by network carriers.

However, as carriers shift towards a combination of a base fare (that is subject to the 7.5 percent domestic passenger ticket tax) and add-on services (that are not subject to this tax), it is logical that the AATF will lose revenues. For example, in 2009, U.S. domestic carriers collected $2.37 billion in reservation change fees (U.S. DOT, 2010). Assuming these fees could have been collected through the base fare, this represents a potential loss of $177 million for the AATF. In 2009, U.S. domestic carriers collected $2.72 billion in baggage fees, which represents an additional potential loss of $204 million for the AATF. Finally, in the last quarter of 2009, airlines collected $736 million in baggage fees, $564 million in reservation change fees, and $611 million from other ancillary fees “such as pet transportation fees and frequent flier award program fees” (Bureau of Transportation Statistics, 2010). Thus, in terms of “other” ancillary fees we estimate an additional potential loss of $183 million for the AATF. Given the total estimated tax receipts for the AATF were $11.282 billion (Federal Aviation Administration, 2009), the potential losses from ancillary revenue streams (~5.0 percent) are noteworthy, particularly if the trend towards debundling continues in the U.S. domestic air market. However, unlike the European Union, in which the percentage of ancillary fees on low cost carriers can exceed 20 percent of the total revenues generated (May 2010), the U.S. is in an unique position in that it has one dominant low cost carrier, Southwest Airlines, that fundamentally does not believe in charging fees. This unique market structure will likely buffer the AATF against dramatic revenue leakage due to ancillary revenue generation.

3.6.3. Integration across Airline Systems

Several examples have been provided to illustrate how implementation of ancillary fees (which seeks to generate additional revenue for a carrier) may actually lead to revenue loss or unintended consequences in performance metrics in other parts of the airline business. These examples include the recent elimination of close-in-ticketing fees by Delta and United (which one may assume is due to long-term lost revenue by customers) and elimination of seat fees by Delta (which from its online blog discussion, one can infer was due to complaints from its premier customers). The discussion of customizing carriers' websites to help customers find lower fares also falls under this category, as it likely improves the number of tickets sold but decreases yield and possibly total operating revenue.

Indeed, the implementation of ancillary fees can have many subtle unintended consequences that are difficult for carriers to quantify. As an example, consider day of departure standby fees. Many carriers charge fees to standby for other flights on the day of departure. These fees are typically categorized into confirmed standby fees and unconfirmed standby fees. Confirmed standby fees apply when a gate agent can automatically rebook a passenger and confirm a seat on an alternate flight. With one exception, confirmed standby fees range from $25-$75 for the carriers shown in Table 3.1. Southwest Airlines is the only exception in that it does not charge standby fees per se, just the difference between the purchased fare and the current fare. Confirmed standby fees are marketed to consumers in lieu of the much higher exchange fees. As seen with the baggage and ticketing exchange fees, many exemptions apply based on the purchased fare class and/or elite membership status.

In contrast to confirmed standby fees, unconfirmed standby fees apply if the gate agent cannot confirm a seat on a desired flight and/or if the airline permits passengers to standby even though a seat can be confirmed. Only a few carriers permit unconfirmed standby for flights at no fee (e.g., US Airways, AirTran, JetBlue, and Virgin America). Further, in the case of JetBlue and Virgin America, their free unconfirmed standby policies are restricted to a subset of flights, i.e., customers must pay a confirmed standby fee if they board flights that depart outside the designated free standby time window.

Similar to the previous discussion of baggage fees, there have been many changes implemented in these fees during the past 12-24 months. Some carriers have made their policies stricter, e.g., American recently changed its unconfirmed standby policy (such that it is not permitted except for tickets purchased with miles). In contrast, other carriers have relaxed their policies, e.g., as of April 2010, United now permits confirmed standbys on all flights on the day of departure; previously this was restricted to those flights departing within three hours of the original ticketed flight. Similarly, AirTran recently decreased its standby fees from $49 to $25, and Continental recently decreased its standby fee from $75 per reservation to a per-person charge of $50 with discounts and/or waivers for elite members.

It is interesting to think about the impact of these standby fees, which restricts the movement of passengers across flights from an operational perspective. Discouraging passengers from standing by for earlier flights may lead to misconnections (if the flights the passengers are on are delayed) or lost opportunities to accommodate other disrupted passengers. That is, the ability to leave earlier than planned essentially provides an extra buffer of time for connecting passengers and helps shift demand to earlier flights, providing more seats later in the day for disrupted passengers. Further, these buffers may actually be quite worthwhile from financial and customer service perspectives. For example, a study by Bratu and Barnhart (2002), based on a major U.S. carrier's data from 2000 shows that approximately 30 percent of its flight legs were delayed and 3.5 percent cancelled, resulting in approximately 4 percent of all passengers being disrupted (2 percent were connecting passengers). From the carrier's perspective, Clarke and Smith (1999) estimate that "the financial impact of irregularities on the daily operations of a single major U.S. domestic carrier may exceed $440 million per annum in lost revenue, crew overtime pay, and passenger hospitality costs" (Lan, Clarke and Barnhart, 2006). This example highlights the difficulties connected to quantifying all short-term and long-term financial costs associated with implementing new ancillary fees and helps explain why, in some cases, carriers may implement new fees, but then eliminate them as the full system-level effects are become clearer. In the case of standby fees, it would be interesting for a carrier such as American that recently implemented a "no free unconfirmed standby" policy to see if passenger misconnections and the average delays experienced by disrupted passengers increased. If so, one may assume that American will revert back to its more generous standby policy (following the lead of similar changes recently implemented by AirTran and Continental).

3.7. Looking Ahead

An examination of ancillary fees reveals that all carriers – including Southwest Airlines – have implemented new fees over the past few years. How carriers have elected to implement these fees, though, varies. Network carriers that have a more loyal repeat customer base are more likely to establish fees while simultaneously creating an elaborate system of fee waivers for their premier customers. Given premier customers typically represent a large percentage of a carrier's ticketing revenue, it seems unlikely that carriers would decide to start charging these customers fees in the future. Exempting premier customers from ancillary fees can be viewed as a way by which carriers can add value to their frequent flyer programs and encourage repeat business.

The analysis of Southwest's implementation of fees is particularly enlightening and helps explain why the debundling trends seen in the United States are distinct from those in Europe and other parts of the world. Southwest is a powerful domestic marketing force, but it is a carrier that historically has had a strong philosophy of not charging for fees that were once bundled into its base fare. Southwest also places a high priority on its brand and maintaining long-term repeat customer business. Through its recent merger with AirTran, Southwest should be able to further expand its domestic market share as well as begin to expand to international markets. As Southwest grows, U.S. carriers may be pressured into revoking those fees that at one time were bundled into the ticket price.

It will be particularly interesting to see, after Southwest completes its merger with AirTran, how much additional pricing pressure Southwest is able to put on Delta out of Atlanta's Hartsfield-Jackson airport. If a major carrier such as Delta revokes baggage fees, all other major carriers will likely do the same. This highlights the importance of viewing the short-term and long-term consequences of ancillary fees in terms of existing market competition. For example, although the events of 2008 and 2009 led to rapid debundling, one of the benefits has been that many airlines did well financially in 2010. However, if demand for air travel starts to outpace available supply, one would expect airlines to start dropping or eliminating fees as they compete to win these additional customers.

Viewing changes through the lens of current market positions also provides insights into why similar campaigns have failed in the past, and which ancillary revenue sources are likely to survive moving forward. One example of a campaign that "failed" is American Airline's promotion of extra leg room throughout coach in the late 1990s and early 2000s. American invested millions of dollars in retrofitting its planes to offer more legroom, but it operated these aircraft primarily on short-haul domestic flights, many of which were facing increasing pricing pressure from Southwest. Consequently, customers were not willing to pay for extra leg room on short flights. In contrast, Delta recently announced that it was adding legroom in coach – but to serve customers in their long-haul international markets. These international markets currently face less price competition, and extra legroom in this context is more valuable to consumers (suggesting they are more willing to pay). However, as with American's experience, if market competition changes and low-cost carriers begin to compete on international markets and/or offer better products on these markets, then Delta's long-term ability to charge a premium for these seats will be diminished.

What is clear from this discussion is that the debundling phenomena in the United States has been rapid and is still in transition. In the long term, it would not be surprising if low cost carriers competing with Southwest Airlines adopted a wider range of ancillary fees, whereas network carriers followed the trends of Delta and United and eliminated many of the fees that were recently introduced for services that once were perceived to be free to consumers. For example, when Delta merged with Northwest, it initially adopted Northwest's practice of charging for preferred seats (Delta Air Lines, 2008); however, due to backlash from its premium customer base, these fees were quickly eliminated. Similarly, United used to charge for close-in ticketing fees for those customers redeeming frequent flyer miles (i.e., fees that were charged if customers redeemed their miles for tickets within 21 days of departure), but recently eliminated these fees. Delta also adopted a similar policy as of June 3, 2010 (Delta Air Lines, 2010). Both of these examples suggest that adoption of ancillary fees is still dynamic. The two major sources of revenue generation – baggage and seat fees – will likely be the longest surviving fees. However, as the U.S. market returns to healthier economic times, even these fees may disappear, particularly if Southwest stays true to its core pricing and customer philosophies.

3.8. Summary

Looking ahead, the "ancillary revenue" phenomenon is likely to continue in the U.S. market among low cost and network carriers. Numerous airlines are reporting the importance of ancillary fees in their investor reports and/or listing generation of these fees as a top priority (e.g., see AirTran Holdings Inc., 2009). In its March 26, 2010, presentation to Barclay Capital High Yield Bond and Syndicated Loan Conference, Continental stated that one of its five top priorities in 2010 was to "increase ancillary revenues through customer choice" (Continental 2010a; Continental 2010b). Continental elaborated, stating that it plans to grow these ancillary revenue streams through product debundling (baggage fees, booking fees, in-flight amenities) and product enhancements including day-of-departure upgrades, preferred coach seating, premium wines and liquors, PetSafe and "many others to come" (Continental, 2010a).

What will be interesting to see is whether future ancillary revenue enhancements follow the trends seen with baggage fees (in which clear market segmentation quickly emerged); or if technological, customer acceptance, market competition, and other constraints will hinder airlines' ability to universally adopt ancillary fees (as in the case of seat pricing). What is clear, however, is that the debundling phenomena has arrived in the United States, and the full implications of debundling have yet to be realized but will likely be important to account for in both the public and private sectors.

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CHAPTER 4: PREMIUM COACH SEAT PURCHASING BEHAVIOR

Mumbower, S., Garrow, L.A. and Newman, J.P. (2013) Investigating airline customers' premium coach seat purchases and implications for optimal pricing strategies. *Working paper,* Georgia Institute of Technology.

4.1. Abstract

We investigate factors that influence airline customers' purchases of premium coach seats using a database of online prices and seat map displays collected from JetBlue's website. Results show that multiple factors influence purchasing behavior; these factors include the amount of the seat fee, how far in advance the ticket is purchased, the number of passengers traveling together, and load factors (as revealed through seat map displays). We find that customers are between 2 and 3.3 times more likely to purchase premium coach seats (with extra legroom and early boarding privileges) when there are no regular coach window or aisle seats that can be reserved for free. In addition, we find that customers who purchase tickets closer to the departure date are less price elastic and are willing to pay higher seat fees. We use these model results to show that JetBlue's seat fees are currently underpriced in many markets; an optimal static fee would increase revenues by 8% whereas optimal dynamic fees would increase revenues by 10.2%. In addition, if JetBlue were to leave their seat fees unchanged and instead blocked certain rows of seats for premier customers, they could potentially increase revenues by 12.8%. This finding underscores the importance of ensuring customers are not inadvertently misled into purchasing premium seats by seat map displays that block seats for premier customers.

4.2. Introduction

Over the course of the last decade, airlines have experienced numerous financial challenges, including ballooning costs and intense competition. Many of these challenges came to a head around 2008, when oil prices soared to more than $130 a barrel (Clifford, 2008) and the global economic crisis hit, dropping the Dow Jones market value by 33.8% (the third worst calendar year performance on record) and triggering a worldwide slowdown in economic activity, including air travel (Seeking Alpha, 2009). Many major airlines had already implemented significant cost-cutting strategies during the early 2000’s as part of their bankruptcy restructuring and merger processes, limiting their ability to cut expenses, and the deep market penetration of the Internet, combined with low cost carrier competition, hindered the ability to raise fares. Consequently, “2009 proved to be the worst year on record for U.S. airlines, in terms of year-over-year revenue declines” (Southwest Airlines, 2009).

In response, many airlines sought to increase revenues without increasing fares by creating new ancillary revenue sources, such as fees for checked baggage, on-board food, and seat reservations and upgrades. These services were once bundled into the base price of a ticket, but airlines began to price them separately. In addition, airlines increased the cost of existing ancillary services, including fees for redeeming mileage award tickets, exchanging tickets, and checking pets. Moreover, rather than being a temporary solution to help get airlines through a rough year, these fees have become a permanent fixture of the air travel marketplace. According to the Bureau of Transportation Statistics, revenues from ancillary fees have rapidly increased in the past few years: for U.S. carriers with operating revenues over $20 million, reported ancillary revenues increased 172% over five years, from $3.6 billion in 2007 to $9.8 billion in 2011 (U.S. DOT, 2012). Similar trends are observed worldwide. A recent report sponsored by Amadeus and IdeaWorks that represents a broader set of airlines and more comprehensive set of ancillary fees finds that in 2007, 23 airlines posted ancillary revenues of $2.45 billion and in 2011, 50 airlines reported revenues of $22.64 billion (Sorensen and Lucas, 2012).

Ancillary revenue streams are important to airlines, sometimes turning a loss-making carrier into a profitable one. That was more or less the case for JetBlue in 2011, which reported a net profit of $86 million and seat fee revenues of more than $120 million (JetBlue Airways, 2011). For some carriers, ancillary revenues can represent a major portion of overall revenues. In the U.S., Spirit Air is notorious for its extremely low base fares and “optional” fees for services such as booking online or by phone, printing a boarding pass at the airport, and carrying on luggage; in 2011, Spirit earned 33.2% of its revenue from these fees. Major carriers such as United/Continental (13.9%), Alaska (14.1%), and American (8.8%) earned a notable percentage of revenue from ancillary fees as well (Sorensen and Lucas, 2012). Given that the margins on the ancillary services are generally quite large, these fees in many cases represent most or all of the carrier’s operating profit.

Despite the prevalence and growing importance of ancillary fees, few studies have examined the direct impact these fees have had on customers’ purchasing behavior, let alone the secondary effects of these fees. For example, when airlines began charging for checked baggage, the amount of carry-on luggage increased. As a result, demand for overhead bin space often exceeded what was available. This ultimately led to higher demand for seats with early boarding privileges that give customers earlier access to overhead space. Thus, it appears that by introducing new fees for checked baggage, airlines were also able to begin charging more for seats with early boarding privileges. Similarly, as aircraft load factors increase, passengers realize the likelihood of having an empty seat next to them drops, and the value of a premium seat with extra personal space increases.

Airline operators continue to search for ways to increase ancillary revenues, without negatively impacting sales of basic tickets so much as to cancel out these revenue gains. A principle avenue for achieving such increases is through making fees for ancillary products more complex and differentiating fees across customer groups (e.g., by reserving or blocking premium seats for premier customers).

On the other hand, customers generally dislike added fees, and in particular dislike fees that appear to be hidden, arbitrary, or unfair. From the regulatory perspective, agencies want to ensure that fees are displayed in a way that is easy for consumers to understand. One issue that is of particular concern is whether the airline practice of blocking seats for preferred customers (i.e., showing certain seats as unavailable for non-preferred customers without elite status in an airline's frequent flier program and/or showing certain seats as unavailable for those customers who do not purchase tickets for higher yield fare classes) effectively "tricks" customers into thinking a plane is full when in fact it is not, leading customers to buy an upgraded premium coach seat. However, answering this question is difficult, not only for regulatory agencies but also for the airlines themselves, because the majority of airlines only keep records of the customers' final seat assignments. Without more extensive data on the allocation of seat assignments across the entire booking horizon, it is difficult to recreate seat map displays shown to customers at the time of booking (i.e., it is difficult to know what seat choices the customer had at the time of booking). Airlines could certainly collect this information directly, but would need to make major investments in technology infrastructure to do so, and they are unlikely to make such an investment unless they have a high level of confidence that they will receive a decent return on their investment. Regulatory agencies also do not have access to proprietary carrier data, and would need to conduct any independent investigations into this issue using publically available data or stated preference surveys.

Our study contributes to the literature on ancillary fees by providing some of the first insights into the role of load factors and seat map displays on customers' premium seat purchases. We investigate airline customers' seat purchasing behavior using a database of revealed preference data that includes online prices and seat maps from JetBlue's website. This data is used to investigate the probabilities that customers will pay between $15 and $65 to reserve a premium coach seat that includes extra legroom and early boarding privileges. By tracking seat maps and prices across the booking horizon, the JetBlue data provides the ability to estimate binary logit models of seat choice, which can be used to understand how demand for its premium coach seat product varies across the booking horizon, across markets, and as a function of load factors (as revealed through seat map displays).

The rest of this paper is organized as follows: Section 2 provides additional background context on premium seat fees. Sections 3 and 4 provide an overview of the data and modeling methodology. Section 5 presents results and Section 6 uses model results to assess different pricing and seat display policies. The paper concludes with a discussion of major findings.

4.3. Premium Seat Fees

One of the more common types of ancillary fees is a premium seat fee, which is charged to customers wanting to reserve a "good" seat on the aircraft. As of 2013, all mainline carriers in the U.S. with annual operating revenues exceeding $1 billion are charging seat fees, with the exception of Alaska and Southwest. The implementation of these fees varies by carrier, and many of the airlines waive certain fees for elite customers and/or high yield tickets. Table 4.1 summaries U.S. airlines' seat fee policies and charges.

Some airlines charge fees to reserve seats that do not provide extra legroom but instead allow customers to board early and gain early access to overhead bin space. With many airlines charging checked baggage fees even for the first bag, early access to overhead bin space is desirable. These priority boarding seats, often called "preferred" seats, typically include seats in popular locations on the plane that were once free to reserve, such as exit and bulkhead rows (which may offer a little extra legroom) and seats near the front of the aircraft, especially aisle and window seats near the front of the plane. Fees for preferred seats range from $4 to $45 per leg for domestic flights.

Other airlines charge fees to reserve seats that provide both extra legroom and often early boarding. These seats are often referred to as "premium" economy or "premium" coach seats. Fees for premium seats range from $5 to $99 per leg for domestic flights.

Table 4.1: U.S. Airlines' Seat Fee Policies as of June 2012

Airline	Extra Legroom?	Fee Exemptions?	Typical Domestic Fees
AirTran	No	Yes	\$6-\$20
Alaska	No	N/A	No charge
American	No	Yes	\$4-\$29
Delta	Yes	Yes	\$19-\$99
Frontier	Yes	Yes	\$5-\$50
JetBlue	Yes	No	\$15-\$65
Southwest[1]	No	Yes	\$10
United	Yes	Yes	\$9-\$89
US Airways	No	Yes	\$15-\$45

[1]Southwest charges \$10 for early check-in which has a high probability of boarding with the first group and improving seat selection.

4.3.1. The Airline Perspective

Due to the need to quickly create additional revenue streams during the crisis, there was little to no research done by airlines to determine customers' willingness to pay for premium and preferred seats prior to implementation of these fees. Further, technology constraints limited how airlines could charge fees. For example, airlines did not have the ability to change seat upgrade fees across the booking horizon; that is, the same fee was charged to customers regardless of how far in advance of departure they booked. This limitation persists today for most airlines, although many are now in a position where they can make investments in revenue enhancing opportunities, including technology to get around these dynamic pricing limitations. There are also other opportunities to create marginal improvements in seat fee revenues. For example, if airlines have a better understanding of customers' behavior and willingness to pay for certain amenities, they can make long range plans to acquire and configure new airplanes appropriately to capture more value from future customers: Are enough customers willing to pay enough money for premium coach seats (with extra legroom) that it is worth sacrificing a row of regular coach seats from the plane? Should airlines invest in technology that will enable them to dynamically price ancillary fees over the booking horizon? If so, what are the optimal revenue-generating fees they should charge?

Although it has been 5 years since ancillary fees became a prominent part of the air travel landscape, few studies have examined customers' willingness to pay for such fees, including premium seat fees. One study based on stated preference data from Resource Systems Group, Inc. found that the average customer was willing to pay $19 more for a window seat and $18 more for an aisle seat without extra legroom (Weinstein and Keller, 2012). However, that study did not control for other factors that influence willingness to pay, such as plane load factors. There is a research need to investigate the role of seat map displays on customers' premium seat fee purchases, and to investigate revenue potential associated with dynamically pricing seat fees across the booking horizon. Our study contributes to this debate by investigating these two research questions. This objective is consistent with prior studies published in Transportation Research Part A that have examined one or more aspects of air travel behavior (e.g., see Brey and Walker, 2011; Chen, 2008; Lee et al., 2012; Lu and Peeta, 2009; Peeta, Paz and DeLaurentis, 2008; Tsamboulas and Nikoleris, 2008).

To our knowledge, only one major airline (United) currently collects data about seat displays across the booking horizon, and uses it to improve yields from its premium coach product. In the quarter after implementing the "Shares" yield management system, which allows for dynamic pricing of Economy Plus seats, United reported a 25% increase in revenues associated with Economy Plus, with only about a third of that increase attributable to an expansion in the number of Economy Plus seats available in the fleet

(Ranson, 2012). As one of the world's largest airlines, United is better positioned than many other airlines to absorb the large fixed cost entailed in developing a dynamic pricing system for ancillary revenues. In contrast with a full rollout of a comprehensive integrated system, the data collection approach we employ in this paper represents a comparatively small investment, which can help an airline decide whether to undertake the larger investment to actually implement a dynamic pricing system.

4.3.2. The Customer Perspective

Seat fee and reservation policies have the potential to greatly impact customer satisfaction levels both positively and negatively. We are not aware of any empirical research that that examines how characteristics of seat fee policies influence customer satisfaction levels. However, searching online through comments that airline customers have posted on various news articles, travel blogs, and travel websites reveals that customers have a wide range of concerns and opinions about seat policies. For example, CNN recently published a series of four articles on their website which discuss seat reservations and how customers feel about seat fees (Hume, 2012a, 2012b; Patterson 2012a, 2012b). One of these articles had nearly 2,000 comments posted by readers. Customer satisfaction with seat reservations seems to be impacted by many factors, including ease of reserving seats for a group traveling together and how seats are displayed on seat maps.

Seat policies that impose fees to reserve window and aisle seats decrease the number of contiguous seats available, which may make it more difficult for groups and families to sit together without paying those fees. Gate agents will generally try to accommodate families as well as they can, but if there are not extra seats available, then they may not always be able to work out a way for families to sit together. Due to widespread media coverage about this issue, Senator Charles Schumer recently (May 27, 2012) requested that Transportation Secretary Ray LaHood issue rules preventing airlines from charging parents more to sit next to their children (Schumer Press Release, 2012). Senator Schumer also asked the industry's trade group, Airlines for America, to try to persuade carriers to voluntarily waive the fee for families. A few days later at a Senate panel, Secretary LaHood responded by saying that he has been urging airlines against charging more for popular seats (without extra legroom). However, he also said that he "can't tell airlines what fees they can charge" (Jansen, 2012). Although charging fees for aisle and window seats may decrease customer satisfaction levels of groups traveling together, it could also negatively impact other travelers. Many customers have noted that people are asking them to trade seats more often now than in the past, and have posted comments on blogs describing scenarios where they paid for a window or aisle seat and someone asked them to trade seats so that they could sit by a family member. On the other hand, policies that reserve and/or charge for window and aisle seats may increase customer satisfaction levels of certain types of travelers. Many business travelers choose to fly coach instead of business class. These travelers often book a flight a few days in advance of the departure date when many seats are full and end up purchasing a ticket that is priced much higher than tickets purchased by people who booked far in advance. Policies that allow these customers to reserve a better seat may increase their satisfaction with the airline. Reserving seats for frequent fliers would also seem to increase satisfaction.

Another major issue of concern that customers have raised is how seat availabilities are displayed on seat maps. Airlines often block certain seats and do not allow customers to reserve these seats in order to set aside a few seats for accommodating passengers with disabilities or special needs. Now, with some airlines adopting policies that also reserve seats for elite members and higher-yield fares only, this means that other customers may be shown that these seats are "unavailable" on seat maps. This seems to have led to some confusion among passengers upon boarding. Some customers have complained that upon booking a ticket, the seat map showed that few regular seats were available, which caused them to consider purchasing an upgraded seat. However, upon boarding the plane, they noticed that many more seats were actually available. Bill McGee, a contributing editor to Consumer Reports and former editor of Consumer Reports Travel Letter, along with other columnists have expressed concerns about how available seats are displayed to customers (McCartney, 2011; McGee, 2012a, 2012b). Comments these columnists have received from customers indicate that some customers feel they have been misled by the information displayed on seat maps, but it could be that they do not completely understand the airlines' seat policies. For example, many of the airlines open up preferred seats (without extra legroom) that can be reserved (sometimes for free) during check-in by non-elite customers, but some people may not understand that or think about that when looking at a seat map. If customers feel like they have been tricked in to purchasing upgraded seats, then this could greatly decrease customer satisfaction with an airline.

In summary, the main concerns issued by customers and government officials relate to decreasing the number of contiguous seats (that are free to reserve) for families to sit together, and misleading customers into making preferred or premium seat fee purchases through displaying seat maps that are difficult to understand and/or that give the impression a plane is near capacity through showing seats as being occupied/unavailable to reserve.

4.4. Data

This section describes the database that was compiled from online pricing and seat map information from JetBlue's website.

4.4.1. Overview

To analyze how customers purchase premium coach seats with extra legroom, automated web client robots (or webbots) were used to query JetBlue's website and obtain detailed itinerary, fare, and seat map information for nonstop flights on a daily basis. Our paper is one of many that have used airline webbot data to analyze pricing and/or demand trends (e.g., see Bilotkach, 2006; Bilotkach and Pejcinovska, 2012; Bilotkach et al., 2010; Button and Vega, 2006; Button and Vega, 2007; Horner et al., 2006; McAfee and Vera, 2007; Mentzer, 2000; Mumbower and Garrow, 2010; Newman et al., 2013; Pels and Rietveld, 2004; Pitfield, 2008; Pope et al. 2009). The period of data collection ran from 8/2/2010 through 10/2/2010. During this time period, queries were run to collect airfares and seat maps for a rolling set of departure dates. For example, when the data collection began on 8/2/2010, information for flights departing on 9/2/2010, 9/3/2010, ... , to 10/2/2010 was obtained. For the next day of data collection, 8/3/2010, information for the same flight departure dates was obtained. Collecting data in this way provides information for each flight in a market for 30 departure dates and over a booking period from 1 to at least 28 days before flight departure.

The dataset includes 22 markets, across several different lengths of haul. Table 4.2 provides a list of airport codes and airport names in our data. Table 4.3 provides a list of the markets collected, along with market characteristics and seat fees, average fares, and number of bookings. A total of 59,242 bookings were observed (46,920 regular coach seat bookings and 12,322 premium coach seat bookings). Thus, 20.8% of the observed bookings are for premium coach seats, hereafter referred to as Even More™ Space (EMS) seats[12], which is the branding used by JetBlue. At the time of data collection, JetBlue's EMS seats provided 4 to 5 more inches of extra legroom over their regular coach seats[13], and also came with early boarding privileges.

After the online data was collected, seat maps for each day were used to compile daily booking (or demand) data for regular coach and premium coach seats. When a customer books a ticket with JetBlue, they have the option to purchase an EMS seat for between $15 and $65, or they can reserve a regular coach seat for free. For the most part, EMS seats are priced by length of haul with higher prices for longer flights. EMS seat prices are the same for every flight in a particular market, for all EMS seats on the aircraft, and over the entire booking horizon.

[12] At the time of data collection, JetBlue referred to these seats as Even More™ Legroom (EML) seats but subsequently rebranded these seats as Even More™ Space (EMS) seats. We use EMS terminology throughout the paper.

[13] Note that JetBlue's regular coach seats have more legroom than other airlines' regular coach seats with a pitch of 32-34 inches as compared to an average pitch of 30-32 inches on most other carriers.

Table 4.2: Airport Codes and Names

Airport Code	Name of Airport, City and State
AUS	Austin-Bergstrom International Airport, Austin, Texas
BOS	Logan International Airport, Boston, Massachusetts
BQN	Rafael Hernández Airport, Aguadilla, Puerto Rico
BUF	Buffalo Niagara International Airport, Buffalo, New York
DEN	Denver International Airport, Denver, Colorado
EWR	Newark Liberty International Airport, Newark, New Jersey
FLL	Fort Lauderdale Hollywood International Airport, Fort Lauderdale, Florida
IAD	Washington Dulles International Airport, Washington D.C.
JFK	John F. Kennedy International, New York City, New York
LAS	McCarran International Airport, Las Vegas, Nevada
LAX	Los Angeles International Airport, Los Angeles, California
LGA	La Guardia Airport, New York City, New York
MCO	Orlando International Airport, Orlando, Florida
OAK	Oakland International, Oakland, California
ORD	Chicago O'Hare International Airport, Chicago, Illinois
PBI	Palm Beach International Airport, West Palm Beach, Florida
PDX	Portland International Airport, Portland, Oregon
SFO	San Francisco International Airport, San Francisco, California
SYR	Syracuse Hancock International Airport, Syracuse, New York

Table 4.3: Market Characteristics and Observed Fares/Bookings, by Market and Type Haul

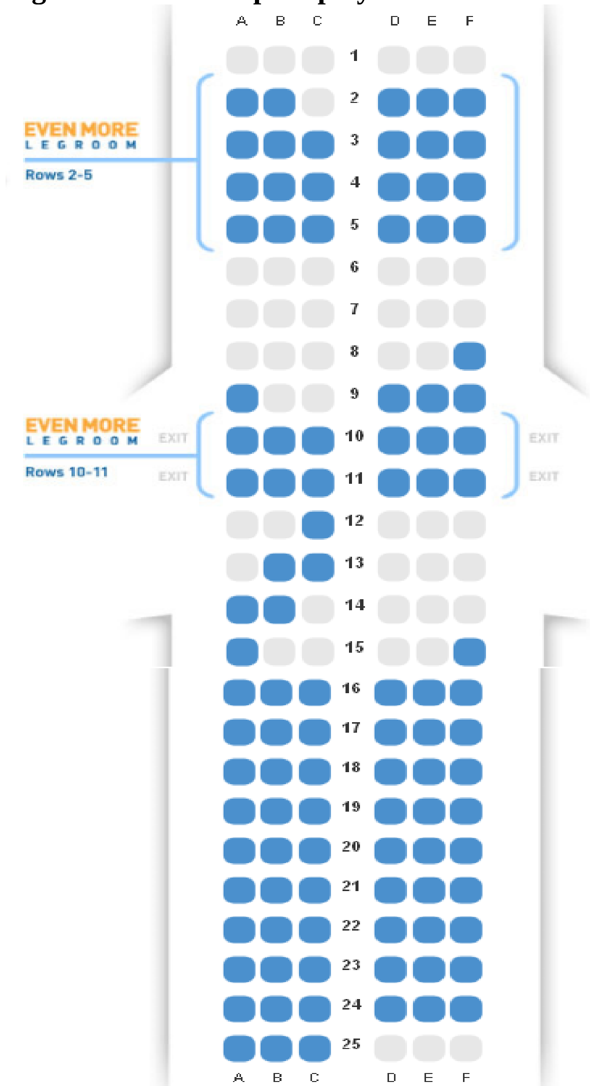
		Market Characteristics				Observed Fares and Bookings			
Market	**Type of Haul**[1]	**One-way Distance**	**Avg. Num Flights**	**One-way Seat Fee**	**Seat Fee per Mile**	**Avg. One-way Fare Paid**[2]	**Total Bookings**	**Total EMS Seats Booked**	**Percent EMS Bookings**
JFKBQN	E-PR	1,576	2	$30	$0.019	$147	2,133	112	5.3%
MCOBQN	E-PR	1,129	1	$25	$0.022	$118	975	54	5.5%
E-C Averages/Totals:		*1,437*	*2*	*$28*	*$0.020*	*$138*	*3,108*	*166*	*5.3%*
BOSIAD	E-E	500	7	$15	$0.030	$92	6,082	1,086	17.9%
BOSMCO	E-E	1,121	5	$30	$0.027	$130	2,407	416	17.3%
BUFMCO	E-E	1,011	1	$25	$0.025	$122	297	55	18.5%
EWRMCO	E-E	937	4	$19	$0.020	$125	2,486	520	20.9%
IADMCO	E-E	758	1	$25	$0.033	$102	734	194	26.4%
JFKFLL	E-E	1,069	7	$35	$0.033	$122	8,998	1,705	18.9%
JFKPBI	E-E	1,028	4	$35	$0.034	$141	4,843	1,152	23.8%
LGAFLL	E-E	1,076	5	$35	$0.033	$126	5,543	1,291	23.3%
SYRMCO	E-E	1,053	1	$25	$0.024	$134	782	163	20.8%
E-E Averages/Totals:		*943*	*5*	*$29*	*$0.031*	*$120*	*32,172*	*6,582*	*20.5%*
BOSDEN	E-MW	1,754	2	$40	$0.023	$183	1,950	376	19.3%
JFKORD	E-MW	740	3	$30	$0.041	$119	2,600	371	14.3%
MCOAUS	E-MW	994	1	$35	$0.035	$128	1,049	150	14.3%
E-MW Average/Totals:		*1,176*	*2*	*$35*	*$0.033*	*$144*	*5,599*	*897*	*16.0%*
BOSLAX	E-W	2,600	2	$50	$0.019	$184	2,549	547	21.5%
BOSSFO	E-W	2,700	2	$55	$0.020	$232	2,071	609	29.4%
FLLSFO	E-W	2,580	1	$50	$0.019	$152	999	150	15.0%
JFKLAS	E-W	2,240	5	$50	$0.022	$252	3,761	980	26.1%
JFKLAX	E-W	2,470	4	$50	$0.020	$214	4,907	1,322	26.9%
JFKOAK	E-W	2,576	2	$60	$0.023	$211	2,109	562	26.6%
JFKPDX	E-W	2,454	1	$50	$0.020	$257	944	160	16.9%
JFKSFO	E-W	2,580	2	$60	$0.023	$285	1,023	347	33.9%
E-W Averages/Totals:		*2,494*	*3*	*$52*	*$0.021*	*$222*	*18,363*	*4,677*	*25.5%*
Avg/Total All Markets:		*1,494*	*4*	*$37*	*$0.027*	*$157*	*59,242*	*12,322*	*20.8%*

[1] E-PR = East coast to Puerto Rico flights, E-E = East coast to east coast flights, E-MW = East coast to Midwest flights, E-W = East coast to west coast flights (JFKLAS is included due to length of haul).
[2] Average fare is the average fare that was paid when tickets/seats were booked.

We determined how many regular coach seats and EMS seats were sold on a particular day by determining when seats changed from being shown as “available” for one day but “reserved” for the next day. At this point, it is helpful to look at a seat map to see what kind of seat choices a customer can make. Figure 4.1 shows a seat map of how JetBlue’s Airbus A320 seats were configured at the time of data collection[14]. Darker-colored seats are “available” and can be reserved, and lighter-colored seats have already been “reserved”. The plane has a total of 150 seats, which include 114 regular coach seats and 36 EMS seats. The seat configuration of the A320 is as follows: rows 1, 6B-E, and 25D-F are always “blocked” and never available for customers to reserve online (blocked seats are typically set aside in order to provide advance seat assignments, as requested, to customers with disabilities); rows 2-5 are EMS seats in the front of the plane; rows 6-9 are regular coach seats in front of the emergency exit rows; rows 10-11 are EMS seats in the emergency exit rows; and rows 12-25 are regular coach seats behind the emergency exit rows.

[14] At the time of data collection, JetBlue operated two types of aircraft: Airbus A320 and Embraer ERJ-190. Because the Embraer aircraft only accounts for 29% of JetBlue’s fleet and contains just four premium coach seats per flight (JetBlue Airways, 2011), only the Airbus A320 aircraft was used in the analysis.

Figure 4.1: Seat Map Display of a JetBlue Plane



Source: JetBlue.com

We assume that any customer who booked a ticket also selected a seat, as regular coach seat selections were free and the website prompts the customer to select a seat during the reservation process. We exclude customers who may have reserved a blocked seat from the analysis, as we have no way to distinguish between instances in which the blocked seat is occupied or is available (to disabled customers). We also exclude negative demand numbers from analysis, which occur when one or more customers cancel their reservations (and no new reservations occur on that booking date for that flight). In this sense, our demand estimates for regular coach and EMS seats can be viewed as lower bounds on demand, as they represent the minimum number of customers who reserved a seat for a given booking date and departure date. The actual demand may be slightly higher than what we can observe from the seat maps, as we cannot account for cases in which new bookings and cancellations occur for the same booking date and departure date combinations. Based on an assessment of the frequency of negative booking counts (which accounted for a small percentage of the observations in the data), we conclude that the assumptions used to create demand estimates are reasonable.

4.4.2. Selection Bias

Using JetBlue as the airline for our analysis enables us to control for potential sources of selection bias. Since JetBlue customers may reserve a regular coach seat for free (or a premium coach seat for a fee) at the time of booking, we expect the majority of customers to reserve seats at the time of booking. Further, JetBlue does not overbook its flights, which means that all customers have the option to select a seat at the time of booking. Importantly, JetBlue is also the only airline in the U.S. that does not waive seat fees for certain customers, i.e., any individual who wants to sit in the premium coach section must pay to do so. Replicating this study on another airline would introduce selection bias, as customers who receive premium seat assignments for free or at a discount cannot be identified from the online data. In our data, however, this source of selection bias does not exist: all customers who reserve a premium seat must pay to do so.

The exact fee that customers pay to reserve a premium seat is known by the researcher and is charged on a per-flight basis. Thus, network-level effects are not relevant in the context of our problem, as connecting passengers would need to pay a separate premium seat fee for each flight on their itinerary. On the other hand, the exact basic fare paid by the customer is not known, as JetBlue offered both non-refundable and refundable fares. At the time of data collection, JetBlue's default website search option displayed one non-refundable fare for each flight. However, customers could search for refundable fares by changing the search options (and one refundable fare for each flight would be displayed). Still, the data does include the price of the non-refundable one-way leg-based fare for the flight, which represents a floor on the actual fare paid, and is strongly correlated with the actual ticket fare. As we are studying price elasticity with respect to the seat upgrade fee and not the basic fare, the noise in the basic fare data represents a loss of some information, but will not trigger a fundamental bias in our results.

Finally, it is important to note that we have not included passengers who choose to purchase a premium seat at the time of check-in. To do this, we would have needed to query JetBlue's website multiple times within the 24 hours check-in period prior to flight departure. Moreover, some data would still be unobservable, as JetBlue does not sell tickets online in the final 90 minutes before departure, but they do sell seat upgrades at the airport during this time. The focus of our paper is on determining if seat map displays shown at the time of booking influence premium seat purchases and determining if airlines have an incentive to make premium seat fees more complex by dynamically pricing them across the booking horizon. Both of these problems require knowledge about bookings that happen prior to the day of check-in. The underlying behavioral problem for day of check-in premium seat purchases is distinct from the problem that looks at seat fee purchases at the time of the initial booking. At the time of booking, the addition of a $40 seat fee on top of a $200 fare may seem large whereas at the time of check-in, faced with sitting in the back of a full plane, a $40 fee may appear reasonable. The delay between the time of purchase and time of departure, in addition to more complete information on load factors at the time of check-in, may influence day-of-departure upgrades. A distinct modeling approach may be advisable to examine day-of-booking seat fee purchases versus day-of-departure seat fee purchases. Examining day-of-departure seat fee purchases is beyond the scope of our study.

4.5. Methodology

A binary logit model was used to calculate the probability of purchasing an EMS seat, given that a ticket was purchased. In this model, a customer can choose between two options[15]:

$$\begin{cases} Y = 1, & Buy\ a\ ticket\ and\ an\ EMS\ seat \\ Y = 0, & Buy\ a\ ticket\ only\ (and\ reserve\ a\ regular\ coach\ seat\ for\ free). \end{cases}$$

Several variables were compiled from the online itinerary displays and seat maps, which are summarized in Table 4.4. For most of the variables, the definitions and descriptions are straight-forward to interpret. Variables related to seat availabilities, prices and group bookings merit additional discussion.

[15] Six observations (bookings) were removed from the data, as the customer did not have both regular coach seats and EMS seats to choose from.

Table 4.4: Variables and Descriptions

Variable	Definition
Price Variables	
seatFeePerMile	One-way EMS seat fee divided by the one-way market distance
lowestPrice	Value of one indicates booking was for the lowest priced flight available on itinerary screen
differenceOverLowestPrice	Price of booked flight minus lowest available priced flight on itinerary screen
Seat Availability Variables[1]	
Regular Coach Front W/A Avail	Value of one indicates regular coach window/aisle seats available in front of plane
EMS W/A Seats Avail	Value of one indicates EMS window/aisle seats available
Regular Coach Back1 W/A Avail	Value of one indicates regular coach window/aisle seats available in back plane section 1
Regular Coach Back2 W/A Avail	Value of one indicates regular coach window/aisle seats available in back plane section 2
Regular Coach Back3 W/A Avail	Value of one indicates regular coach window/aisle seats available in back plane section 3
Regular Coach Front Seats Avail	Value of one indicates regular coach seats available in front of plane
Regular Coach Back1 Seats Avail	Value of one indicates regular coach seats available in back plane section 1
Regular Coach Back2 Seats Avail	Value of one indicates regular coach seats available in back plane section 2
Regular Coach Back23 W/A Interaction	Value of one indicates regular coach window/aisle seats available in back plane sections 2 and 3
Regular Coach Back123 W/A Interaction	Value of one indicates regular coach window/aisle seats available in back plane sections 1, 2 and 3
Group Travel Variables	
NumberBookTogether1	Value of one indicates a booking made for an individual
NumberBookTogether2	Value of one indicates a booking made for a pair traveling together
NumberBookTogether3	Value of one indicates a booking made for three people traveling together
NumberBookTogether4	Value of one indicates a booking made for four people traveling together
NumberBookTogether5or6	Value of one indicates a booking made for five or six people traveling together
Day of Week Variables	
ddow1, …., ddow7	Value of one indicates flight departs on a Sun, Mon.,…., Sat
bdow1, …., bdow7	Value of one indicates flight was booked on a Sun, Mon.,…., Sat
Number of Days from Flight Departure Dummy Variables	
dfd1, dfd2,…, dfd28	Value of one indicates a booking made 1, 2, …, 28 days from flight departure

[1]Corresponding row numbers for each section of the plane are provided in Table 4.5.
Note: EMS = Even More™ Space

Table 4.4: Variables and Descriptions (Continued)

Variable	Definition
Departure Time of Day Variables	
earlymorning	Value of one indicates flight departs 5am-7:59am
morning	Value of one indicates flight departs 8am-11:59am
afternoon	Value of one indicates flight departs Noon-4:59pm
evening	Value of one indicates flight departs 5pm-8:59pm
lateevening	Value of one indicates flight departs 9pm-11:59pm
Seat Fee and Days from Flight Departure (DFD) Interaction Variables	
seatFeePerMile_DFD1-7	seatFeePerMile for bookings made 1 to 7 days from flight departure, zero otherwise
seatFeePerMile_DFD8-14	seatFeePerMile for bookings made 8 to 14 days from flight departure, zero otherwise
seatFeePerMile_DFD15-28	seatFeePerMile for bookings made 15 to 28 days from flight departure, zero otherwise
Other Variables	
Market Dummies	Dummy variable for each market

Note: EMS = Even More™ Space;

4.5.1. Seat Availability Variables

Seat availability variables account for seat choices available to customers when booking a flight. These variables divide the plane into sections and provide information on whether a given section has window, aisle, and/or middle seats available. The "Row/Section Description" column in Table 4.5 shows how we grouped each of the rows into five main sections of the plane. Creating a set of variables to describe seat maps proved to be challenging due to two underlying factors: (1) planes fill up in a systematic way, i.e., customers prefer seats in the front of the plane; and, (2) when a section of a plane fills up, window and aisle seats always sell out before middle seats, i.e., customers prefer window and aisle seats.

In order to capture these two underlying factors, two seat availability variables are associated with each section of the plane. For example, when the *Regular Coach Front Seats Avail* dummy variable is 1 (indicating that seats are available in this section) and the *Regular Coach Front W/A Avail* dummy variable is 0 (indicating that no window or aisle seats are available in this section), this indicates that only middle seats are available in the Regular Coach Front of Plane section. When both of the indicator variables are 1, this indicates that at least one window or aisle seat in addition to at least one middle seat are available in that section. When both indicators are zero, this means no seats are available to reserve in that section. Note that not all dummy variables for each section of the plane are included in the model specification due to the systematic way in which planes fill up. First, there were only six observations in which all EMS seats were sold; these observations were excluded from the analysis, thus we do not include an indicator for the EMS middle seats. Also, there were no observations in which a plane had all middle seats in the back of the plane section 3 sold, so we do not include an indicator for the middle seats of this section.

Table 4.5 shows mean seat occupancy rates calculated from seat maps observed the day before the flight departs. A value of 0.84 means that a seat was reserved before departing for 84% of the planes observed. Table 4.5 confirms that passengers prefer seats at the front of the plane and, in general, prefer window and aisle seats over middle seats, although middle seats towards the front of the plane have occupancy rates similar to window or aisle seats in the back of the plane. Middle seats in the EMS section have the lowest occupancy rates on the plane.

Table 4.5: Mean Seat Occupancies the Day before Flight Departure

Row Number	Mean Seat Occupancies A Window Seats	B Middle Seats	C Aisle Seats	D Aisle Seats	E Middle Seats	F Window Seats	Row/Section Description
1	*Blocked*	*Blocked*	*Blocked*	*Blocked*	*Blocked*	*Blocked*	Blocked Row
2	0.72	0.43	0.79	0.77	0.35	0.63	EMS Seats
3	0.56	0.30	0.72	0.68	0.27	0.50	
4	0.44	0.26	0.62	0.60	0.22	0.39	
5	0.39	0.21	0.55	0.55	0.19	0.35	
6	0.98	*Blocked*	*Blocked*	*Blocked*	*Blocked*	0.98	Regular Coach Front of Plane
7	0.99	0.92	0.98	0.99	0.91	0.97	
8	0.99	0.89	0.99	0.98	0.87	0.98	
9	0.95	0.78	0.98	0.98	0.77	0.93	
10	0.25	0.13	0.43	0.43	0.09	0.19	EMS- Exit Row
11	0.26	0.10	0.44	0.43	0.09	0.24	
12	0.97	0.81	0.98	0.98	0.79	0.96	Regular Coach Back of Plane Section 1
13	0.96	0.75	0.97	0.97	0.72	0.95	
14	0.96	0.75	0.96	0.97	0.72	0.95	
15	0.95	0.71	0.96	0.97	0.69	0.94	
16	0.94	0.69	0.95	0.95	0.68	0.94	
17	0.94	0.64	0.94	0.93	0.64	0.92	Regular Coach Back of Plane Section 2
18	0.92	0.63	0.92	0.92	0.61	0.90	
19	0.90	0.59	0.91	0.90	0.55	0.88	
20	0.86	0.56	0.87	0.88	0.53	0.85	
21	0.83	0.51	0.86	0.84	0.51	0.83	
22	0.81	0.46	0.82	0.82	0.45	0.80	Regular Coach Back of Plane Section 3
23	0.79	0.43	0.79	0.78	0.40	0.75	
24	0.75	0.36	0.75	0.75	0.35	0.69	
25	0.58	0.10	0.63	*Blocked*	*Blocked*	*Blocked*	

4.5.2. Flight Price Variables

We included two variables in the model that provides information as to whether the customer purchased a ticket for a nonstop flight that had the lowest fare available. These variables do not imply that all customers purchased the lowest fare. These variables do, however, provide information as to whether a customer purchased a fare on a flight when a lower fare was available for the same departure date, but at a different departure time. Intuitively, we expect customers who purchase a fare on a flight that does not have the lowest fare to be more willing to also purchase seat upgrades.

A total of 10,699 itinerary screens (which provide a list of available flight choices and fares to customers) are observed in this dataset. Over all of the observed itinerary screens, tickets were booked for flights with fares ranging between $39 and $654 (with mean $157 and median $129). Out of these screens, 57% of the screens offer customers the same price for every flight, and 43% of the screens have at least one flight with a different price. *LowestPrice* is a dummy variable that indicates whether the booking was for the lowest priced flight[s] available on the itinerary screen.

For the screens that offer customers flights with different prices, the fare difference between the highest and lowest priced flights offered on the screen ranges from a difference of $4 to a difference of $417 (with mean difference of $40 and median difference of $15). *DifferenceOverLowestPrice* provides information on how much more expensive the booked flight was relative to the lowest priced flight available to purchase. For itinerary screens with varied flight prices, 59% of the observed bookings were made for the lowest priced flights. *A priori*, it is expected that customers who purchase tickets on higher priced flights are less price elastic (less price-sensitive) and may be more likely to purchase an EMS seat.

4.5.3. Group Booking Variables

Dummy variables (*NumberBookTogether1*, *NumberBookTogether2*,…, *NumberBook-Together5or6*) were created to represent groups of people booking flights together. To do this, a few assumptions had to be made. If only one seat in a row was booked, then the booking is assumed to be made by an individual. If two seats were booked together in a row, then the booking is assumed to be a pair traveling together. The same logic is used to determine whether three, four, five, or six people booked together. We also assume that people traveling together do not book seats in different rows. Since there are six seats in a row, any groups larger than 6 would not be counted as the same group[16].

An estimated 53% of the bookings are for individuals traveling alone, 32% of the bookings are made for two people traveling together, 9% of the bookings are made for three people together, 4% are for four people together, and the remaining 2% of bookings are made for groups of five or six people.

4.6. Model Results

Model coefficients, shown in Table 4.6 are intuitive and indicate that EMS seat purchases are influenced by seat fees and seat displays, along with flight and passenger characteristics.

[16] Although these assumptions are not perfect, they are necessary because no customer information could be collected.

Table 4.6: Binary Logit Model Results

	Coefficient	z	P>z[1]
Price and Travel Time			
seatFeePerMile_DFD1-7 Interaction	-32.5201	-10.24	0.000
seatFeePerMile_DFD8-14 Interaction	-38.0552	-12.37	0.000
seatFeePerMile_DFD15-28 Interaction	-44.7677	-11.25	0.000
lowestPrice	-0.3471	-5.45	0.000
differenceOverLowestPrice	0.0011	1.91	0.056
Seat Availability Variables			
Regular Coach Front W/A Avail	0.0972	2.30	0.021
EMS W/A Seats Avail	0.3045	3.16	0.002
Regular Coach Back1 W/A Avail	0.2493	3.57	0.000
Regular Coach Back2 W/A Avail	0.1304	1.06	0.290
Regular Coach Back3 W/A Avail	-0.4214	-6.03	0.000
Regular Coach Front Seats Avail	-0.0609	-2.04	0.042
Regular Coach Back1 Seats Avail	-0.1694	-3.04	0.002
Regular Coach Back2 Seats Avail	-0.2027	-2.03	0.042
Regular Coach Back23 W/A Interaction	-0.4153	-3.30	0.001
Regular Coach Back123 W/A Interaction	-0.3001	-3.39	0.001
Group Travel Variables *(reference variable is NumberBookTogether5or6)*			
NumberBookTogether1 (Individual)	0.6736	2.43	0.015
NumberBookTogether2 (Pair)	0.9388	3.57	0.000
NumberBookTogether3	0.7990	3.00	0.003
NumberBookTogether4	0.6083	1.98	0.048
Departure Day of Week Variables *(reference variable is ddow7-Saturday Departure)*			
ddow1 (Sunday Departure)	0.2619	3.16	0.002
ddow2 (Monday Departure)	0.0806	1.86	0.063
ddow3 (Tuesday Departure)	0.1902	2.74	0.006
ddow4 (Wednesday Departure)	0.2095	2.65	0.008
ddow5 (Thursday Departure)	0.2750	4.29	0.000
ddow6 (Friday Departure)	0.2043	2.76	0.006
Booking Day of Week Variables			
bdow1 (Book on Sunday)	-0.1094	-2.01	0.045
Number of Days from Flight Departure Dummies *(reference variables are dfd19-dfd28)*[2]			
dfd1	0.7607	6.19	0.000
dfd2	0.3998	2.16	0.031
dfd3	0.5096	3.56	0.000
dfd4	0.4883	3.05	0.002
dfd5	0.5387	3.64	0.000
dfd6	0.2216	1.59	0.112
dfd7	0.3108	2.05	0.041
dfd8	0.4461	2.96	0.003
dfd9	0.3991	2.59	0.010
dfd10	0.1677	1.14	0.253
dfd11	0.1640	1.15	0.249
dfd12	0.3175	2.25	0.025
Departure Time of Day *(reference variable is evening-depart 5pm-8:59pm)*			
earlymorning (depart 5am-7:59am)	-0.1370	-1.01	0.311
morning (depart 8am-11:59am)	0.2027	3.22	0.001
afternoon (depart Noon-4:59pm)	0.2132	3.64	0.000
lateevening (depart 9pm-11:59pm)	-0.3478	-3.47	0.001

[1]Reported z-statistics and p-values are based on clustering standard errors by market.

[2]Note: Variables not reported include dfd13,…,dfd18, market dummies & constant term. LL= -27,779.

4.6.1. Seat Availabilities

The coefficients associated with the seat availability dummy variables show that premium coach seat purchases are influenced by seat displays. To visualize the influence of seat availabilities on premium seat purchases, we identified 13 representative seat map displays or "scenarios" from the data. Because customers tend to make free seat reservations systematically (closer to the front of the plane is preferred over further back, and widow and aisle seats are preferred over middle seats), these 13 scenarios represent 86% of the seat map displays viewed by customers at the time of booking.

Descriptive statistics for these 13 seat map displays are shown in Table 4.7, along with the partial utilities calculated from the seat availability variables from the binary logit results. One interesting finding of note is that the utility associated with purchasing an EMS seat varies quite little among the first six scenarios, when there are still plenty of window and aisle seats available in the front and back of the plane (especially back sections 1 and 2). On the other hand, the utility of the upgrade increases dramatically after there are no window and aisle seats left (Scenarios 10-13), and large increases are observed with every block of middle seats that fills. Customers who book 1 to 3 days from departure (DFD) are two times more likely to purchase an EMS seat when faced with a full plane (Scenario 13) vs. an empty plane (Scenario 1) (i.e., 37.9% of bookings made 1 to 3 days from departure include an EMS seat for Scenario 13 vs. 18.7% for Scenario 1). Comparing seat availabilities scenarios for each DFD category indicates that customers are between 2 and 3.3 times more likely to purchase EMS seats when faced with reserving a seat on a full plane versus an empty plane. These results suggest that the ability of JetBlue to collect seat reservation fees is strongly tied to seat map displays and corresponding load factors.

4.6.2. Premium Seat Fees

Table 4.7 also allows us to investigate price sensitivities of bookings made closer to departure while also controlling for load factors at the time of booking. For example, those customers who book a flight on an empty plane (Scenario 1) between 1 and 3 DFD are 1.7 times more likely to purchase an EMS seat than those customers who book further in advance (DFD 22 to 28) on an empty plane (18.7% vs. 10.8% of observed bookings include an EMS purchase). Comparing bookings made closer to departure (DFD 1 to 3) to bookings made further in advance (DFD 22 to 28) for each scenario indicates that customers are between 1.1 and 2.1 times more likely to purchase EMS seats when they book closer to departure. This is also reflected in the coefficients associated with the premium seat fees, i.e., the *seatFeePerMile* for purchases made 15-28 days from departure is more negative (-44.77) than the coefficients associated with purchases made 8-14 days from departure (-38.05) and 1-7 days from departure (-32.5). These coefficients show that customers who purchase closer to flight departure are less price-sensitive. This suggests that airlines may be able to dynamically price seat fees and charge higher seat fees closer to the departure date.

Table 4.7: Percent of EMS Bookings by Seat Availability Scenarios and Days from Flight Departure (DFD)

Scenario Number	Are Window and/or Aisle Seats Available?					Are Middle[1] Seats Available?			Percent EMS Bookings by DFD						Partial Utility
	EMS	Regular Coach Sections							DFD 1 to 3	DFD 4 to 7	DFD 8 to 14	DFD 15 to 21	DFD 22 to 28	Over all DFD	
		Front	Back1	Back2	Back3	Front	Back1	Back2							
Scenario with regular coach window and/or aisle seats available in Front, Back 1, Back 2, Back 3															
1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	18.7%	16.8%	13.2%	13.1%	10.8%	12.7%	-0.788
Scenarios with regular coach window and/or aisle seats available only in Back 1, Back 2, Back 3															
2	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	21.7%	18.7%	13.6%	12.0%	11.9%	13.7%	-0.886
3	Yes	No	Yes	Yes	Yes	No	Yes	Yes	18.5%	19.0%	16.3%	12.3%	14.7%	15.1%	-0.825
Scenarios with regular coach window and/or aisle seats available only in Back 2, Back 3															
4	Yes	No	No	Yes	Yes	Yes	Yes	Yes	23.2%	19.3%	15.7%	14.9%	12.6%	16.4%	-0.835
5	Yes	No	No	Yes	Yes	No	Yes	Yes	24.9%	17.5%	16.6%	15.8%	11.5%	16.7%	-0.774
6	Yes	No	No	Yes	Yes	No	No	Yes	30.1%	22.3%	18.9%	18.6%	22.3%	21.1%	-0.604
Scenarios with regular coach window and/or aisle seats available only in Back 3															
7	Yes	No	No	No	Yes	Yes	Yes	Yes	29.8%	26.4%	21.9%	20.8%	17.6%	23.5%	-0.550
8	Yes	No	No	No	Yes	No	Yes	Yes	29.3%	24.2%	24.7%	20.0%	20.1%	24.3%	-0.489
9	Yes	No	No	No	Yes	No	No	Yes	37.3%	35.0%	22.3%	32.4%	20.0%	31.1%	-0.320
Scenarios with no regular coach window and/or aisle seats available in any section of the plane															
10	Yes	No	No	No	No	Yes	Yes	Yes	38.2%	41.5%	40.7%	30.9%	31.3%	38.4%	-0.129
11	Yes	No	No	No	No	No	Yes	Yes	40.3%	34.0%	35.0%	26.8%	32.1%	35.1%	-0.068
12	Yes	No	No	No	No	No	No	Yes	40.8%	44.1%	34.0%	32.6%	36.5%	38.9%	0.102
13	Yes	No	No	No	No	No	No	No	37.9%	47.7%	42.3%	43.3%	26.3%	42.2%	0.304

Note: EMS = Even More™ Space. See Table 4.5 for details about the row numbers that correspond to each section.
[1]Middle seat availabilities for EMS and regular coach back section 3 are excluded because there are no observations in the data without available middle seats in these sections.

4.6.3. Nonstop Flight Characteristics

EMS seat purchases are influenced by many itinerary characteristics including the price that paid for the flight, departure day of week and time of day, and market effects.

The model coefficients for *lowestPrice* and *differenceOverLowestPrice* show that customers who purchased a ticket on a flight with a higher fare when a lower fare was available on a flight departing at a different time of the day are more likely to purchase an EMS seat. Moreover, the higher the fare difference that customers paid over the lowest priced flight, the more likely they are to purchase a seat. This corroborates our intuition that customers who purchase a fare on a flight that does not have the lowest fare are less price-sensitive.

Flight day of week and time of day effects also impact EMS seat purchases. Customers are more likely to purchase EMS seats for Sunday and Thursday departures, which are days in which business customers are likely to travel. With respect to departure time, customers who book flights with departure times between 8:00 am and 4:59 pm are more likely to purchase EMS seats than other flight times.

Market level fixed effects (dummy variables) are included in the model and are significant, but are not included in the table for space purposes. Coefficients on the markets showed that two markets were especially different than the other markets. For the two markets with destinations in Puerto Rico, customers were much less likely to purchase EMS seats. Seat fees are already priced particularly low in these markets. Flights from JFK to Rafael Hernández Airport (BQN) in Aguadilla, Puerto Rico have an EMS seat fee of $30, which is 1.9 cents per mile and is the lowest seat fee per mile out of all the markets collected. Flights from Orlando International Airport (MCO) in Florida to

BQN have an EMS seat fee of $25, which is 2.2 cents per mile and is the third lowest seat fee per mile out of all the markets collected. The low price of the seat fees in these markets, coupled with model results indicating that customers are far less likely to purchase EMS seats in these markets shows that customers flying to Puerto Rico are highly price-sensitive. The demographics of New York and Orlando also suggest that these flights may have a larger percentage of customers who are visiting friends and family and neither traveling on business nor splurging on a vacation.

4.6.4. Passenger Characteristics

EMS seat purchases are influenced by several passenger characteristics including group bookings, booking day of week, and how far in advance of departure the customer books a flight.

The group booking variables indicate that two people traveling together are more likely to purchase EMS seats than individuals and larger groups. Also, a group of three people booking together are more likely to purchase EMS seats than individuals and larger groups. The results show that groups of four or more are the least likely to purchase EMS seats, which seems to reflect price sensitivity of families traveling together. A family of four who purchases EMS seats could expect to pay an extra $60 to $260 one-way, or $120 to $520 round-trip, for the family to sit in an EMS section. These prices may be too high for many families who are already paying for multiple plane tickets.

With respect to the booking day of week, customers who book on Sunday are less likely to purchase EMS seats; this is the only significant booking day of week variable.

4.6.5. Prediction Accuracy

The results related to days from departure, price sensitivities, and seat map displays may be confounded in the sense that the least desirable seat maps occur closer to flight departure when we expect price-insensitive business travelers to book. This suggests that the estimated binary logit model could really be capturing different passenger mixes across the booking horizon, and not the effects of seat map displays. To test the robustness of results, we compared predicted EMS seat purchase percentages across the booking horizon to observed predicted EMS seat purchase percentages, shown in Table 4.8. In general, the model performs well, particularly at the aggregate level over all days from departure and over all scenarios. For example, the predicted percentage of EMS seat purchases over all DFD for Scenario 1 has an error of 0.23. Table 4.7 showed that 12.7% of bookings were observed to include an EMS seat purchase. Thus, the model predicts that 12.93% of bookings include an EMS seat purchase.

Table 4.8: Prediction Accuracy of EMS Seat Purchases for Seat Availability Scenarios and Days from Flight Departure (DFD)

Scenario Number[1]	Difference Between Predicted and Observed Percent of EMS Purchases (Number of Bookings Made Under Each Scenario) for:					
	DFD 1 to 3	DFD 4 to 7	DFD 8 to 14	DFD 15 to 21	DFD 22 to 28	Over all DFD
1	1.54 (386)	0.15 (871)	1.15 (2,457)	-1.02 (3,614)	0.63 (4,748)	0.23 (12,076)
2	-0.20 (503)	-1.63 (921)	0.66 (2,309)	0.26 (2,325)	0.05 (2,372)	0.08 (8,430)
3	-0.29 (173)	-1.76 (305)	-1.33 (882)	0.49 (927)	-2.59 (832)	-1.11 (3,119)
4	-1.25 (715)	0.29 (1,414)	0.84 (2,757)	-0.01 (1,967)	1.13 (1,102)	0.39 (7,955)
5	-3.39 (394)	0.91 (750)	0.55 (1,637)	-0.46 (1,009)	2.80 (513)	0.29 (4,303)
6	-8.49 (73)	0.49 (148)	0.33 (254)	-0.66 (145)	-6.04 (94)	-1.58 (714)
7	-1.14 (449)	0.41 (656)	0.63 (1,116)	0.33 (475)	0.79 (284)	0.28 (2,980)
8	-0.83 (501)	1.59 (920)	-1.78 (965)	0.23 (444)	-1.47 (189)	-0.28 (3,019)
9	-6.10 (212)	-6.77 (223)	4.11 (233)	-10.31 (68)	0.60 (20)	-3.35 (756)
10	1.76 (314)	-3.83 (489)	-8.12 (548)	-1.26 (262)	-5.8 0(96)	-3.90 (1,709)
11	1.17 (760)	3.28 (995)	-1.95 (882)	1.95 (306)	-7.56 (81)	0.80 (3,024)
12	3.94 (610)	-0.87 (576)	2.38 (579)	1.32 (175)	-2.80 (63)	1.67 (2,003)
13	10.85 (264)	-0.74 (241)	-0.53 (241)	-2.02 (67)	15.39 (19)	3.26 (832)
Over all Scenarios:	0.00 (7,118)	0.00 (10,414)	0.00 (17,316)	-0.17 (13,088)	0.20 (11,306)	0.30 (59,242)

[1]See Table 4.5 for the seat availabilities of each scenario and observed probabilities

4.7. Policy Analysis

In this section, we investigate revenue potentials associated with optimizing the current static seat fee structure, dynamically pricing seat fees, and by changing seat displays by showing seats as being unavailable to customers. The latter would occur if an airline decided to reserve additional seats for its premier customers.

4.7.1. Optimizing Static Seat Fees

We can use the results from our binary logit model to determine optimal seat fees by calculating the expected revenue for each customer. This is found by multiplying the upgrade fee by the probability that a customer will actually purchase an upgrade. Although customers' price sensitivities are seen to vary as a function of days from departure, most airlines currently do not have the technological capability to charge different fees across the booking horizon. Thus, it is interesting to examine whether the static seat fees currently charged by JetBlue are optimal.

The optimal static seat fees derived from our model are shown in Table 4.9. With the exception of two markets (JFKORD and MCOAUS), JetBlue's seat fees are currently underpriced, particularly in the east coast to west coast markets. Charging optimal static fees would increase expected revenues by 8.0% (from \$476,245 to \$514,530) for the observed data.

To test the sensitivity of the seat fee optimization results, we generated a distribution for the revenue forecast by using the variance-covariance matrix of parameter estimates from the binary logit model. The estimated seat fee revenue that the optimal seat fees would generate at the 25th percentile of the distribution is \$509,740 and at the

75th percentile is $519,145, which represents a 7.0% and 9.0% revenue increase, respectively.

Table 4.9: Optimal Seat Fees by Market

Market	Optimal Dynamic Seat Fees DFD 1 to 7	Optimal Dynamic Seat Fees DFD 8 to 14	Optimal Dynamic Seat Fees DFD 15 to 28	Optimal Static Seat Fee	Current Seat Fee	Type Haul[1]
JFKBQN	$52	$44	$36	$44	$30	E-PR
MCOBQN	$37	$31	$26	$33	$25	E-PR
BOSIAD	$20	$16	$13	$17	$15	E-E
BOSMCO	$45	$37	$30	$37	$30	E-E
BUFMCO	$39	$32	$26	$34	$25	E-E
EWRMCO	$38	$30	$24	$31	$19	E-E
IADMCO	$35	$28	$22	$38	$25	E-E
JFKFLL	$44	$35	$28	$38	$35	E-E
JFKPBI	$46	$37	$30	$37	$35	E-E
LGAFLL	$47	$37	$30	$40	$35	E-E
SYRMCO	$43	$35	$28	$34	$25	E-E
BOSDEN	$69	$57	$45	$57	$40	E-MW
JFKORD	$32	$25	$20	$25	$30	E-MW
MCOAUS	$40	$32	$26	$33	$35	E-MW
BOSLAX	$104	$82	$67	$85	$50	E-W
BOSSFO	$116	$95	$76	$96	$55	E-W
FLLSFO	$93	$76	$63	$80	$50	E-W
JFKLAS	$94	$76	$62	$79	$50	E-W
JFKLAX	$106	$86	$68	$87	$50	E-W
JFKOAK	$110	$90	$71	$89	$60	E-W
JFKPDX	$93	$77	$62	$76	$50	E-W
JFKSFO	$116	$92	$76	$99	$60	E-W

[1]E-PR = East coast to Puerto Rico flights, E-E = East coast to east coast flights, E-MW = East coast to Midwest flights, E-W = East coast to west coast flights (JFKLAS is included due to length of haul).

4.7.2. Dynamically Pricing Seat Fees

Since the binary logit model results indicate that customers who book tickets closer to the date of flight departure are less price sensitive, we examine a pricing strategy which sets fees by route and three DFD categories: 1-7 days, 8-14 days, and 15 or more days. Within each route and DFD category, prices are set to maximize expected revenue based on the actual observations in the data. The optimal dynamic seat fees for each market are shown in Table 4.9.

The seat fees calculated using this dynamic pricing approach appear reasonable. Optimal seat fees for 15 days from departure and up are similar to the current seat fees that JetBlue is charging in each market. However, our results show that there is potential to charge higher prices closer to departure. Optimal dynamic seat fees would increase expected seat fee revenues by 10.2% (from $476,245 to $524,875) for the observed data. Compared to the baseline that optimizes static seat fees, this represents an additional 2.0% increase in expected seat fee revenues. A sensitivity analysis of these dynamic fees shows that the estimated seat fee revenue that the optimal seat fees would generate at the 25th percentile of the distribution is $518,510 and at the 75th percentile is $531,075, which represents an 8.9% and 11.5% revenue increase, respectively. Compared to the baseline that optimizes static seat fees, optimal dynamic seat fees represent an additional 0.8% to 3.2% increase in expected seat fee revenues.

Our results suggest that future increases in seat fees are likely; however the revenue gains associated with dynamically pricing fees across the horizon are not at a level that will likely justify technological investments for an airline the size of JetBlue. The expected revenue gains from dynamic pricing are only on the order of about $1-4 million, set against a cost of upgrading reservations and data systems that may well exceed that. Larger airlines, on the other hand, whose seat fee revenues are several times larger than JetBlue’s, may find it profitable to follow United’s lead in dynamic pricing of premium seats.

4.7.3. Influence of Seat Map Displays that Block Seats

We can also use our model to examine the revenue potential of strategically blocking certain regular coach seats from reservations during the booking process, effectively making the plane appear more fully reserved than it is at the time of booking. We apply the same simulation technique as described above for determining optimal static seat fees, but artificially close certain seating positions for all new reservations. When all regular coach seats in the front of the plane (rows 6-9) and back of the plane section 1 (rows 12-16) are indicated as "unavailable" for every traveler making a new reservation, using the actual seat fees offered by JetBlue, the model indicates that the interquartile range of expected revenue is \$523,250 to \$550,290, with a mean of \$537,350 (which represents a 9.9% to 15.5% revenue increase, with a mean of 12.8%). In other words, if JetBlue were to leave their seat fees unchanged and instead blocked certain rows of seats for premier customers, they could potentially increase revenues by 9.9% to 15.5%.

Of course, implementing such a reservation system is a complex change, and the effects would reach far beyond the seat fee revenues. Once the rear sections of the plane filled, either regular coach seats in these sections (front of the plane and back of the plane section 1) would need to be released (improving free seat availability in the late DFD times when willingness to pay is higher) or JetBlue would need to abandon its policy of allowing all travelers to choose seats at the time of booking (altering an important branding feature and potentially negatively impacting other revenues). Moreover, if passengers learn to expect that those seats are vacant and/or will be filled before departure, some of them (especially frequent fliers, who may have a higher willingness to pay for upgrades but also a larger expectation of receiving access to otherwise blocked seats) may shop for EMS upgrades more strategically, with results that cannot be predicted using the current data and model. However, the results suggest that, with or without other pricing changes, by blocking some seats from the reservation process it may be possible to nudge some customers into purchasing EMS seats when they would not otherwise do so.

4.8. Discussion

The results of this study are based on a subset of JetBlue markets and equipment types. This prevents us from extrapolating our results to different markets, different equipment types, and different airlines. However, this does not prevent us from quantifying the relative importance of two questions that are at the core of tensions among customers, regulatory agencies, and airlines: customers and regulatory agencies are focusing on the importance of fee transparency and fairness, but airlines want to add complexity to further differentiate fees across customer groups (e.g., by blocking seats for preferred customers) so as to capture more of the consumer surplus.

The results from our study suggest that in the future, we can expect to see further increases in premium seat fees as airlines begin to better understand customers' willingness to pay for seat products. However, changing an airline's technological infrastructure to facilitate dynamic pricing imposes relatively high fixed costs. These costs are probably reasonable and recoupable for the mega-carriers emerging from the past few years of airline mergers, but we do not anticipate seeing dynamic pricing of ancillary fees on existing smaller carriers in the near future.

Further, it is interesting to note that blocking seats (and leaving current seat fees unchanged) has as much revenue potential as optimizing current static fees. That is, by reducing the number of "good" seats that are available to reserve for free to all passengers, it is possible to increase seat fee revenues overall. Some airlines already implement some form of this system, such as British Airways, which limits all seat reservations before check-in to premier and fee-paying customers. This underscores the importance of ensuring customers are not inadvertently misled into purchasing premium seats by seat map displays that block seats for premier customers.

At the industry level, our study provides some insights into potential strategic directions of airlines. As airlines make plans to acquire and configure new aircraft, they must make decisions about cabin layout and amenities, and ideally these decisions should seek to provide the best return on investment over the long term. Although there have been some limited stated-preference studies into customer behavior (Weinstein and Keller, 2012), it is unclear what customers really value in a premium product. Further, airlines currently use two basic approaches to designing a premium product. They can create a product that is appealing to customers based on the attributes that it offers, or they can make the basic coach experience so unpleasant that customers will be willing to pay to escape to the upgraded offering. From a customer's perspective, it is obvious which the preferred approach is, but when considered simply as a business decision taken by an airline, it is less clear. There is an obvious tradeoff between the revenue from seats that provide extra legroom and the number of seats that can be put on a plane. As noted in our findings, there are many price sensitive customers that are not willing to pay more for extra legroom, especially in markets dominated by customers who are visiting friends and relatives (e.g., Puerto Rico) and for vacation markets (e.g., Orlando), and the airline might be better off with more tickets/seats to sell. This may lead airlines to consider two different configurations with the same fleet type, one with more premium seats and one with more coach seats.

The industry is still trying to figure out the best model for seat upgrades, and the landscape continues to change. For example, Spirit makes no claim to have a more comfortable experience then their competitors, and they do not have a premium product, yet their business model is viable. That could, and likely would, change if industry capacity increases, but for now their business model is paying off. Virgin America has the opposite model. They have first class seats that are quite appealing, but they have not been able to get a price premium that justifies the opportunity cost and are currently in dire financial straits. Looking ahead, we can expect to see premium seat fee models evolve and potentially change as a function of industry load factors.

4.9. Conclusion

This paper has provided one of the first studies of airline customers' premium coach seat purchasing behavior. This is also the first study we are aware of that uses an online database of airline fares and seat maps. All prior studies using online airline data have been based solely on fare information and have excluded seat maps.

Our study provides several new behavioral insights. As planes fill up, customers are more likely to purchase a premium coach seat, regardless of how far in advance they purchase a ticket. Results indicate that JetBlue (and other airlines) can dynamically price seat fees as a function of days from departure and/or seat map displays. The revenue gains associated with dynamically pricing seat fees are expected to be modest, and likely insufficient for smaller airlines to justify the large fixed costs of technology investments required to implement dynamic seat fees.

The results of this study also suggest that the willingness of customers to pay seat fees is strongly tied to load factors (as revealed through seat maps). This has several implications. First, concerns expressed by customers and government officials about the importance of clearly communicating airlines' seat policies appear valid. It is important to ensure that customers are not being misled into making premium seat fee purchases by the information displayed on seat maps. Second, the U.S. airline industry is currently going through a series of mergers and acquisitions, and has seen a reduction in overall domestic capacity, which has led to record-high load factors. In an environment in which load factors are high, the airlines' ability to generate revenues from seat fees is strong, and several industry pricing models related to seat fees are viable. However, if load factors decrease in the future, we would expect that the incremental revenues generated from seat fee reservations would also decrease.

There are several extensions of our work that could be addressed by using stated preference surveys. Currently, it is unclear what specific attributes of premium coach seats are valued by customers, and how these valuations may differ across customer segments. For example, do customers purchasing JetBlue's premium coach seats value extra legroom? Do they value the ability to board first and store luggage in overhead bins? Do they value the ability to deplane first and have more time to make connecting flights? Do they value having an empty middle seat next to them? Determining the value of each of these components will help airlines better design products and bundles that provide the most value for customers. It will also help airlines determine whether they should invest in adding sections in coach that offer extra legroom, or simply sell existing coach seats that provide early boarding and alighting privileges. This is a particularly important decision for carriers, as removing planes from service to remove row(s) of seats to add extra legroom is costly, particularly when planes are flying near record-high load factor levels. The revenues generated by selling extra legroom seats needs to outweigh any revenues lost by removing seats from the aircraft. As suggested by our analysis, carriers should consider a range of load factors in any break-even analysis related to adding extra legroom seats to coach.

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CHAPTER 5: REVIEW OF PRICE ENDOGENEITY

5.1. Abstract

Price endogeneity occurs when correlation exists between price and the error term (or unobserved factors) in a model. In demand models, prices are generally considered to be endogenous because prices are strongly influenced by demand and demand is, in turn, strongly influenced by prices. Price endogeneity is well documented in economics literature and is known to cause problems when analyzing data, as endogeneity can lead to unrealistic and misleading model coefficient estimates. Although price endogeneity has been shown to be prevalent in many industries, few studies of air travel demand have explored endogenous airline prices. In this chapter, we explain the causes of endogeneity and review literature that has corrected for price endogeneity, focusing on empirical studies that have demonstrated endogeneity bias in coefficient estimates. Instrumental variable methods, which are used to correct for endogeneity, are discussed. Also, several different types of instruments are reviewed, and studies that have utilized each type of instrument are cited as examples. Finally, tests for endogenous regressors, valid instruments, and weak instruments are discussed, and corresponding Stata® codes are provided.

5.2. Background

An explanatory variable is called endogenous when there is correlation between that variable and the error term (or unobserved factors) in a model. In Ordinary Least Squares (OLS) regression models, this correlation means that the conditional expectation of the error term on the explanatory variable will not be equal to zero, which violates a main assumption required to ensure estimator consistency (Greene, 2003). Similarly, in discrete choice models, this correlation will lead to inconsistent estimators. Thus, models that are estimated without correcting for endogeneity will lead to inconsistent parameter estimates where some level of unobserved bias will exist.

In this chapter, we explain the causes of endogeneity and review some of the literature that has corrected for price endogeneity, focusing on empirical studies that have demonstrated endogeneity bias in coefficient estimates. Instrumental variable methods, which are used to correct for endogeneity, are discussed and different types of instruments are reviewed. Finally, tests for endogenous regressors, valid instruments, and weak instruments are discussed, and corresponding Stata® codes are provided.

This chapter provides an overview of the main concerns related to endogeneity and provides a literature review of some of the most cited papers. Where appropriate, applications in travel demand are discussed. Readers are referred to books by Greene (2003) and Train (2009) and a dissertation by Guevara-Cue (2010) for excellent comprehensive reviews of endogeneity.

5.2.1. Causes of Endogeneity

There are several known causes of endogeneity. One of the main causes of price endogeneity is referred to as simultaneity of supply and demand, which occurs when price influences demand, and demand influences price. As an example, airline revenue management strategies change prices in response to demand (ticket purchases). Also, consumers are expected to change their purchasing behavior in response to price. Thus, airfares are expected to be endogenous.

Omitted variables can also cause endogeneity when one or more relevant explanatory variables have been omitted from the model. Endogeneity occurs when the omitted variable (often unobserved attributes of the product) affects demand and is also correlated with price. Theoretically, airline demand models could suffer from omitted variable bias if there are unobserved attributes of flights that influence customer choice and are also correlated with price. For example, variables that are not often captured in discrete choice models are variables related to entertainment (such as free Wi-Fi on some flights or equipment types). If free Wi-Fi influences customer choice of a flight and is also correlated with the price of a flight, then Wi-Fi would be an example of an omitted variable that causes endogeneity.

Endogeneity can also occur as a result of measurement error when an independent variable is not measured perfectly. This could occur in airline demand models if we do not know the actual price a customer paid for a ticket.

5.2.2. Endogeneity Bias

When models are estimated without correcting for price endogeneity, parameter estimates are not consistently estimated, i.e., the model suffers from endogeneity bias. The endogeneity bias will be present in the coefficient of the endogenous variable, but is often present in the coefficients of the exogenous variables as well. When variable coefficients are biased, other common measures calculated from the coefficients, such as price elasticities and value-of-time (VOT) estimates, will also be biased.

To understand the direction of the bias better, it is helpful to think through the problem. In supply and demand models, when demand for a product is high firms often increase prices, and customers are willing to pay the higher prices to have access to the inventory. As a result, traditional modeling techniques will underestimate the influence of price on demand. In fact, sometimes traditional modeling techniques may even estimate that price positively impacts demand, which is counterintuitive.

5.2.2.1. Evidence of Endogeneity Bias in Air Travel Demand Literature

Within the airline literature, few studies have corrected for price endogeneity in models of air travel demand. Hsiao (2008) estimates discrete choice models of aggregate quarterly air passenger demand using aggregate quarterly data from DB1B and T100. Hsiao finds that without correcting for endogeneity, fare coefficients are underestimated, VOT estimates are greatly overestimated, and price elasticities are counterintuitive. For example, in three uncorrected models, VOT is estimated to be between $614 and $726 per hour (between 39 and 46 times larger than the median wage rate of 2004)[17]. After correcting for endogeneity, VOT is estimated to be $16.7 and $21.3 per hour, which is much more reasonable. Additionally, Hsiao shows that in models which did not account for endogeneity, mean fare elasticity estimates of market demand were inelastic (between -0.154 and -0.365), whereas in models that corrected for endogeneity the mean fare elasticity estimates of market demand were elastic (between -1.052 and -2.662).

In a more recent study, Granados, Gupta and Kauffman (2012) estimate log-linear regression models and estimate price elasticity of demand for air travel booked through online and offline channels. The authors use a dataset of airline bookings sold by travel agencies through global distribution systems (GDSs)[18]. In a model estimated on the whole dataset, price elasticity of demand is estimated to be inelastic (-0.14) in an OLS regression model that did not correct for endogeneity. However, in a model that corrected for endogeneity, fare elasticity of demand is estimated to be approximately unit elastic (-1.03).

Berry and Jia (2009) estimate the impact of demand and supply changes on airline profitability using a random-coefficient discrete choice model of demand and aggregate quarterly data from DB1B. Gayle (2004) uses aggregate quarterly data from DB1B to

[17] Hsiao (2008) notes that these percentages are based on the U.S. median wage rate of 2004, which was $15.96 per hour (Bureau of Labor Statistics, 2008).

[18] GDSs include ticket sales made via online and offline channels through travel agencies but exclude airline direct sales.

investigate air passenger itinerary choice behavior. Both studies correct for price endogeneity but do not report the change in parameter estimates for uncorrected models.

5.2.2.2. Evidence of Endogeneity Bias in Other Travel Demand Literature

In an empirical study of demand for high speed rail travel (Pekgün, Griffin and Keskinocak, 2013), price elasticity estimates across several models of different passenger segments are consistently shown to be biased towards zero when endogeneity is unaccounted for. For example, in a model of advanced purchasers (booked at least 21 days in advance) who booked economy class tickets with a Saturday night stay, price elasticities of demand are estimated to be -0.407 in an OLS model which did not correct for endogeneity, and -1.972 in a two-stage least squares (2SLS) model which corrected for endogeneity.

5.2.2.3. Evidence of Endogeneity Bias in Other Industry Demand Literature

Although there are few studies within the airline industry that have corrected for price endogeneity, there are many empirical studies of demand that have corrected for price endogeneity using data from other industries. Most studies have shown that price coefficients are underestimated if endogeneity is not corrected. Examples of recent empirical studies that have demonstrated that price coefficients are underestimated if endogeneity is not corrected include the following: household choice of television reception options (Goolsbee and Petrin, 2004; Petrin and Train, 2010), household choice of residential location (Guevara and Ben-Akiva, 2006; Guevara-Cue, 2010), choice of yogurt and ketchup brands (Villas-Boas and Winer, 1999), consumer-level choice of and aggregate product demand for the make and model of a new vehicle (Berry, Levinsohn and Pakes, 1995, 2004; Train and Winston, 2007), and brand-level demand for hypertension drugs in the U.S. (Branstetter, Chatterjee and Higgins, 2011).

5.3. Methods to Correct for Price Endogeneity

Instrumental variable (IV) methods can be applied to models to take into account endogeneity, which allows consistent parameter estimation when endogenous explanatory variables are present. The modeling methods differ depending on whether models being estimated are linear or non-linear.

For linear models, such as least squares regression, IV methods have been used for many years, with the first application dating back to 1928 (see Stock and Trebbi, 2003 for a history of the first applications in IV methods). Most statistical programs provide functions which easily implement IV methods, such as two-stage least squares (2SLS) regression.

However, discrete choice models are non-linear and other methods must be used to account for endogeneity. Dealing with endogeneity in discrete choice models is a newer problem and most statistical programs do not have built-in functions to do this. At a conference workshop, Bhat (2003) identifies the endogeneity problem as an emerging methodological issue in discrete choice models.

There are several approaches for dealing with endogeneity in discrete choice models. Readers are referred to Train (2009) for a more detailed description of these methods, along with derivations, advantages, and disadvantages of each method. One approach, which many researchers refer to as the BLP approach (developed in Berry, 1994; Berry, Levinsohn and Pakes, 1995) has been used in several studies. However, the BLP approach is often not appropriate when observed shares for some products in some markets are zero or nearly zero (Petrin and Train, 2010; Train, 2009). When modeling daily demand for flights, we observe days when no tickets were sold. Thus, the BLP approach may not be appropriate for modeling daily flight-level demand.

Another approach is called the control function approach (Blundell and Powell, 2004; Guevara and Ben-Akiva, 2009; Petrin and Train, 2010; Villas-Boas and Winer, 1999), which can be used for datasets with observations of zero demand. Essentially, a regression on price is estimated using a set of instruments, and then the residuals are used in the discrete choice model as a new variable. This approach is easy to implement and is appropriate for modeling daily flight-level demand.

5.4. The Search for Instrumental Variables

The search for and identification of a valid set of instruments is not easy and is often controversial. In general, most researchers agree that any set of instruments that satisfy the following two conditions will generate consistent estimates of the parameters, subject to the model being correctly specified (Rivers and Vuong, 1988; Villas-Boas and Winer, 1999):

1.) Instruments should be correlated with the endogenous variable (price), and

2.) Instruments should be independent of the error term in the model.

Therefore, we need to find instruments that are correlated with price but are not correlated with the error term. The error term in the choice of an itinerary represents all variables that influence customer choice of a particular flight but are not included in the model, which means that we need instruments that are correlated with price but do not influence customer choice of a flight (or customer purchase).

There are several types of instrumental variables that have been used in the literature. In the following sections, we describe these different types of instruments. Table 5.1 summarizes each of the types of instruments that will be discussed in the next sections and offers a few possible instruments that have been used (or could be used) in air travel demand models.

5.4.1. Cost-Shifting Variables as Instruments

Variables that shift cost and are uncorrelated with demand shocks are common instruments that have been used in many applications of aggregate demand. For example, within the airline industry, Hsiao (2008) used route distance multiplied by unit jet fuel cost as instruments in discrete choice models of aggregate quarterly air passenger demand. Both route distance and unit jet fuel cost can be thought of as cost shifters because they are expected to impact the price of tickets. Theoretically, these make sense to use as instruments if one believes that route distance and unit jet fuel cost are correlated with ticket prices, but not with customer decisions to travel (uncorrelated with demand).

Hausman (1996) estimates empirical models of brand choice in the ready-to-eat cereal industry. When aggregate demand for cereal is estimated, he uses factors which shift the cost of cereal (such as ingredients, packaging, and labor) as instruments. However, in his more disaggregate model of brand choice (such as Cheerios) he notes that the usual strategy of using cost shifters as instruments does not work because "there may be an insufficient number of input prices, or they may not be reported with high enough frequency." This is the same problem that we expect to encounter in estimating disaggregate models of flight-level demand (which will be further discussed in Chapter 6). Cost-shifting instruments (such as route distance or unit jet fuel cost) would be unable to capture day-to-day fluctuations in price, which are more likely to be driven by revenue management practices and competitor price matching.

The first row of Table 5.1 summarizes these instruments, and the remaining rows of this table will be described in the following sections.

5.4.2. Hausman-Type Price Instruments

Hausman (1996), discussed in the previous section, estimates disaggregate empirical models of brand choice in the ready-to-eat cereal industry where cost-side instruments are not appropriate. Hausman's solution for finding instruments is to exploit the panel structure of the data, in which quantities and prices are observed in several different cities. In this context, the price instrument for the city of interest is the prices of the same brand in other cities (many researchers now refer to this type of instrument as "Hausman-type price instruments"). The basic idea is that after eliminating city-specific and brand-specific effects (by including fixed-effects in the model), the price of a brand in city *j* will be correlated with the prices of the brand in other cities due to the common marginal costs, but the price of a brand in city *j* will (ideally) be uncorrelated with common demand shocks. Nevo (2000b, 2001) further explores similar sets of instruments in the ready-to-eat cereal industry (price instruments are averaged across all twenty quarters of available data).

Table 5.1: Summary of Instrument Types and Examples of Instruments in the Airline Context

Instrument Type and Reference	Instrument Description	Examples of Instruments in the Airline Context
Cost-Shifting Instruments Hausman (1996); Hsiao (2008); Berry and Jia (2009); Granados, Gupta and Kauffman (2012)	Variables that impact a product's cost but that are uncorrelated with demand shocks	Hsiao (2008) uses route distance and unit jet fuel costs. Berry and Jia (2009) and Granados, Gupta, and Kauffman (2012) use a hub indicator. Granados, Gupta, and Kauffman (2012) use distance.
Hausman-Type Price Instruments- Hausman, Leonard and Zona (1994); Hausman (1996); Nevo (2000b, 2001); Guevara and Ben-Akiva (2006); Guevara-Cue (2010); Petrin and Train (2010)	Prices of the same brand in other geographic contexts are used as instruments of the brand in the market of interest	Gayle (2004) uses an airline's average prices in all other markets with similar length of haul (also used in this dissertation in Chapter 6).
Measures of Competition and Market Power- Stern (1996); Berry and Jia (2009); Granados, Gupta, and Kauffman (2012)	Measures of the level of market power by multiproduct firms, and measures of the level of competition	Berry and Jia (2009) use the number of all carriers offering service on a route. Granados, Gupta, and Kauffman (2012) use the degree of market concentration, calculated as the Herfindahl index. Number of daily nonstop flights in the market operated by the airline of interest and by competitor airlines (used in this dissertation in Chapter 6).
Measures of Non-Price Characteristics of Other Products- Berry, Levinsohn and Pakes (1995, 2004); Train and Winston (2007); Berry and Jia (2009)	Average non-price characteristics of the other products supplied by the same firm in the same market	Average flight capacity of other flights operated by the airline of interest in the same market.
	Average non-price characteristics of the other products supplied by the other firms in the same market.	Berry and Jia (2009) use the percentage of rival routes that offer direct flights, the average distance of rival routes, and the number of rival routes.

Many other studies have used Hausman-type price instruments. For example, Petrin and Train (2010) model household choice of television reception options (antenna, cable packages, and satellite) and calculate "the price instrument for market *m* as the average price in other markets that are served by the same multiple-system operator as market *m*".

In discrete choice models of household residential location choice, a price instrument for dwelling unit *d* is calculated as the average prices of other similar dwelling units located within the same vicinity (between 500 and 2,500 meters away for one instrument, and between 2,500 and 5,000 meters away for a second instrument) (Guevara and Ben-Akiva, 2006; Guevara-Cue, 2010).

In an airline context, Hausman-type price instruments for a market are an airline's average prices in all other markets with a similar length of haul. Gayle (2004) uses aggregate quarterly data from DB1B to investigate air passenger itinerary choice behavior and uses this formulation of instruments, along with cost-shifting instruments.

5.4.3. Measures of Competition and Market Power as Instruments

Stern (1996) introduces measures of the level of market power by multiproduct firms and measures of the level of competition as instruments. Stern (1996, p.18) notes that "Unless consumers value products sold by a particular firm *because* it is a multiproduct firm, measures of multiproduct ownership will be correlated with price and advertising, but be uncorrelated with unobserved quality." Levels of market power focus on the number of products in the market and also the time since a product (and/or firm) was introduced into the market. In the context of pharmaceutical drugs, he measures the level of market power by multiproduct firms as the number of products produced within a drug category by the firm which produces product *j*, and the sum of the time since entry over each of all other products (excluding product *j*).

Stern (1996, p.18) also notes that "measures of the level of competition in the market, such as the number and characteristics of other products, will also affect price but, under the assumption that entry is exogenous, be uncorrelated with unobserved quality". For example, one instrument Stern uses to capture measures of the degree of competition facing product *j* is the number of manufacturers in the market.

Many other studies have used similar types of instruments (for examples see Branstetter, Chatterjee, and Higgins, 2011; Cleanthous, 2003; Dick, 2008; Dutta, 2011).

Based on Stern's approach, in the airline context, the number of flights in a market or the number of carriers in a market could be used as instruments. Berry and Jia (2009) use the number of all carriers offering service on a route as an instrument. Granados, Gupta, and Kauffman (2012) include an instrument that measures the degree of market concentration, calculated as the Herfindahl index.

5.4.4. Non-Price Product Characteristics of Other Products as Instruments

Berry, Levinsohn and Pakes (1995) derive a set of instruments using observed exogenous product characteristics, where price and other potentially endogenous variables are excluded. The instruments are: 1.) observed product characteristics for a firm, 2.) if the firm produces more than one product, the sums of the values of the same product characteristics of other products offered by that firm, and 3.) the sums of the values of the same characteristics of the same products offered by other firms. Instruments of this type have been used in many applications, including choice of an automobile (Berry, Levinsohn and Pakes, 1995, 2004; Train and Winston, 2007) and demand for pharmaceutical drugs.

Nevo (2000a) provides a clear description of how these instruments have been used within the automobile industry: “Suppose the product has two characteristics: horsepower (HP) and size (S), and assume there are two firms producing three products each. Then we have six instrumental variables: The values of HP and S for each product, the sum of HP and S for the firm’s other two products, and the sum of HP and S for the three products produced by the competition.”

5.4.5. Other Types of Instruments

There are a few other sets of instruments that have been used in the literature. Ater and Orlov (2010) investigate the relationship between Internet access and flight on-time performance (a measure of flight quality). As an instrument for the log of average quarterly airfares, the authors use an airline’s average segment fare on all other segments of a similar distance, which is a Hausman-type price instrument. However, as a second instrument, they use an airline’s rivals’ average fare on the reverse segment, which is a price characteristic of other products. The authors do not test for validity of instruments or explain the logic behind using the second instrument.

In a working paper by Pekgün, Griffin and Keskinocak (2013), data from a high speed rail operator is used to estimate price elasticities of demand. The authors note that since inventory reading days (or inventory check points) are control points where supply and demand interact through the revenue manager’s decisions, they aggregate the data by inventory reading days (instead of over the number of days left until train departure). Then, for each departure date and fare classification group, the price instruments are average prices lagged by inventory reading days.

5.5. Tests for Instruments

There are three tests that instruments should pass to be considered valid instruments. For linear IV models, most statistical programs provide tests that can be used to easily check to see if a set of instrumental variables is valid. These methods are well known and documented in past literature. The following three tests can be run in Stata® (SE version 10) as post estimation commands after running a 2SLS regression using the command *ivregress 2sls*:

1. Test for weak instruments

   Post-estimation command: *estat first stage*

   Interpretation: If "Prob > F" is insignificant and/or the F statistic is less than 10, then the set of IV's are considered to be weak instruments.

2. Test for an endogenous regressor

   Post-estimation command: *estat endog*

   Interpretation: The null hypothesis is that the variable being tested is exogenous. A significant p-value indicates the variable is endogenous.

3. Test for validity of instruments

   Post-estimation command: *estat overid*

   Interpretation: The null hypothesis is that the instruments are valid. A significant p-value indicates the instruments may not be valid. So, the goal is to find a set of instruments with an insignificant p-value for this test.

For non-linear models, there are currently no Stata® functions to perform these tests, and until recently there was not an easy way to test for validity of instruments.

Guevara-Cue (2010) proposes a new test, called the Direct Test, which is simple to calculate from the log likelihoods of two discrete choice models, one in which endogeneity has not been controlled for and one in which endogeneity has been controlled for. Guevara-Cue shows that this simple test out performs other more complicated tests (see Guevara-Cue, 2010 for details about the test).

Since most statistical programs currently provide modules for running IV models and testing for validity of instruments in linear models but not non-linear models, when searching for a valid set of instruments it may be easier to first use linear models and tests readily available in Stata® and later move to non-linear models.

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CHAPTER 6: FLIGHT-LEVEL DAILY DEMAND MODELS WITH CORRECTION FOR PRICE ENDOGENEITY

6.1. Abstract

Due to a lack of publically available data, few studies within the airline industry have used daily pricing and demand data to investigate the impact of price fluctuations on customer purchases. At the same time, many airline demand models have not corrected for price endogeneity, which is known to lead to biased coefficient estimates. In this chapter online pricing and seat map data, collected from JetBlue's website, is used to build models of daily flight-level demand. An instrumented variable approach (two-stage least squares regression) is used to control for price endogeneity, allowing consistent parameter estimation. A set of instruments are found to pass all validity tests, and are offered as instruments that can be used in disaggregate air travel models of demand. The price coefficient of a model corrected for price endogeneity is found to be 2.9 times more negative than the price coefficient for an uncorrected model, demonstrating the importance of correcting for endogeneity. Further, models that do not correct for endogeneity find inelastic demand estimates whereas models that do correct for endogeneity find elastic demand. Price elasticities are then estimated from the corrected models as a function of advance purchase, showing that customers are less price-sensitive for bookings made closer to the date of flight departure.

6.2. Background

Within the airline industry, there is an interest in better understanding how airfares (or prices) influence bookings and customer purchasing behavior. A better understanding of how customers make tradeoffs among price and itinerary characteristics (such as departure time of day and departure day of week) can potentially influence scheduling decisions, revenue management strategies, and the design of website screen displays. There are two main factors that have hindered the ability to fully understand the influence of price on customer purchasing behavior. First, due to a lack of publically available data for researchers, few models have been built using detailed flight-level pricing data. Thus, relationships between daily airfares and daily demand are not well understood. Second, within the airline industry, most studies have failed to address price endogeneity and have assumed that prices are exogenous, which contradicts basic economic theory of supply and demand. Thus, the objectives of this research are to: 1.) determine whether it is possible to use online prices and seat maps to build detailed flight-level models of daily bookings, and 2.) determine whether price endogeneity can be corrected by finding a valid set of instrumental variables (IVs) and using IV estimation methods such as two-stage least squares (2SLS) regression.

In the next section, an overview of the current literature on the topic of demand modeling and price elasticity estimation is provided. Next, the data and markets are described and descriptive statistics are presented (focusing on the relationship between demand and price across variables such as advance booking, departure day of week and time of day, booking day of week, and competitor promotional sales). Methodology and results are then presented. Bookings are modeled and elasticities are estimated using daily online prices and seat maps from airline websites. By tracking the seat maps across the booking horizon, we estimate daily bookings (a measure of demand) for airline tickets and seats at the flight-level. Using this data, we estimate airfare price elasticity using ordinary least squares (OLS) regression without correcting for price endogeneity and 2SLS regression, accounting for price endogeneity. To our knowledge, this is the first time online seat maps have been used to estimate price elasticities, and this is also one of the first studies to correct for price endogeneity in models of airline demand. Additionally, this is one of the only studies in models of airline demand that performs formal tests for validity of instruments[19].

6.2.1. Demand Forecasting

Traditionally, quality of service index (QSI) models, developed by the U.S. government in 1957, were used during the regulation era to evaluate carriers' requests to increase fares on specific routes (Civil Aeronautics Board, 1970). These QSI models allocated demand across different routes as a function of three quality of service attributes (aircraft equipment type, number of stops, and flight frequency) in order to estimate market shares and passenger volumes. Later, after airline deregulation in 1978, quality of service attributes were expanded to include attributes such as departure and arrival times, departure day of week, carrier preference, and average airfares. QSI models are still used

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[19] Most published studies do not report tests for validity of instruments. In these studies, it is unclear whether they performed tests, but did not report results, or whether they did not perform tests (which means they may not have a valid set of instruments).

extensively in the airline industry. Most QSI models use Origin and Destination Data Bank 1A or Data Bank 1B (DB1A or DB1B)[20] data. These databases do not contain detailed pricing information, but instead contain average quarterly prices per airline/market. Due to a lack of detailed pricing information in these datasets, there is a limited ability to use QSI models to understand how prices impact customer choices.

More recently, discrete choice models (or air passenger itinerary share/choice models) have been used to forecast demand. Depending on how the discrete choice model is designed, the model can incorporate different types of competition patterns among itineraries. For example, a discrete choice model can incorporate increased competition among flights that depart during similar times of the day, such as morning flights as compared to afternoon and evening flights.

A dissertation by Coldren (2005) was the first to model demand at the itinerary level. Computer reservation system (CRS) bookings data for over 24,000 markets, multiple carriers, and several levels-of-service[21] were used to compare airline demand forecasts produced from QSI and discrete choice models. The study used multinomial logit (MNL) models to investigate the impact of air carrier service attributes on passenger choice and also used more advanced discrete choice models (multi-level generalized nested logit and ordered generalized extreme value models) to investigate underlying

[20] DB1A and DB1B are maintained by the U.S. Department of Transportation and represent a ten percent sample of flown tickets collected from passengers as they board aircraft operated by U.S. airlines.
[21] The levels-of-service included were for nonstop and direct flights, as well as connecting flights with a maximum of two connections.

competitive dynamics (substitution patterns) across itineraries. Importantly, the study found that the discrete choice models performed significantly better than the QSI models, reducing the magnitude of forecast errors by 10 to 15 percent (Coldren, et al., 2003). Strengths of the study included the large number of markets included in the data, the advanced model specifications that were investigated, and the ability to compare forecasts with those of an actual airline's QSI model. A limitation of the study is that detailed itinerary-level fare information was not available, so average quarterly fare data was used[22].

A later dissertation was the first to model the joint choice of an itinerary and fare product (Carrier, 2008). Carrier's work combined booking data with fare rules and seat availability data for 3 short-haul markets in Europe (for one airline's nonstop, outbound itineraries only). Strengths of the study include the availability of disaggregate fare data[23] (the lowest fares available for each alternative), the ability to base alternatives in a choice set on seat availabilities data so that flights without any available seats were not included in a customers' choice set, and a latent class choice model which accounted for heterogeneity of passenger behavior (business versus leisure passengers). The main limitations of the study were that data was available for only 3 markets and due to the small sample size, advanced logit model specifications were not estimated.

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[22] "Superset" data (Data Base Products, Inc. 2000, 2001), a cleaned version of DB1A/B data was used for fare information. Fares are based on averages for each carrier across all itineraries for each airport-pair within a quarter.

[23] Fares offered and their fare rules were obtained from Sabre® global distribution system and accessed through the Travelocity® website.

To sum up the studies by Coldren and Carrier, both have different strengths and weakness that are quite opposite. As shown in Table 6.1, Coldren had a comprehensive airline dataset with over 24,000 markets, 10.6 million bookings, several airlines, and 4 levels-of-service, which allowed the estimation of advanced discrete choice models. However, he only had aggregate fare information for average quarterly fares paid for each airline/market. Carrier, on the other hand, did not have a comprehensive airline dataset. Instead, he had a dataset of 3 markets, one airline, and nonstop flights only, which did not allow the estimation of advanced discrete choice models. However, he had disaggregate fare information for actual offered fares of each fare product in a choice set. In both of these studies, price endogeneity was not explored.

Table 6.1: Summary of Studies Investigating Demand at the Itinerary Level

Study	Total Markets	Total Bookings	Carriers	Level-of-Service	Advanced Models	Fares
Coldren (2003)	24,298	10,556,275	All offering service	Nonstop, Direct, Single-Connect, Double-Connect	Yes: Multi-level generalized nested logit and ordered generalized extreme value	Average: quarterly fare per airline/market
Carrier (2008)	3	2,015	1	Nonstop	No: MNL only	Detailed: lowest offered price of each fare product in a choice set

From a discrete choice modeling perspective, there is still an open research need for exploring advanced discrete choice model specifications using disaggregate flight-level fare data. This could help decision-makers better understand the impact of prices on itinerary share, and could lead to new behavioral insights about the underlying competitive dynamic between itineraries. In these models, however, there is also a need to correct for endogeneity of airfares in order to estimate the unbiased effect of prices on customer purchasing decisions. Given the rather small sample size of our dataset, the objective of this chapter is to focus on the second research question: correcting for endogeneity of airfares. More advanced model specifications are left for future research.

6.2.2. Price Elasticity of Demand

Although Coldren and Carrier's work focused on building discrete choice models of demand capable of better understanding customer tradeoffs and decisions, there are many other studies that have focused on estimating price elasticity of demand, which is the percent change in demand caused by a percent change in price (a measure of how responsive customers are to changes in price). Estimated elasticities in past literature have varied widely depending on the data used, the modeling methodology, and the markets and time period used. Some studies have corrected for price endogeneity, and others have not. Most studies have used aggregate data to estimate price elasticity.

InterVISTAS (2007) reviews 22 papers on airfare elasticities published between 1986 and 2006, including two meta analyses of multiple publications, and finds that estimated price elasticities differ across many dimensions of air travel, including: business versus leisure travel, short-haul versus long haul travel, and level of aggregation (airline, market, national, and pan-national levels). Business travelers are generally less elastic (less price sensitive) than leisure travelers because people traveling for business have less flexibility to postpone or cancel their trip. Travelers in short-haul markets are generally more elastic (more price sensitive) because of the availability of more inter-modal substitutes (such as driving or taking a bus). A meta-study by Gillen et al. (2002) found that market-level price elasticities in the literature have ranged from -0.198 in long-haul international business markets to -1.743 in short-haul leisure markets.

The level of aggregation of the data also impacts estimated price elasticities. Airline-level price elasticities are generally estimated to be more elastic than market-level elasticities, and market-level elasticities are generally estimated to be more elastic than national or pan-national price elasticities (InterVISTAS, 2007). InterVISTAS (2007) developed price elasticity estimates at the route, national, and pan-national levels using DB1B and corrected for price endogeneity using 2SLS. They find an average elasticity of -1.4 at the route/market-level, -0.8 at the national-level, and -0.6 at the pan-national level (airline specific price elasticities were out of the scope of their project).

Hsiao (2008) estimates discrete choice models of aggregate quarterly air passenger demand using aggregate quarterly data from DB1B and T100 and corrects for price endogeneity. Hsiao finds price elasticity estimates of market demand that range between -1.052 and -2.662.

In a more recent study, Granados, Gupta, and Kauffman (2012) estimate log-linear 2SLS regression models that correct for price endogeneity to investigate price elasticities of demand for air travel booked through online and offline booking channels. The authors use a dataset of airline bookings sold by travel agencies through global distribution systems (GDSs)[24]. In a model on the whole dataset, price elasticity of demand is estimated to be approximately unit elastic (-1.03). The authors further break price elasticity estimates out by leisure versus business travel and by bookings made through three channels (offline, transparent online travel agents, and opaque online travel agents). The price elasticities for the business travel booked through the three channels are -0.34, -0.89, and -1.29, respectively. For the leisure travel booked through the three channels, price elasticity estimates are -1.33, -1.56, and -2.28, respectively.

6.3. Description of Data

Automated web client robots (or webbots) were used to query the websites of JetBlue and one online travel agent (OTA). The webbots collected detailed itinerary, fare, and seat map information for nonstop flights on a daily basis from 8/5/2010 through 9/21/2010. During this time period, queries were run to collect airfares and seat maps for a rolling set of 21 departure dates. For example, when the data collection began on 8/5/2010, information for flights departing on 9/2/2010, 9/3/2010, ... , to 9/22/2010 was obtained. For the next day of data collection, 8/6/2010, information for the same flight departure dates was obtained. Collecting data in this way provides information for each flight in a market for 21 departure dates and over a booking period from 1 to 28 days before flight departure.

[24] GDSs include ticket sales made via online and offline channels through travel agencies but exclude airline direct sales.

6.3.1. Selection of Markets

In selecting the sample of markets to use in this study, we control for several factors. We control for differences in market competition by selecting four markets where JetBlue and Virgin America compete head-to-head, with both offering nonstop flights. These markets are all long haul markets with similar flight times and lengths of haul. All of the markets are transcontinental flights that originate on the East coast. In selecting these markets, we are also controlling for equipment type. Specifically, both Virgin America and JetBlue mainly use Airbus 320 planes. In these markets, JetBlue flies the A320 exclusively, and Virgin America flies the A320 in all flights in all markets with one exception. In JFKSFO, Virgin America offered flights on their smaller plane, the Airbus 319, for six departure dates.

Table 6.2 provides a list of airport codes and airport names in our data. Table 6.3 provides a list of the airline codes and names, and Table 6.4 contains a list of the 4 markets included in this study, along with nonstop competitors, average fares, and number of bookings. A total of 7,522 bookings were observed for JetBlue.

Table 6.2: Airport Codes and Names

Airport Code	Name of Airport, City and State
BOS	Logan International Airport, Boston, Massachusetts
FLL	Fort Lauderdale Hollywood International Airport, Fort Lauderdale, Florida
JFK	John F. Kennedy International, New York City, New York
LAS	McCarran International Airport, Las Vegas, Nevada
LAX	Los Angeles International Airport, Los Angeles, California
SFO	San Francisco International Airport, San Francisco, California

Table 6.3: Airline Codes and Names

Airline Code	Airline	Type Carrier
AA	American Airlines	Major
B6	JetBlue Airways	Low Cost
DL	Delta Airlines	Major
UA	United Airlines	Major
VX	Virgin America	Low Cost

Table 6.4: JetBlue Descriptive Statistics: Markets, Competitors, Bookings and Prices

Market	Nonstop Competitors	Flight Number	DTOD[1]	Total Book-ings	Min Price	Mean Price	Max Price
BOSLAX	AA, B6, UA, VX	473	8	844	\$114	\$205	\$586
		483	18	927	\$114	\$191	\$466
JFKLAS	AA, B6, DL, VX	187	7	451	\$129	\$254	\$463
		191	18	405	\$129	\$231	\$463
		197	10	458	\$129	\$282	\$586
		199	21	313	\$129	\$225	\$463
		711	14	481	\$129	\$251	\$526
JFKLAX	AA, B6, DL, UA, VX	671	11	691	\$129	\$257	\$586
		673	16	671	\$129	\$244	\$586
		675	7	974	\$129	\$205	\$526
		677	19	747	\$129	\$223	\$466
JFKSFO	AA, B6, DL, UA, VX	641	8	339	\$129	\$300	\$586
		647	17	221	\$129	\$287	\$586
		Totals/Averages:		7,522	\$114	\$233	\$586

[1]DTOD= Flight Departure Time of Day, in military time. For example, a DTOD of 18 means the flights departed sometime between 6:00pm and 6:59pm.

6.4. Descriptive Statistics

The level of observation is the number of daily bookings at the flight-level. In the sample, we observe between 0 and 16 bookings per flight per day, with a mean of 1.9 bookings and a median of 1 booking[25]. Demand and prices are observed to vary based on several factors, such as advance booking, departure day of week, departure time of day, booking day of week, during promotional sales of low cost competitor Virgin America, and during Labor Day Holiday. The next several sections take a closer look at how average prices and average demand are influenced by these variables.

6.4.1. Correlation Between Demand, Prices, and Advance Booking

As the flight departure date approaches, average prices are observed to increase, which is typical in the airline industry due to revenue management practices. Additionally, average demand increases as the date of departure draws nearer. This means that when prices are high, demand is also high. This relationship is demonstrated in Figure 6.1.

Table 6.5 shows the correlation between average bookings, average prices and days from departure (DFD). Looking at the correlation coefficients also shows moderate to high correlations between these variables. As the day of flight departure approaches, average prices increase, with a correlation coefficient of -0.76. As the flight departure

[25] Throughout this chapter, we use the terms "number of bookings" and "demand" interchangeably, although we realize that the two measures are not exactly the same. JetBlue's flights rarely sellout, so in general, there is not more demand for flights than we can observe from the actual bookings.

date approaches, average bookings increase, with a correlation coefficient of -0.56. We observe higher demand for higher prices, with a correlation coefficient of 0.52.

Table 6.5: Average Bookings, Average Price and DFD Correlation Coefficients

	Mean Bookings	Mean Prices	DFD
Mean Bookings	1		
Mean Prices	0.52	1	
DFD	-0.56	-0.76	1

Note: DFD= Days from departure

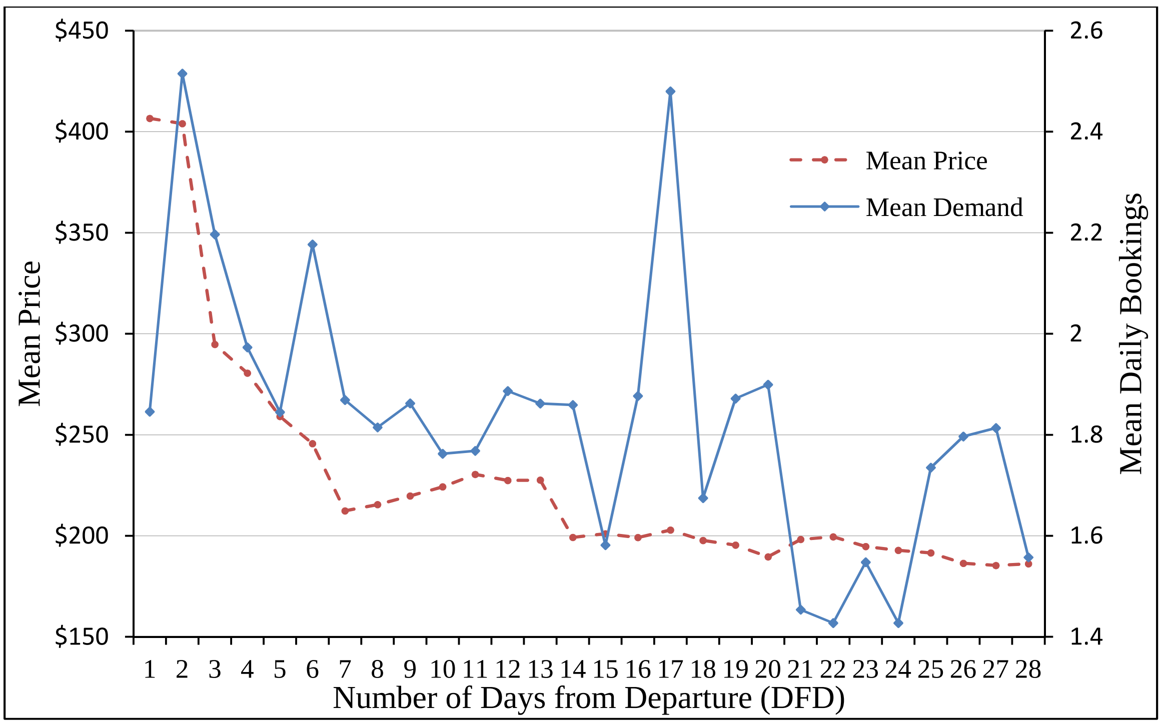

Figure 6.1: Average Daily Demand and Prices as a Function of Days from Departure

6.4.2. Correlation Between Demand, Prices, and Departure Day of Week

Average daily demand and average prices are observed to differ by a flight's departure day of week, as shown in Figure 6.2. Looking at the figure seems to show an inverse relationship between average prices and demand. Departures on Saturdays have the lowest prices, and departures on Mondays have the highest prices. This is intuitive, as many leisure travelers travel on Saturdays, whereas many business travelers pay travel on Mondays.

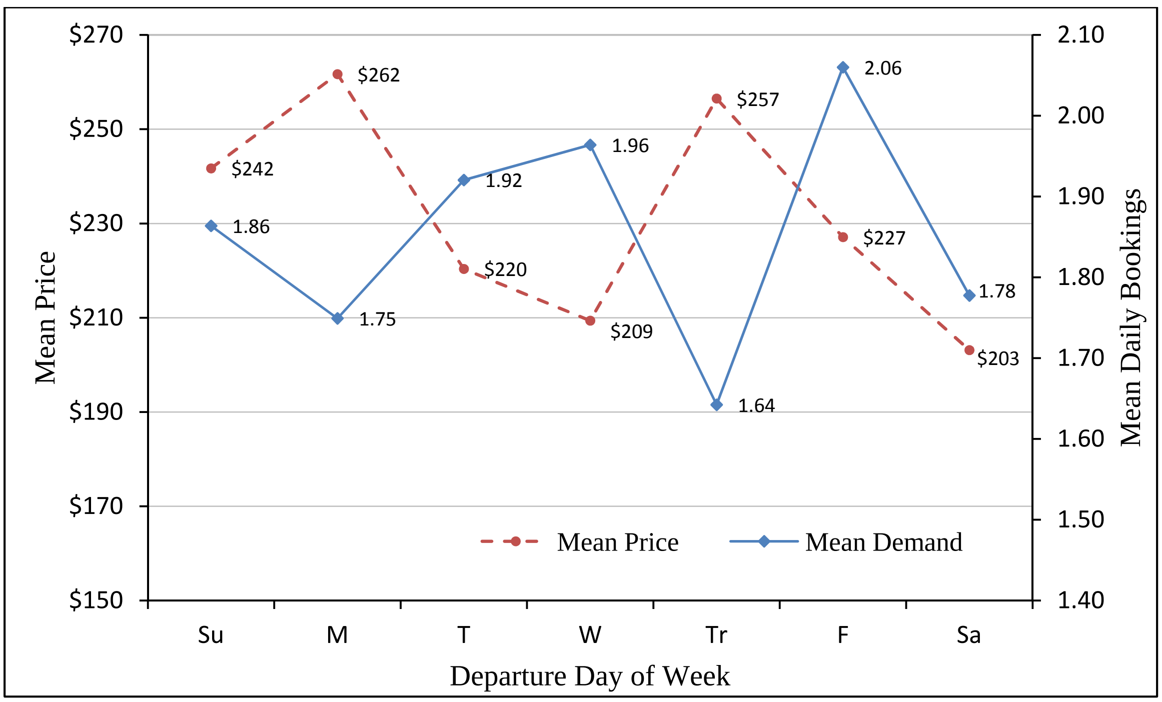

Figure 6.2: Average Daily Demand and Prices as a Function of Departure Day of Week

6.4.3. Correlation Between Demand, Prices, and Departure Time of Day

Average daily demand and average prices are also observed to differ by a flight's departure time of day, as shown in Figure 6.3. Flights departing at 10am and 5pm have the highest average prices but also have some of the lower average demands. Flights departing at 7am have one of the lower average prices, but also have the highest observed average demand. Once again, looking Figure 6.3 seems to show an inverse relationship between average prices and demand for many of the departure times.

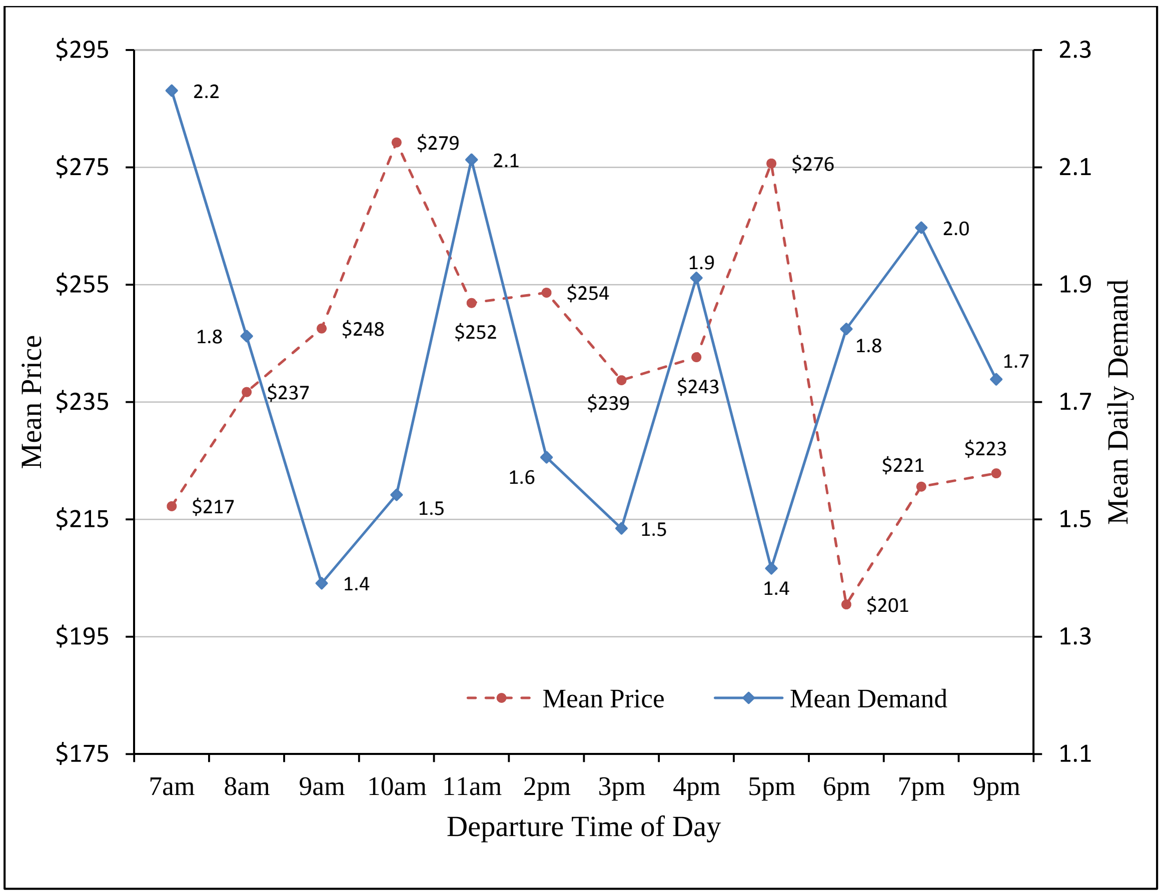

Figure 6.3: Average Daily Demand and Average Prices as a Function of Departure Time of Day

6.4.4. Correlation Between Demand, Prices, and Booking Day of Week

Average daily demand and average prices are also observed to differ by booking day of week, as shown in Figure 6.4. The figure shows that prices stay relatively constant for each booking day of the week (with a range of only $215-$258), which makes sense. Airlines generally do not charge significantly higher or lower prices for booking a flight on a Saturday versus on a Monday. The price differences would be expected to vary more by DFD and departure day of week. Although prices are observed to stay relatively constant for each booking day of the week, there does seem to be a difference in average demand. The figure seems to show that significantly fewer tickets are sold on Saturdays and Sundays as compared to weekdays.

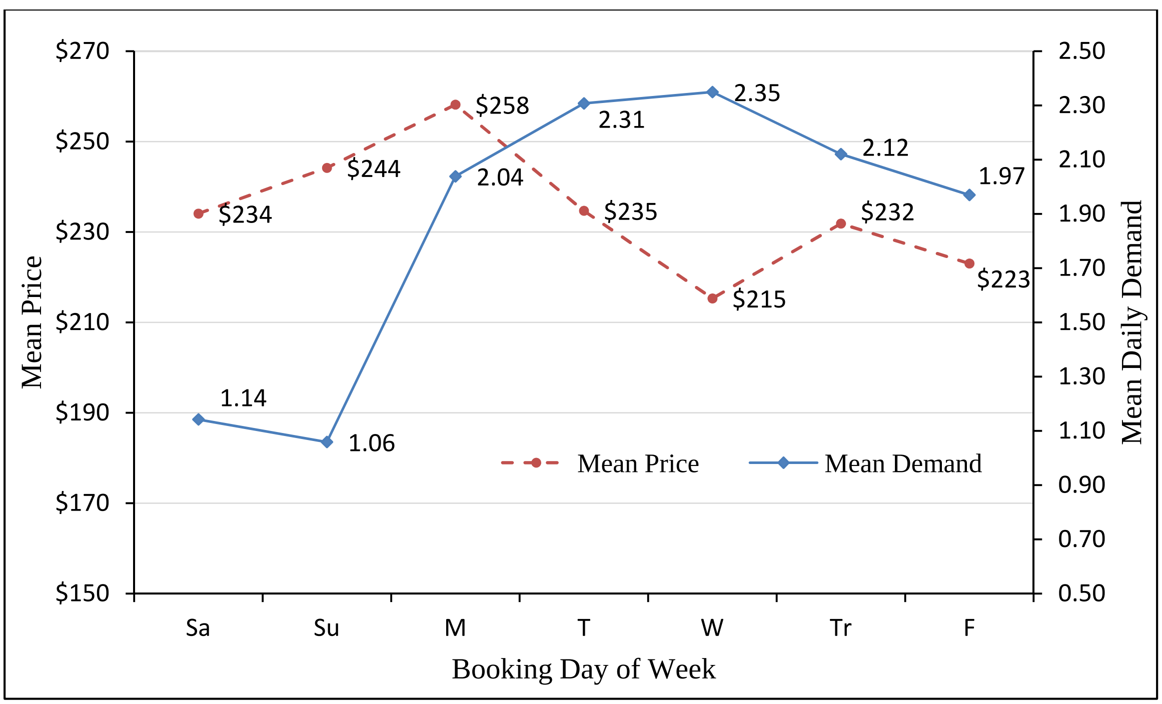

Figure 6.4: Average Daily Demand and Average Prices as a Function of Booking Day of Week

6.4.5. Promotions, Sales, and Holidays

During the time of data collection, low cost competitor Virgin America had three promotional sales. Promotional sales were identified from both the Virgin America website and from Travelzoo® emails.

As an example, one sale included a largely advertised three day system-wide fare sale when Virgin America announced plans to launch new service to Los Cabos and Cancun, Mexico. Virgin America teamed with Loopt® to offer customers a special promotion if they checked-in (with the free Loopt® Star App on their iPhone) at SFO, LAX or one of Virgin America's mobile taco truck locations during a four hour time period. Customers could get a $1 two-for-one taco deal along with a two-for-one ticket offer valid on Virgin America's new flights to Los Cabos and Cancun (Virgin America, August 31, 2010). Virgin America is quoted as saying "….significant online buzz circulating about the promotion, helped make it the fifth highest sales day" in Virgin America's history (Arrington, 2010).

The data shows a significant decrease in JetBlue bookings during Virgin America's promotional sales. We control for Virgin America promotions by introducing dummy variables into the following models for bookings made during the sale dates.

During the time of data collection, there was one holiday. Labor Day holiday was observed on Monday, September 6, 2010. We control for the holiday by introducing dummy variables for bookings made for flights departing on Labor Day (September 6) and the day after Labor Day (September 7).

6.5. Methodology and Results

Regression models were run on daily bookings at the flight-level, across 21 departure dates (3,952 observations). In order to correct for price endogeneity, 2SLS was used with a set of valid instruments. Table 6.6 below provides variable definitions for all variables, and the last three rows of the table are the instrumental variables. The price variable is the one-way price captured from JetBlue's website.

The set of instruments includes three variables. The main instrument is based on Hausman-type price instruments, which uses a firm's own prices in other markets as instruments for a market of interest (Hausman, 1996; Hausman, Leonard and Zona, 1994). We build these instruments by using JetBlue's equivalent one-way price from the OTA website (round-trip prices divided by two). The second instrument is based on Stern (1996), which introduces measures of the level of market power by multiproduct firms and measures of the level of competition as instruments. Based on Stern's approach we use the number of daily flights in a market as a proxy for multiproduct firms. The third instrument is the square of the number of days from departure that a flight is booked.

In order to compare OLS to 2SLS coefficient estimates, all observations missing an instrumental variable were dropped. This decreased the total number of bookings by 2.3%, for a total number of bookings of 7,352. Table 6.7 below shows the results of the OLS and 2SLS regressions; both use robust standard errors clustered by market. Notice that the price coefficient for the 2SLS regression becomes more negative, as expected. Another point of interest is that many of the coefficient estimates in the OLS regression are insignificant. However, after correcting for endogeneity, most of the coefficient estimates become significant.

The set of instruments used were tested against the three tests discussed in Chapter 5, Section 4, and requirements of all tests were satisfied. The test for weak instruments, rejected the null hypothesis that instruments are weak, with a p-value of 0.04. The adjusted R-square of the first stage regression on price is 0.49. The null hypothesis that price is actually an exogenous regressor was rejected, with a p-value of 0.006, and the test for instrument validity did not reject the null hypothesis that the instruments are not valid, with a p-value of 0.10.

Table 6.6: Variables and Descriptions

Variable	Variable Description
Price	Price of the flight (JetBlue's one-way price)
vxsaledum	Indicates a date that Virgin America was offering promotional sales
travelsep6	Indicates bookings made for travel on Labor Day holiday
travelsep7	Indicates bookings made for travel the day after Labor Day holiday
earlymorning	Indicates flight departure is 5am-7:59am
morning	Indicates flight departure is 8am-11:59am
afternoon	Indicates flight departure is Noon-4:59pm
evening	Indicates flight departure is 5pm-8:59pm
dfd1	Indicates a booking made 1 day from flight departure
dfd2	Indicates a booking made 2 days from flight departure
dfd3	Indicates a booking made 3 days from flight departure
dfd4	Indicates a booking made 4 days from flight departure
dfd5	Indicates a booking made 5 days from flight departure
dfd6	Indicates a booking made 6 days from flight departure
dfd7	Indicates a booking made 7 days from flight departure
dfd8_14	Indicates a booking made between 8 and 14 days from flight departure
dfd15_21	Indicates a booking made between 15 and 21 days from flight departure
dfd22_28	Indicates a booking made between 21 and 28 days from flight departure
ddow1, …., ddow7	Indicates flight departs on a Sun, Mon,…., Sat
bdow1, …., bdow7	Indicates flight was booked on a Sun, Mon,…., Sat
Market Dummies	Dummy variable for each market
lnmeanb6priceothermkt	Instrumental variable: Natural log of JetBlue's mean prices in other markets
avgflts_vx	Instrumental variable: The average number of nonstop flights in a market offered by Virgin America
Dfdsq	Instrumental variable: The square of number of days from departure that a flight was booked

Table 6.7: OLS and 2SLS Regression Results

	OLS		2SLS	
	Coeff	P-value	Coeff	P-value
price	-0.0051	0.025	-0.0148	0.000
vxsaledum	-0.2765	0.162	-0.3456	0.009
travelsep6	-0.6780	0.022	-0.8827	0.045
travelsep7	-0.0266	0.901	0.6145	0.000
Departure Time of Day *(reference variable is evening-depart 5pm-8:59pm)*				
earlymorning (depart 5am-7:59am)	0.2929	0.295	0.2853	0.000
morning (depart 8am-11:59am)	0.1391	0.175	0.4302	0.057
afternoon (depart Noon-4:59pm)	0.0167	0.661	0.2320	0.070
Number of Days from Flight Departure Dummies *(reference variable is dfd22_28)*				
dfd1	1.3405	0.094	3.2414	0.000
dfd2	1.9657	0.016	3.8990	0.000
dfd3	1.1688	0.014	2.0446	0.000
dfd4	0.9298	0.074	1.6683	0.000
dfd5	0.6374	0.055	1.1600	0.000
dfd6	0.9048	0.088	1.3096	0.000
dfd7	0.5484	0.010	0.6695	0.000
dfd8_14	0.4870	0.069	0.7072	0.001
dfd15_21	0.2888	0.112	0.3440	0.022
Departure Day of Week Variables *(reference variable is ddow7-Saturday Departure)*				
ddow1 (Sunday)	0.1446	0.182	0.4442	0.000
ddow2 (Monday)	0.4711	0.059	1.0689	0.000
ddow3 (Tuesday)	0.2861	0.018	0.2505	0.035
ddow4 (Wednesday)	0.2384	0.102	0.3052	0.000
ddow5 (Thursday)	0.1558	0.085	0.6312	0.024
ddow6 (Friday)	0.3050	0.086	0.4338	0.125
Booking Day of Week Variables *(reference variable is ddow6-Friday Departure)*				
bdow1 (Sunday)	-0.8179	0.049	-0.6684	0.016
bdow2 (Monday)	0.2920	0.398	0.5821	0.009
bdow3 (Tuesday)	0.4089	0.040	0.5044	0.000
bdow4 (Wednesday)	0.3700	0.113	0.3015	0.075
bdow5 (Thursday)	0.2536	0.034	0.3230	0.000
bdow7 (Saturday)	-0.8112	0.023	-0.7332	0.000
Market Dummies *(reference is jfklas)*				
boslax	0.0811	0.158	-0.3536	0.049
jfklax	0.5272	0.000	0.4047	0.000
jfksfo	0.0869	0.294	0.4335	0.000
_cons	2.1420	0.002	3.7022	0.000
	R-Square=0.133			

Note: Both models use robust standard errors, clustered by market.

6.5.1. Average Price Elasticities for Corrected and Uncorrected Models

Table 6.8 shows the comparison between the price elasticities of demand estimated by the OLS and 2SLS regression models. For the OLS regression model, the estimated price elasticity of demand evaluated at the mean price is -0.64, which represents inelastic demand. After correcting for endogeneity using 2SLS, the estimated price elasticity of demand is -1.84, which represents elastic demand. This difference is important, as pricing recommendations differ for inelastic and elastic models. Specifically, inelastic models suggest that prices should be raised whereas elastic models suggest prices should be lowered. Evaluating the price elasticities at the median price gives similar results, as shown in Table 6.9.

Table 6.8: OLS and 2SLS Price Elasticity Results (At the Mean of Price)

	At Price=$232 (mean)	95% Confidence Interval	
OLS	-0.64	-0.94	-0.34
2SLS	-1.84	-2.71	-0.98

Note: Price elasticities are calculated over the means of all variables.

Table 6.9: OLS and 2SLS Price Elasticity Results (At the Median of Price)

	At Price=$199 (median)	95% Confidence Interval	
OLS	-0.50	-0.72	-0.29
2SLS	-1.25	-1.71	-0.79

Note: Price elasticities are calculated over the means of all non-price variables.

6.5.2. Price Elasticities as a Function of Advance Booking

Price elasticities were calculated from the 2SLS model as a function of number of days from flight departure. Table 6.10 provides the price elasticities of demand at both the mean of price and also the median of price. The table shows that JetBlue's customers are less price sensitive closer to flight departure. This is intuitive, as leisure passengers generally book further in advance of departure and business passengers often book closer to departure.

Table 6.10: 2SLS Price Elasticity Results as a Function of Days from Departure

DFD	Price = $232 (mean)	Price = $199 (median)
1 to 7	-1.14	-0.84
8 to 14	-2.06	-1.37
15 to 21	-2.59	-1.62
22 to 28	-3.40	-1.97

Note: DFD=Days from Flight Departure

6.6. Conclusions and Future Research Directions

An instrumented variable approach (two-stage least squares regression) is used to control for price endogeneity, allowing consistent parameter estimation. A set of instruments are found to pass all validity tests, and are offered as instruments that can be used in disaggregate air travel models of demand. The instruments are based on Hausman-type price instruments, which use a firm's own prices in other markets as instruments for a market of interest, as well as measures of the level of market power by multiproduct firms (as in Stern, 1996). We build the instruments by using prices and flight frequencies from data compiled from an OTA website.

The price coefficient of the 2SLS regression model, which corrected for price endogeneity, is found to be 2.9 times more negative than the price coefficient for an uncorrected model, demonstrating the importance of correcting for endogeneity. For the OLS regression model, the estimated price elasticity of demand (evaluated at the mean of price) is -0.64, which represents inelastic demand. After correcting for endogeneity using 2SLS, the estimated price elasticity of demand is -1.84, which represents elastic demand.

It would be interesting to aggregate our data and/or to mis-specify the model using average prices instead of disaggregate prices. A priori, it is expected that price elasticities from an aggregated model would be less elastic than the price elasticities of our model. This is because on a daily basis, airline customers can choose to purchase departure dates with lower prices, or they can choose a different airline with a lower price offering for the day, or they can wait to purchase when a lower price is offered. This dynamic would not be captured in aggregate data.

We find that the total number of bookings is decreased during ongoing promotional sales of JetBlue's low cost competitor Virgin America. In future research, it would be interesting to model JetBlue and Virgin America demand together in the same model using a nested logit model to capture the degree of substitution between the airlines. JetBlue and Virgin America are likely to be close substitutes. Incorporating a major carrier into the models could add insight about the substitutability of LCCs versus major carriers.

Also, there is a future research need for incorporating competitor prices into revenue management forecasts. Within the airline industry, there has been growing interest in developing the next generation of revenue management (RM) systems that can more accurately represent how customers make decisions in today's online environments. The development of these next-generation "choice-based" RM systems require information about the prices (or "choices") viewed by customers at the time of booking – both on the carrier of interest and, potentially, across several different competitors.

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CHAPTER 7: CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

7.1. Introduction

This dissertation accomplished four main research objectives, each related to leveraging online data to better understand airline pricing and product strategies, and how these strategies impact customers, as well as the industry in general. The chapters of this dissertation are written in journal format, with each chapter focusing on one of the objectives. Chapter 2 investigated the relationship between airline prices and competitive market structures. Chapter 3 identified and reviewed product debundling trends that recently occurred in the U.S. airline industry. Chapter 4 focused on one debundling trend: seat reservation fees. We investigated factors that influence airline customers' premium coach seat purchases and estimated revenue impacts of different seat pricing strategies. Chapter 5 reviewed the subject of price endogeneity, and Chapter 6 used online prices and seat maps to model daily flight-level bookings and price elasticities. A valid set of instrumental variables were found and used to correct for price endogeneity. This dissertation also includes Appendix A, which provides more detailed information about an online dataset of competitor prices that was compiled using automated web client robots. Finally, this last chapter (Chapter 7) summarizes major findings related to each chapter's research objective and outlines directions for future research.

7.2. Major Conclusions and Directions for Future Research

7.2.1. Competitive Airline Pricing Policies

The first research objective of this dissertation explored airline pricing policies in markets with different types of competitive market structures using a dataset of online prices from 2007 (Chapter 2). Several observations were made using the disaggregate pricing dataset. In contrast with findings of past research on price dispersion, we found that low price dispersion can be associated with both low and high market concentration, depending on the characteristics of the market and the specific carriers offering flights. The presence of low cost carriers (LCCs) was seen to have an impact on pricing of other carriers.

We also found that pricing strategies in low cost carrier monopoly routes are different than major carrier monopoly routes. Even in a monopoly situation, low cost carriers (especially Southwest) demonstrate flat pricing and price dispersion as the day of departure approaches. These differences in monopoly routes highlight the importance of understanding price dispersion at the detailed, disaggregate level when analyzing the impact of future mergers and acquisitions.

An additional finding was that markets with codeshares (specifically codeshares between US Airways and United Airlines) sometimes exhibit unusually high price dispersion on the airline that is selling tickets for a flight operated by another airline. There is a need for more research, at the disaggregate level, on how codesharing affects pricing within a market. As more and more airlines begin to use codeshares, understanding the impacts on the market will become more important.

Additionally, two markets where two nonstop LCCs compete (which occurs rarely in the U.S.) were investigated. Competition between LCCs is increasing in the U.S., so an important area of future research is to better understand competition in these markets. We offer a database of markets where low cost carriers compete in Appendix A, which can be used in future research.

Most importantly, this part of the dissertation demonstrated the importance of disaggregate data that describe individual airline behavior, as aggregate data can hide important details in the data. In future research, there is a need for publically available sources of disaggregate demand and pricing data, which could lead to new insights into the impact of mergers and acquisitions on consumer welfare.

7.2.2. Product Debundling

The second research objective of this dissertation identified and reviewed product debundling trends that occurred in the U.S. in 2009-2010 (Chapter 3). We estimate the debundling phenomenon has diluted revenues to the U.S. Airport and Airways Trust Fund (AATF) by at least five percent. This is important as the AATF finances investments in the airport and airway system. The AATF was established as a source of funding that would increase concurrently with the use of the system, and assure timely and long-term commitments to capacity increases. The finding that debundling has diluted revenues to the AATF means that policy-makers may need to tax ancillary fees in the future in order to maintain the viability of the fund.

We anticipate that the "ancillary revenue" phenomenon is likely to continue in the U.S. market among low cost and network carriers. In future research, there is a need to better understand how ancillary fees impact customer satisfaction and loyalty. There is also a need to understand what factors drive customers to purchase add-on services, what aspects of the services that they value, and how these valuations may differ across customer segments.

7.2.3. Premium Coach Seat Purchasing Behavior

The third research objective of this dissertation investigated factors that influence airline customers' premium coach seat purchases, and also estimated revenue impacts of different seat pricing strategies (Chapter 4). Several new behavioral insights into seat reservation fees were found. As planes fill up, customers are more likely to purchase a premium coach seat (with extra legroom and early boarding), regardless of how far in advance they purchase a ticket. This suggests that the ability of airlines to charge seat fees is strongly tied to load factors, which has several implications. First, concerns expressed by customers and government officials about the importance of clearly communicating airlines' seat policies appear to be valid. It is important to ensure that customers are not being misled into making premium seat fee purchases by the information displayed on seat maps. Second, the U.S. airline industry is currently going through a series of mergers and acquisitions, and has seen a reduction in overall domestic capacity, which has led to record-high load factors. In an environment in which load factors are high, the airlines' ability to generate revenues from seat fees is strong, and several industry pricing models related to seat fees are viable. However, if load factors decrease in the future, we would expect that the incremental revenues generated from seat fee reservations would also decrease.

We also find that customers who purchase tickets closer to the departure date are willing to pay higher seat fees, and that JetBlue could increase profits by optimizing prices. We find that JetBlue's seat fees are currently underpriced in many markets; an optimal static fee would increase revenues by 8 percent whereas optimal dynamic fees would increase revenues by 10.2 percent. In addition, if JetBlue were to leave their seat fees unchanged and instead blocked certain rows of seats for premier customers, they could potentially increase revenues by 12.8%. This finding underscores the importance of ensuring customers are not inadvertently misled into purchasing premium seats by seat map displays that block seats for premier customers.

There are several extensions of this work that could be addressed by using stated preference surveys. Currently, it is unclear what specific attributes of premium coach seats are valued by customers, and how these valuations may differ across customer segments. For example, do customers purchasing JetBlue's premium coach seats value extra legroom? Do they value the ability to board first and store luggage in overhead bins? Do they value the ability to deplane first and have more time to make connecting flights? Determining the value of each of these components will help airlines better design products and bundles that provide the most value for customers. It will also help airlines determine whether they should invest in adding sections in coach that offer extra legroom, or simply sell existing coach seats that provide early boarding and alighting privileges. This is a particularly important decision for carriers, as removing planes from service to remove row(s) of seats to add extra legroom is costly, particularly when planes are flying near record-high load factor levels.

7.2.4. Flight-Level Demand Models with Correction for Price Endogeneity

The last objective of this dissertation was to model daily flight-level bookings and estimate price elasticities using methods that correct for price endogeneity. Daily online prices and seat maps from airline websites were used to compare airfare price elasticity estimates using ordinary least squares (OLS) regression without correcting for price endogeneity and two-stage least squares (2SLS) regression which corrects for endogeneity. Results show the importance of correcting for price endogeneity. For the OLS regression model, the estimated price elasticity of demand is -0.64, which represents inelastic demand. After correcting for endogeneity using 2SLS, the estimated price elasticity of demand is -1.84, which represents elastic demand. This difference is important, as pricing recommendations differ for inelastic and elastic models, i.e., inelastic models suggest prices should be raised whereas elastic models suggest prices should be lowered. Further, a set of instruments are found to pass validity tests and can be used in future models of daily flight-level demand. To our knowledge, this is the first time online seat maps have been used to estimate price elasticities. This is also one of the first studies to correct for price endogeneity in models of airline demand and to test for validity of instruments.

We also find that the total number of bookings is decreased during ongoing promotional sales of JetBlue's low cost competitor Virgin America. In future research, it would be interesting to model JetBlue and Virgin America demand together in the same model using a nested logit model to capture the degree of substitution between the airlines. JetBlue and Virgin America are likely to be close substitutes. Incorporating a major carrier into the models could add insights about the substitutability of LCCs versus major carriers.

For future research it would be interesting to aggregate our data and/or to mis-specify the model using average prices instead of disaggregate prices. A priori, it is expected that price elasticities from an aggregated model would be less elastic than the price elasticities of our model. This is because on a daily basis, airline customers can choose to purchase departure dates with lower prices, or they can choose a different airline with a lower price offering for the day, or they can wait to purchase when a lower price is offered. This dynamic would not be captured in aggregate data.

Also, there is a future research need for incorporating competitor prices into revenue management forecasts. Within the airline industry, there has been growing interest in developing the next generation of revenue management (RM) systems that can more accurately represent how customers make decisions in today's online environments. The development of these next-generation "choice-based" RM systems require information about the prices (or "choices") viewed by customers at the time of booking – both on the carrier of interest and, potentially, across several different competitors.

7.3. Concluding Thoughts

Although this disssertation has shown how online data can be leveraged to better understand airline and air passenger behavior, it is important to note that the use of competitive price information is somewhat controversial, despite the fact that today the majority of large U.S. carriers purchase competitive price information from firms such as QL2® or Infare Solutions.

The pricing and seat maps we collected from the internet allowed us to explore questions that airlines themselves would not be able to explore using their own data. For example, JetBlue is not able to recreate the seat maps viewed by customers at the time of purchase. To do this, they would need to invest hundreds of thousands of dollars to collect this information through their website. Our approach offers a more cost-efficient way to examine this problem and provides some of the first insights that are needed for airlines to justify investments required to collect more detailed online data. Our approach is also one that can be replicated by government agencies or public advocacy groups interested in understanding the role of seat map displays on customer purchasing behavior.

Looking ahead, we expect online data to play an even more critical role in aviation studies. We also expect continued discussions around maintaining privacy of individual-level consumer data, and the ultimate benefit to firms and consumers of using competitive price information. Using competitor information could lead to lower price offerings in markets as carriers match fares. It could also lead to spiral down of profits for carriers, and an attempt to return to more opaque pricing through debundling product attributes and recreating bundles from these separate products. In turn, this would likely lead to increased tensions among carriers and global distribution systems, the latter of which currently do not have the ability to distribute detailed debundled products themselves.

Ancillary fees are often tied to different fares and/or frequent flyer status, which may encourage customers to book on airline websites rather than travel agency websites. For some airlines, the ability to reserve premium seats can only be done online if customers first log in to the website using their frequent flyer account. By requiring that customers log in, the airline is able to tailor seat selections to each customer. The airline also indirectly benefits from encouraging customers to log in at the beginning of the search process (versus when a ticket is ultimately purchased) in the sense that it can unobtrusively observe the sequence of screens across a single or multiple website session, which can provide valuable marketing information. However, the ability to track individuals during their online search process may also raise new privacy concerns that need to be addressed in the future.

APPENDIX A: ONLINE PRICING DATABASE

Mumbower, S. and Garrow, L.A. (2013) Online pricing data for multiple U.S. carriers. Submitted to *Manufacturing & Service Operations Management.* Invited for second round review on June 27, 2013.

A.1. Abstract

This section describes a database of online airline prices collected from a major online travel agent and one low cost carrier. The database provides detailed pricing data for all nonstop flights offered in a market. Data are provided for 42 domestic U.S. markets across a 28-day booking horizon for 21 departure dates. Each of the 42 markets is served by one or more low cost carriers. These data can be used to investigate the evolution of prices and price dispersion for monopoly, duopoly, and oligopoly markets. The data can also be used to create simulated datasets for benchmarking the performance of revenue management algorithms that consider competitors' prices. We hope to address research gaps by making this dataset publically available for other researchers to use.

A.2. Introduction

The U.S. airline industry is fiercely competitive market and one in which it has historically been difficult to raise fares. According to the Air Transport Association (2010), in the first 30 years after passenger deregulation (which occurred in the U.S. in 1978), domestic airline prices fell 41.2% in real terms. This decline is due to multiple factors, including the increased use of the internet as a major distribution channel and the increased market penetration of low cost carriers (LCCs). For example, in 2007, approximately 55 million (or one in four) U.S. adults traveled by commercial air and were internet users (PhoCusWright, 2008). In 2009 Southwest Airlines was the largest U.S. domestic carrier, carrying over 101.3 million passengers; 81% of these passengers made their bookings via southwest.com (Southwest Airlines 2009, 2010).

Since deregulation, there has been continued interest in understanding how competitive factors and industry consolidation influence ticket prices. However, the majority of these studies have been based on aggregate quarterly fare data that is publically available in the T100 or DB1A/1B databases (Bureau of Transportation Statistics 2010a, 2010b). Examples include studies by Borenstein (1989) Borenstein and Rose (1994), Dai, Liu and Serfes (2012), Gerardi and Shapiro (2007), Hayes and Ross (1998), Verlinda (2005) and Verlinda and Lane (2004). Only a few pricing studies have been based on disaggregate data, including one study by Giaune and Guillou (2004) that used ticket observations from 20 routes from a global central reservation system, and a second study by Bilotkach (2006) that used pricing information for three routes collected from Travelocity®. The lack of detailed pricing data across the booking horizon has inhibited researchers' ability to fully understand customers' willingness to pay for different service attributes (e.g., departure time and carrier preferences). Researchers' ability to fully evaluate consumer welfare benefits associated with deregulation, mergers and acquisitions, and alliances has also been limited because the T100 and DB1A/1B databases do not provide information about the distribution of ticket prices and number of lower-priced tickets sold to consumers.

Within the airline industry, there has been growing interest in developing the next generation of revenue management (RM) systems that can more accurately represent how customers make decisions in today's online environments. This interest is driven by the recognition that today's market conditions are distinct from those seen during the first two decades following deregulation when the first generation of RM systems was developed. The development of these next-generation "choice-based" RM systems require information about the prices (or "choices") viewed by customers at the time of booking – both on the carrier of interest and, potentially, across different competitors. It is becoming more common for aviation and other service firms to systematically collect pricing information by programming webbots and/or by purchasing the services of firms that specialize in the extraction of unstructured internet data. For example, Travelocity® reported that it used webbots to query its competitors' sites to investigate how often (and why) it was not price competitive (Smith et al., 2007).

Although pricing data is routinely collected by industry, the amount of data available to researchers for empirical testing and benchmarking of different RM algorithms has been limited. There are only a few studies that have used industry data for choice-based RM applications, including one by Vulcano, van Ryzin and Chaar (2010) that is based on a single airline market, one by Newman et al. (2013) that is based on a single hotel property, one by Farias, Jagabathula and Shah (forthcoming) that uses data from a car dealership and data from Amazon on DVD sales, and one by Gaur, Muthulingam and Swisher (2013) that is based on sales of college textbooks. Although these studies have used industry data, they are limited in the sense that they exclude pricing effects or only consider a single firm's prices.

The objective of this appendix is to help address these research gaps by providing pricing information over a four week booking horizon for 42 U.S. markets and 21 departure dates. This airline pricing database contains over 228,000 price observations and can be used to investigate the evolution of prices across flights for a range of competition structures. The database can also be used to create simulated datasets for benchmarking the performance of RM systems, including those that incorporate information about competitor prices and consider the impact of low cost carriers. The datasets are available to all researchers as long as the researcher cites this document as the source. In the following sections, we describe the data, the data collection process (accomplished through the use of daily automated queries, or webbots) and highlight potential limitations in the data.

A.3. Description of Datasets

Pricing data was collected in 42 markets for all nonstop flights departing between September 2, 2010 and September 22, 2010. A booking horizon of four weeks was collected for each departure date. This section describes the fields available for analysis, the process used to select the markets included in the database, and basic descriptive statistics.

A.3.1. Data Fields

Round-trip prices for nonstop flights were obtained from a major online travel agency (which we refer to as OTA). These round-trip prices represent the lowest price (or fare) available for a particular outbound flight for a trip that involves a one-night stay; the inbound flight that would be required to obtain this lowest fare is not known. Equivalent round-trip prices for nonstop flights were obtained from one low cost carrier's website (which we refer to as LCC1). The "equivalent round-trip price" is obtained by multiplying LCC1's one-way fare by two and is comparable to the "round-trip price" obtained for other carriers through the OTA.

There are two databases: one for the OTA prices and one for LCC1 prices. Descriptions of the fields available in these databases are provided in Table A.1, and a list of airport codes are provided in Table A.2. Both databases include the same variables. The majority of the fields are self-explanatory; however, those related to affiliate relationships merit further discussion.

Table A.1: Fields Available in Dataset

Name	Definition
Market	Indicates the origin and destination airports associated with the nonstop flight. For example, BOSLAX represents a flight that originated at Logan International Airport in Boston and landed at the Los Angeles International Airport. Table A.2 provides a list of airport codes.
Price	For the OTA dataset this is the round-trip price, excluding taxes. For the LCC1 dataset this is the one-way price, excluding taxes, multiplied by two.
FlightNumber	Flight number assigned by airline.
DepartureTime	Scheduled departure time (In military hours and based on the local time at departure airport).
DepartureTime_hr	Hour of scheduled departure time (In military hours and based on the local time at departure airport).
DepartureTime_min	Minutes past the hour of scheduled departure time (based on the local time at departure airport).
CaptureDate	Date the pricing query was made.
DepartureDate	Departure date (based on the local time at departure airport).
DFD	Number of days from flight departure that the query was made (defined as departuredate minus capturedate).
MarketingAirline	Code associated with the marketing airline that is selling a ticket for the flight.
OperatingAirline	Code associated with the airline that operates the flight.
Affiliate	Value of 1 indicates a flight in which an affiliate carrier operates on behalf of a parent airline. Only the parent airline markets the flight.
Dcapturedate	Day of capture date.
Mcapturedate	Month of capture date.
Ddeparturedate	Day of departure date.
Mdeparturedate	Month of departure date.
Ddow	Departure day of week, 1=Sunday, … 7=Saturday
Cdow	Capture day of week, 1=Sunday, … 7=Saturday

Airlines can own other airlines or establish operating contracts with regional airlines. These wholly-owned subsidiaries and regional (or affiliate) carriers operate flights on behalf of the parent airline. For example, American Eagle is a wholly-owned subsidiary that operates flights on behalf of American Airlines, and SkyWest is a regional carrier that operates flights on behalf of Alaska and Delta. In an affiliate relationship, the parent airline is the one that markets (or sells seats on) that flight whereas the affiliate carrier is the one that operates the flight. A flight that is operated by an affiliate carrier is identified in the data when the *Affiliate* variable is set equal to one. The *Marketing Airline* will be populated with a code for the parent airline and the *Operating Airline* will be populated with a code for the affiliate partner. Lists of parent and affiliate airline codes are listed in Tables A.3 and A.4 (note that actual airline codes have been masked). An example is given in Table A.5, which gives a sample of observations from the OTA data (first four rows) and LCC1 data (last four rows). The unit of observation in the databases is an outbound flight that is uniquely identified by the market, capture date, departure date, marketing airline, and flight number. The third row of Table A.5 shows that flight number 3131 is marketed by parent airline M4 and operated by affiliate airline A8.

Table A.2: Airport Codes and Names

Airport Code	Name of Airport, City and State
ATL	Hartsfield-Jackson International Airport, Atlanta, Georgia
AUS	Austin Bergstrom International Airport, Austin, Texas
BOS	Logan International Airport, Boston, Massachusetts
BUF	Buffalo Niagara International Airport, Buffalo, New York
BWI	Baltimore-Washington International Thurgood Marshall Airport, Baltimore, Maryland
CAK	Akron Canton Airport, Green, Ohio
DEN	Denver International Airport, Denver, Colorado
FLL	Fort Lauderdale Hollywood International Airport, Fort Lauderdale, Florida
IAD	Washington Dulles International Airport, Washington D.C.
ICT	Wichita Mid-Continent Airport, Wichita, Kansas
IND	Indianapolis International Airport, Indianapolis, Indiana
JAX	Jacksonville Airport, Jacksonville, Florida
JFK	John F. Kennedy International, New York City, New York
LAS	McCarran International Airport, Las Vegas, Nevada
LAX	Los Angeles International Airport, Los Angeles, California
LGA	La Guardia Airport, New York City, New York
MCO	Orlando International Airport, Orlando, Florida
MDW	Chicago Midway International Airport, Chicago, Illinois
OAK	Oakland International, Oakland, California
ORD	Chicago O'Hare International Airport, Chicago, Illinois
PBI	Palm Beach International Airport, Palm Beach, Florida
PDX	Portland International Airport, Portland, Oregon
PHL	Philadelphia International Airport, Philadelphia, Pennsylvania
PIT	Pittsburgh International Airport, Pittsburgh, Pennsylvania
ROC	Greater Rochester International Airport, Rochester, New York
SAN	San Diego International Airport, San Diego, California
SEA	Seattle-Tacoma International Airport, Seattle, Washington
SFO	San Francisco International Airport, San Francisco, California
SNA	John Wayne Airport, Orange County, Santa Ana, California
SYR	Syracuse Hancock International Airport, Syracuse, New York

Table A.3: List of Parent Airline Codes

Airline Code	Pricing Structure	Type Carrier
L1	One-way	LCC
L2	One-way	LCC
L3	One-way	LCC
L4	One-way	LCC
L5	One-way	LCC
M1	Round-trip	Major
M2	Round-trip	Major
M3	One-way	Major
M4	One-way	Major
M5	Round-trip	Major

Table A.4: List of Affiliate Airline Codes

Affiliate Airline Code	Associated Parent Airline Codes
A1	M1
A2	M1, M3
A3	M1
A4	M2
A5	M1
A6	M5
A7	M1
A8	M4
A9	M1
A10	M1
A11	M4

Table A.5: Sample Observations

Market	Price	Flight Number	Departure Time	Capture Date	Departure Date	DFD	Marketing Airline	Operating Airline	Affiliate
PHLMCO	$249	863	18:15	2010-09-01	2010-09-04	3	M4	M4	0
PHLMCO	$220	629	18:30	2010-09-01	2010-09-04	3	L2	L2	0
PHLMCO	$249	3131	20:35	2010-09-01	2010-09-04	3	M4	A8	1
PHLMCO	$220	627	20:40	2010-09-01	2010-09-04	3	L2	L2	0
PHLMCO	$318	364	10:20	2010-09-01	2010-09-04	3	L1	L1	0
PHLMCO	$278	2061	15:30	2010-09-01	2010-09-04	3	L1	L1	0
PHLMCO	$278	2609	8:25	2010-09-01	2010-09-04	3	L1	L1	0
PHLMCO	$318	3408	12:55	2010-09-01	2010-09-04	3	L1	L1	0

A.3.2. Market Selection and Descriptive Statistics

Data was collected for a sample of U.S. markets in which at least one low cost carrier (LCC) provided daily nonstop service. A stratified sample was used to select a minimum of four markets for each competitive structure, shown in Table A.6. However, some competition structures appeared less than four times in the U.S. network, and thus less than four markets were included for these cases. The markets included in the dataset are described in Table A.6, along with the market structure (number of low cost and major carriers offering nonstop flights) and median prices for each competitor.

The database of OTA prices contains a total of 186,268 unique prices that correspond to a specific market, search date, departure date, marketing airline, and nonstop flight number. The database of LCC1 prices contains a total of 42,434 unique prices. These prices can be used for a range of different analyses. Figure A.1 shows an example of median lowest fares that each carrier offered for each unique departure date and search date. The median prices are for one market (BOSLAX) across the 28 day booking horizon. The variation in fares across the booking horizon highlights one of the key strengths of the database, namely the ability to investigate the evolution of fares across the booking horizon.

Table A.6: Median Prices, by Market and Competition Structure

Market Structure	Market	Median Ticket Price (U.S. Dollars)									
		Low Cost Carriers					Network Carriers				
		L1	L2	L3	L4	L5	M1	M2	M4	M3	M5
1 LCC, 0 Major	BWILAS	$458	-	-	-	-	-	-	-	-	-
	BWIMDW	$254	-	-	-	-	-	-	-	-	-
	JFKOAK	-	-	$390	-	-	-	-	-	-	-
	JFKPBI	-	-	$232	-	-	-	-	-	-	-
	LGACAK	-	$178	-	-	-	-	-	-	-	-
	SYRMCO	-	-	$222	-	-	-	-	-	-	-
1 LCC, 1 Major	ATLICT	-	$153	-	-	-	$225	-	-	-	-
	BOSIAD	-	-	$118	-	-	-	$174	-	-	-
	BOSMCO	-	-	$217	-	-	$212	-	-	-	-
	IADSFO	-	-	-	$455	-	-	$433	-	-	-
	JFKFLL	-	-	$212	-	-	$176	-	-	-	-
	JFKPDX	-	-	$476	-	-	$467	-	-	-	-
	LGAIND	-	$161	-	-	-	$190	-	-	-	-
	SNASFO	$202	-	-	-	-	-	$202	-	-	-
1 LCC, 2 Major	IADLAX	-	-	-	$388	-	-	$313	-	-	$278
	JFKORD	-	-	$235	-	-	$255	-	-	-	$225
	LGAATL	-	$228	-	-	-	$272	-	-	-	$258
	SEALAX	-	-	-	$224	-	-	$269	-	$244	-
	SEASFO	-	-	-	$220	-	-	$203	-	$180	-
1 LCC, 4 Major	LASLAX	$194	-	-	-	-	$194	$175	$175	-	$175
2 LCC, 0 Major	BWIJAX	$228	$148	-	-	-	-	-	-	-	-
	BWIMCO	$190	$168	-	-	-	-	-	-	-	-
	FLLAUS	$280	-	$218	-	-	-	-	-	-	-
	FLLSFO	-	-	$268	$292	-	-	-	-	-	-
	MCOAUS	$218	-	$211	-	-	-	-	-	-	-
	PITMCO	$226	$178	-	-	-	-	-	-	-	-
	ROCMCO	-	$178	$198	-	-	-	-	-	-	-
2 LCC, 1 Major	BOSDEN	$288	-	$308	-	-	-	$478	-	-	-
	FLLLAX	-	-	-	$271	$290	$248	-	-	-	-
	IADMCO	-	$163	$180	-	-	-	$173	-	-	-
	LGAFLL	-	-	$206	-	$169	$181	-	-	-	-
	PHLMCO	$220	$162	-	-	-	-	-	$162	-	-
	SANSFO	$154	-	-	$132	-	-	$116	-	-	-
2 LCC, 2 Major	BOSLAX	-	-	$308	$298	-	-	$298	-	-	$298
	BOSSFO	-	-	$378	$375	-	-	$369	-	-	$345
	JFKLAS	-	-	$417	$496	-	$382	-	-	-	$370
	LASSFO	$178	-	-	$210	-	-	$188	$184	-	-
2 LCC, 3 Major	JFKLAX	-	-	$358	$390	-	$338	$380	-	-	$380
	JFKSFO	-	-	$460	$457	-	$363	$447	-	-	$408
2 LCC, 4 Major	LAXSFO	$118	-	-	$128	-	$114	$108	-	$156	$108
3 LCC, 0 Major	BOSBWI	$124	$78	$101	-	-	-	-	-	-	-
	BUFMCO	$210	$210	$219	-	-	-	-	-	-	-

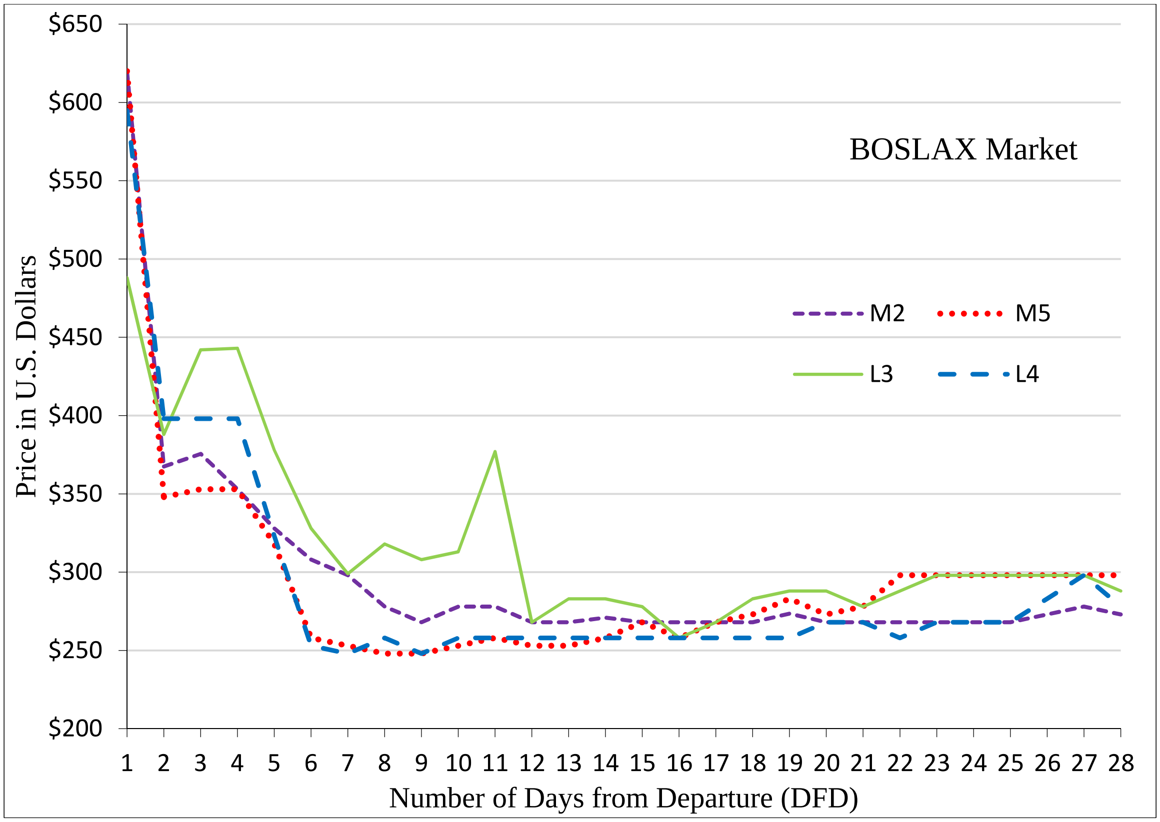

Figure A.1: Example of a Market's Median Lowest Prices, by Days from Flight Departure and Airline

A.4. Additional Data Details

This section describes in more detail the process used to create a database of airline prices from the websites of the OTA and LCC1, and also discusses the strengths and limitations of the data.

A.4.1. Overview of the Data Collection Process

Web client robots (or webbots) written in PHP were used to collect airfares for a rolling set of departure dates. The period of data collection ran from 8/5/2010 through 9/21/2010. When the data collection began on 8/5/2010, information for flights departing on 9/2/2010 (or 28 days in advance) were collected. On 8/6/2010, information for flights departing on 9/2/2010 (or 27 days in advance) as well as information for flights departing on 9/1/2010 (or 28 days in advance were collected). The process completed until 28 days of pricing information were collected for flights departing on 9/2/2010 to 9/22/2010. After the webpages were collected, PHP scripts were written to extract (or parse) itinerary and fare information.

We collected round-trip prices from the OTA and one-way prices from LCC1. This is because airlines use different pricing methods. Round-trip pricing is used by many major airlines, including American, Continental, Delta, and United. Round-trip pricing enables an airline to offer different prices for customers who are traveling over a Saturday night and/or for customers who are traveling for a minimum number of days. In combination with advance purchase restrictions, round-trip pricing enables airlines to tailor prices for more price-sensitive (and often leisure) travelers who could purchase further in advance of departure and stay over a Saturday night. In round-trip pricing, a price is generated for each unique combination of an outbound (or departing) and inbound (or returning) itinerary. A one-day round-trip price refers to a price that is generated when the length of stay is equal to one night away from home (this occurs when the inbound date minus the outbound date is equal to one).

Due to computational constraints, we could not collect round-trip prices for every possible combination of outbound and inbound flights. Nor could we collect round-trip prices for multiple lengths of stay. We restricted the data collection to one-day round-trip prices. Our database associates a round-trip price for each outbound nonstop flight displayed on the OTA. This round-trip price reflects the *minimum* price that would be available to the customer if he/she selected that outbound flight; however, the inbound flight that generates this lowest fare is not recorded.

Although major carriers offer both round-trip and one-way fares, we did not collect one-way fares through the OTA, as the sum of the one-way fares was much higher than the equivalent round-trip fares for those carriers that used round-trip pricing. It was thus necessary to associate a one-day round-trip fare with each outbound itinerary in order to create a database of "comparable" fares across carriers.

Because we were not able to capture LCC1 prices from the OTA, we collected LCC1 fares directly from their website. LCC1 uses one-way prices (i.e., each flight has a unique price). An ideal data collection would have been to run two one-way queries for each LCC1 market, one for the outbound departure date and airport pair and the second for the inbound departure date and airport pair. Then, an equivalent one-day round-trip price for each outbound flight could have theoretically been obtained. However, this would have greatly increased the number of queries performed on LCC1's website.

Instead, we generate an “equivalent round-trip” fare, using the one-way price for a market multiplied by two.

A.4.2. Limitations

The pricing data contained in the online database is representative of airline prices that were available to consumers, but they may not always represent the actual prices viewed by or purchased by consumers. For example, the prices displayed on the OTA’s website may differ from prices displayed on different online travel agency websites, carrier websites, or other distribution channels. In addition, for data collected through the OTA, it may not be possible to track prices for a given flight across the booking horizon, as OTA displays (and specifically which flights they choose to show) can be influenced by online travel agencies’ profit-maximizing strategies (Smith et al., 2007). This includes the practice of providing more display space for itineraries operated by a specific carrier in order to drive sales to that carrier, thereby enabling online travel agencies to reach sales volume hurdles that result in substantial commission revenue (Smith et al., 2007).

An additional limitation is that the “equivalent round-trip” LCC1 price in the database is not exactly the same as the OTA round-trip prices. Although the prices should be similar, there is potential measurement error when directly comparing LCC1 prices to other competitor prices collected from OTA.

A.4.2.1. Completeness of Data

The database is approximately 80 percent complete. This is due to the fact that, for certain data collection dates, query times were longer than normal and/or failed to return information. These types of problems can occur for various reasons and may be more prevalent when demands on the OTA and LCC1 sites are high, i.e., when many individuals are searching for information.

The final dataset for the OTA (representing 40 markets) should contain 23,520 unique market, departure date, and capture date observations; 15.2 percent of these observations were not collected. The final dataset for LCC1 (representing 16 markets) should contain 9,408 unique observations; 21.2 percent of these observations were not collected. For the OTA, missing data is approximately randomly distributed across the different days from departure. However, for LCC1, the distribution of missing data is not random; the data is more complete for those flights that are closer to their departure date (or have smaller days from departures). For example, for data collected at days from departure 28, a total of 32 percent is missing whereas for data collected at days from departure one, only six percent of the data is missing. When the data from the OTA and LCC1 is merged, there are a total of 24,696 possible unique observations, of which 21.5 percent are missing.

Despite these limitations, to the best of our knowledge, this dataset represents the largest, dataset of detailed airline prices that is publically available and the only one that can be used to look competitive pricing of different types of low cost carrier competition. This database should provide new insights that will be of interest to researchers from economics, marketing, revenue management, pricing, and flight scheduling areas.

A.5. Conclusions

To summarize, the datasets contain one-day round-trip fares for all outbound nonstop flights departing between September 2, 2010 and September 22, 2010 in a market that is served by at least one low cost carrier. A minimum booking horizon of four weeks for each departure date is included. The OTA fares represent the lowest available round-trip fare for a particular outbound flight for a trip that involves a one-night stay; the inbound flight that would be required to obtain this lowest fare is not known. The LCC1 fares represent an "equivalent round-trip" fare, which is the one-way fare multiplied by two.

This airline pricing database is unique in that it provides detailed daily pricing data that is not publicly available through government data sources such as T100 and DB1A/1B (which provide average fare information over a quarter). The datasets can be used to create simulated datasets for benchmarking the performance of RM systems, including those that incorporate information about competitor prices. The data can also be used to investigate the evolution of prices across a range of competition structures to answer questions related to which airline(s) are price leaders (e.g., who drops prices first and which airlines follow?). The data can be used to investigate how an airline's pricing policies differ when facing various airline competitors and market structures. This data is also unique in that it provides detailed pricing information in a subset of markets where two or more low cost carriers offer nonstop flights, which can be used to investigate how low cost carriers compete over the booking horizon.

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