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Carriers' pricing behaviors in the United States airline industry

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ABSTRACT

This paper examines the pricing behaviors of United States air carriers in domestic markets. With quarterly observations in 2000 and 2005, we use a heteroskedasticity-adjusted Instrumental Variable technique to investigate the carriers' pricing strategies. The results show differential pricing strategies practiced by United States air carriers. American, United, Continental, and Northwest Airlines have higher airfares than Delta and Southwest Airlines in 2005. In 2000, all the carriers, except Delta have the same relationships with airfares. Furthermore, the findings suggest that the carriers' pricing strategies can vary under the same market condition, indicating that carriers' managerial decisions may influence their airfares.

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1. Introduction

Since a deregulation of the United States (US) airline industry in 1978, market competition has increased in domestic airline markets and real airfares have declined in most airline markets. Although the incidents of September 11, 2001 had a negative impact on domestic airline markets, the upward trend of domestic passenger-miles was fully recovered in 2005 (Bureau of Transportation Statistics, 2007), and air travel demand is expected to keep growing. However, there is a concern about the poor financial performance of US carriers in the domestic markets. In the face of increasing market competition and soaring fuel prices, the US airline industry experienced a net loss, totaling $35.1 billion, for the period of 2001–2005 (Air Transport Association of America, 2007). Domestic carriers need to develop effective pricing strategies to increase their profits and survive in the markets. Although US air carriers' pricing strategies are known to be both complicated and incomprehensible (Botimer, 1994), there is a need to develop a pricing behavior model that enables researchers to have more comprehensive information about carriers' pricing strategies.

Because previous literature deals with the economic impacts of operating costs, demand, and market power variables, the relationship between these variables and airfares in the domestic airline markets is fairly well understood. Borenstein (1989) addresses the importance of route and airport dominance by using a price function, which includes characteristics of route, airport, and airline. His study suggests that an airline's dominant market power allows the airline to charge higher airfares than other competing airlines and therefore provides evidence of the benefits of a carrier's dominant power. The importance of market dominance is supported by the findings of Bitzan and Chi (2006), who examine the price differences for flights serving small and large communities. Their study finds that market power and operating costs are crucial determinants of airfares. Moreover, Vowles (2006) also supports that carrier's market dominance and market concentration play prominent roles in determining airfares. In examining carriers' primary and secondary hub routes, the dominant routes are positively associated with airfares, while the secondary-to-secondary routes are inversely related to airfares.

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Pricing behavior in the US airline industry has been extensively analyzed in existing literature. However, individual carriers' pricing strategies under different market conditions are less understood. This information is important for both policymakers and carrier managers. The information helps policymakers understand and classify individual carriers' pricing strategies in their markets (e.g., competitive- and monopoly-type pricing strategies). This further helps their decision making on possible regulation on the carriers that practice monopoly-type prices and reduce benefits to society. From the managerial perspective, it is crucial to understand competitors' pricing strategies in order to determine carrier's pricing strategies and increase its benefits.

This paper addresses the reasons for including individual carrier effects in a price model for city-pair markets. Individual carriers have different operating costs, service factors, and market shares. For this reason, carriers may have developed unique pricing strategies to achieve their business goals. Different business goals, such as the maximizations of profit and/or market share in the segment markets, may lead to different pricing strategies in such markets. For example, a carrier that enters new markets is likely to lower airfares to increase its market share in the short term. The carrier, however, may change its pricing strategy after it obtains a certain level of market share. Thus, individual carriers need to be included to examine their pricing strategies in a price model.

In addition, the carrier's operation and customer service characteristics may affect passengers' preference to carriers, thereby influencing airfares. The Air Travel Consumer (ATC) reports show that flight delay and cancellation rates varied among the US carriers (Bureau of Transportation Statistics, 2000 and 2005; Gursoy et al., 2005). For example, Northwest Airlines had an 8.8% air carrier delay, while United Airlines had a 3.9% air carrier delay in November, 2006. Also, the number of consumer complaints varied by carrier, reporting 0.87 and 0.21 consumer complaints per 100,000 enplanements for American and Southwest Airlines, respectively in the same month. This implies that passengers' satisfaction may vary by carrier, which affects demand and price for its air-passenger service.[1]

Furthermore, domestic carriers have different resources for their air-passenger service in terms of the number of aircrafts, the aircraft type, and the crew members (Moody's Investors Service, 2000). This unequal allocation of air transportation resources by carrier may affect the demand for their air-passenger service. For example, air carriers using newer aircrafts may provide safer and more comfortable features, which also influence the pricing behaviors of their air-passenger services. For these reasons, it is important to include individual carriers in a pricing behavior model.

The objective of this paper is to advance our understanding of the US carriers' differential pricing strategies practiced under various market conditions. Using origin and destination (DB1B) data, we estimate a price model for US air-passenger services, focusing on explaining the pricing behaviors of major US carriers. We include carriers' interaction with market conditions to determine whether the impacts of individual carriers on airfares depend on the market conditions. This gives insight into a pricing strategy regarding the tendency for a carrier to use different strategies, depending on market conditions and whether strategies vary by carrier under the same market conditions. Because carriers' pricing strategies may vary over a period, the effects of individual carriers are examined in different periods. Thus, we test whether carriers' pricing strategies change over the period of 2000–2005.

The rest of the paper is organized as follows. Section 2 provides a conceptual framework. Section 3 examines the empirical model, with a discussion of the data description and model specification. Section 4 presents econometric procedures of the price model to produce robust and unbiased estimations. Section 5 discusses the empirical results that highlight the pricing behaviors of individual carriers. The final section, Section 6, concludes the paper.

2. Conceptual framework

A price model used for this paper is derived from supply and demand functions for air-passenger service. Following McCarthy (2001), the supply function of air-passenger service from origin i to destination j is based on carrier's profit maximization as:

$$S_{ij} = f_S(P_{ij}; P_{Lij}, P_{Fij}, P_{Kij}, \gamma_{ij}, F_{ij}) \tag{1}$$

where S_{ij} is air passenger-miles between origin i and destination j, P_{ij} is airfare per passenger-mile, P_{Lij}, P_{Fij} and P_{Kij} are the input prices for labor, fuel and capital, respectively, γ_{ij} is a parameter reflecting the current state of service quality and technology, and F_{ij} is firm effects (e.g., carrier's pricing strategies).

The demand function for air-passenger service based on consumer's utility maximization (Phu, 1991; Liew and Liew, 1979) is specified as follows:

$$D_{ij} = f_D(P_{ij}; INC_{ij}, X_{ij}) \tag{2}$$

where D_{ij} is air passenger-miles from origin i to destination j, INC_{ij} is travel budget, and X_{ij} is other exogenous factors related to travel.

A price model is derived at the market clearing equilibrium condition from origin i to destination j ($D_{ij} = S_{ij}$) as follows:

$$P_{ij} = f_P(P_{Lij}, P_{Fij}, P_{Kij}, \gamma_{ij}, F_{ij}, INC_{ij}, X_{ij}) \tag{3}$$

[1] Forbes (2008) finds that an additional minute of flight delay decreases prices by $1.42 on average.

In this paper, the supply factors (P_{Lij}, P_{Fij}, P_{Kij}, γ_{ij}, and F_{ij}) include capacity, load factor, frequency, distance, round trip, ticket restriction, market concentration, market share, and low-cost carrier (LCC) competition. Demand factors (INC_{ij}, and X_{ij}) are income, population, tourism areas, and market factors (e.g., hub airport, slot-controlled airport, and multiple airports).

3. The empirical model

This paper collects data from the US Department of Transportation, the US Census Bureau, the US Department of Labor, and the US Department of Commerce. The airfare data of economy class are obtained from the Origin and Destination Survey (DB1B), which is a 10% sample of airline tickets from reporting carriers (Bureau of Transportation Statistics, 2007). To build frequency, capacity, load factor, Herfindahl–Hirschman index[2], and market share variables, the paper uses the T-100 domestic segment data, which contain scheduled departures, aircraft capacity, and transported passengers. Because the T-100 segment data are not available for all origin–destination pairs, these variables are used at the airport level (e.g., frequency at origin).

This paper collects 2000 and 2005 datasets to determine whether the impacts of the variables are consistent over the different periods. These years are chosen because we attempted to exclude the negative impacts of the terrorist attacks of 2001 and these years do not appear to have decreases in passenger-miles for domestic air service before and after the terrorist attacks.[3] The passenger-miles distracted by the terrorist attacks returned to the normal market condition in 2005 (Bureau of Transportation Statistics, 2007).

To eliminate outliers (e.g., free tickets and data input errors), this paper considers two methods: a method of eliminating the top and bottom one percents of airfare data (Bitzan and Chi, 2006) and a method of eliminating airfares that are five times higher than the US Department of Transportation's Standard Industry Fare Level (Borenstein, 2005). After carefully comparing the two methods, this paper employs the former method.[4] In addition, the paper uses the average airfares weighted by the number of passengers from origin to destination.

Based on Eq. (3), the empirical price model for the city-pair markets from origin i to destination j is specified as follows[5]:

$$\begin{aligned} P_{ij} = {} & \alpha + \beta_1 \ln ORICAP_i + \beta_2 \ln ORILOAD_i + \beta_3 \ln ORIFREQ_i + \beta_4 \ln DESCAP_j + \beta_5 \ln DESLOAD_j + \beta_6 \ln DESFREQ_j \\ & + \beta_7 \ln DIST_{ij} + \beta_8 \ln AVGDIST_{ij} + \beta_9 ROUND_{ij} + \beta_{10} TOUR_{ij} + \beta_{11} RESTRICT_{ij} + \beta_{12} \ln AVGPOP_{ij} + \beta_{13} \ln AVGINC_{ij} \\ & + \beta_{14} ORIHUB_i + \beta_{15} ORISLOT_i + \beta_{16} \ln ORIHERF_i + \beta_{17} \ln ORISHARE_i + \beta_{18} DESHUB_j + \beta_{19} DESSLOT_j + \beta_{20} \ln DESHERF_j \\ & + \beta_{21} \ln DESSHARE_j + \beta_{22} LOWCOST_{ij} + \beta_{23} ORIMULTIPLE_i + \beta_{24} DESMULTIPLE_j + \beta_{25} AA_{ij} + \beta_{26} UA_{ij} + \beta_{27} DL_{ij} \\ & + \beta_{28} CO_{ij} + \beta_{29} NW_{ij} + \beta_{30} SW_{ij} + \beta_{31} Q1 + \beta_{32} Q2 + \beta_{33} Q3 + \varepsilon_{ij} \end{aligned} \quad (4)$$

where the α is the intercept and the β_s are the estimated coefficients of independent variables. The description and summary statistics of the variables in Eq. (4) are presented in Table 1. In addition, Appendix A provides discussion of expected sign of the variables.

The data are rearranged by origin, destination, carrier, and quarter. The empirical model includes dummies for individual carriers to incorporate carrier effects. The six major US carriers (American, United, Delta, Continental, Northwest, and Southwest) are selected based on the passenger-miles ranked in 2005 (Bureau of Transportation Statistics, 2007).[6] In addition, other variables (round trip, ticket restriction, and slot-controlled airport) associated with operating cost characteristics are added.[7] The dummy for a hub airport is included on the basis of better service of flights, which may increase demand for air-passenger service.[8] The variables affecting operating cost characteristics may influence demand for air-passenger service (Bitzan and Chi, 2006). For example, a high load factor may result in lower demand due to less comfortable seating in addition

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[2] Herfindahl–Hirschman (Herfindahl) index is used to measure market concentration at origin and destination. It is calculated by summing the squares of market share by carrier. Following Bitzan and Chi (2006), this paper uses the market share of ticketing carriers instead of operating carriers, based on the codesharing information in the DB1B data.

[3] Ito and Lee (2005) find that the terrorist attacks resulted in both a negative transitory shock of over 30% and an ongoing negative demand shock amounting to 7.4% of pre-September 11 demand. They also find that demand shock had yet to dissipate as of November 2003. In this paper, the data were selected based on the data availability and the year 2005 was the most recent annual data available in February, 2006. This paper uses a real term in 2000 dollars (e.g., per-capita income) because we perform our analysis for 2000 and 2005.

[4] \$1.22 and \$1.20 per passenger-mile are used to eliminate outliers for the 2000 and 2005 data, respectively. Any tickets that charged \$0 are eliminated because it is considered a keypunch error. A free award ticket generally costs \$10 in 2005 because of the September 11 Security Fee.

[5] The semi-log form is used because it has the largest number of significant variables among the forms tested.

[6] This paper excludes US Airways because it was ranked 7th and was merged with America West Airlines in September 2005. Airfares of US Airways may be influenced largely by its merger and this may not be a good comparison with other carriers' pricing strategies as well as its pricing strategies for the period 2000-2005. It should be noted that a dummy for individual carriers may have limited strength to measure individual carriers' pricing strategies. Given that carriers' pricing strategies can be affected by too many factors (financial situation, management personnel and operational objectives, etc.) and limited data are available, we used a dummy for individual carriers to represent their pricing strategies. In this paper, we can determine whether carriers practice monopoly-type (competitive-type) pricing strategies that lead to higher (lower) average airfares.

[7] Increases in round-trip flights and restricted tickets are likely to decrease operating costs per passenger by utilizing their service resources. On the other hand, an increase in slot-controlled airport operation is likely to increase operating costs per passenger due to high slot and landing fees.

[8] Bailey et al. (1985) find that service at large hub airports can provide the shortest delay (40 min) and fastest travel speed (351 mph) among the examined market categories. The air-passenger service at a large hub airport is therefore expected to increase demand for air-passenger service.

Table 1
Description of variables and summary statistics in the price model in 2000 and 2005[a].

Variable	Description	2000		2005	
		Mean	Std. dev.	Mean	Std. dev.
P_{ij}	Average airfare per passenger-mile ($) from origin i to destination j	0.26	0.22	0.21	0.19
$ORICAP_i$	Average seat capacity[b] at origin i	120	42	98	48
$ORILOAD_i$	Average load factor[c] at origin i	0.66	0.11	0.72	0.10
$ORIFREQ_i$	Total frequency of flights by carrier at origin i	2490	5746	1930	4807
$DESCAP_j$	Average seat capacity at destination j	119	42	98	48
$DESLOAD_j$	Average load factor at destination j	0.66	0.11	0.72	0.11
$DESFREQ_j$	Total frequency of flights by carrier at destination j	2415	5671	1879	4755
$DIST_{ij}$	Total distance (miles) from origin i to destination j	1319	866	1320	850
$AVGDIST_{ij}$	Average segment distance[d] from origin i to destination j	701	426	700	423
$AVGPOP_{ij}$	Average population of origin and destination cities	2891,166	2846,296	2836,287	2829,904
$AVGINC_{ij}$	Average per-capita income of origin and destination cities	31,114	3986	35,669	4317
$ORIHERF_i$	Herfindahl index[e] at origin i	0.35	0.21	0.34	0.20
$ORISHARE_i$	Carrier's market share[f] at origin i	0.25	0.26	0.29	0.26
$DESHERF_j$	Herfindahl index at destination j	0.35	0.21	0.33	0.19
$DESSHARE_j$	Carrier's market share at destination j	0.25	0.26	0.27	0.25
Dummy					
$ROUND_{ij}$	Dummy for a round trip	0.56	0.50	0.56	0.50
$TOUR_{ij}$	Dummy for an origin or destination city that is located in tourism areas	0.81	0.39	0.79	0.41
$RESTRICT_{ij}$	Dummy for ticket restrictions	0.64	0.48	0.80	0.40
$ORIHUB_i$	Dummy for a hub airport[g] at origin i	0.89	0.31	0.85	0.35
$DESHUB_j$	Dummy for a hub airport at destination j	0.90	0.31	0.90	0.30
$ORISLOT_i$	Dummy for a slot-controlled airport[h] at origin i	0.05	0.21	0.04	0.19
$DESSLOT_j$	Dummy for a slot-controlled airport at destination j	0.05	0.21	0.05	0.21
$ORIMULTIPLE_i$	Dummy for multiple airports available at origin city	0.30	0.46	0.27	0.45
$DESMULTIPLE_j$	Dummy for multiple airports available at destination city	0.30	0.46	0.30	0.46
$LOWCOST_{ij}$	Dummy for the competition with a low-cost carrier (LCC) from origin i to destination j	0.34	0.47	0.44	0.50
AA_{ij}	Dummy for American Airlines[i]	0.10	0.30	0.06	0.24
UA_{ij}	Dummy for United Airlines[i]	0.11	0.31	0.07	0.25
DL_{ij}	Dummy for Delta Air Lines[i]	0.16	0.37	0.11	0.31
CO_{ij}	Dummy for Continental Airlines[i]	0.05	0.22	0.03	0.18
NW_{ij}	Dummy for Northwest Airlines[i]	0.12	0.33	0.09	0.29
SW_{ij}	Dummy for Southwest Airlines[i]	0.06	0.24	0.06	0.24
Q1	Dummy for quarter 1	0.24	0.43	0.24	0.43
Q2	Dummy for quarter 2	0.26	0.44	0.25	0.43
Q3	Dummy for quarter 3	0.25	0.43	0.25	0.43

Data sources: US Department of Transportation, US Census Bureau, US Department of Labor, and US Department of Commerce.

[a] The summary statistics are calculated from the regression data used in this paper. The data are arranged by route (airport)-carrier-quarter-ticket restriction-round trip and according to this data format, the average dummy for restricted ticket should be 50%. However, some route observations do not have non-restricted tickets in the sample data (DB1B). An average dummy for ticket restrictions of .64 for 2000 does not mean that 64% of all purchased tickets are restricted tickets. It means that 64% of total observations in the regression data in this paper are restricted tickets. Standard deviation is abbreviated to std. dev. in the table.

[b] Seat capacity is the number of available seats. The average capacity is weighted by the number of departures.

[c] Load factor is the number of purchased seats divided by the number of available seats. The average load factor is weighted by the number of departures.

[d] The average segment distance is the total distance divided by the number of stops made to the destination. The average segment distance is weighted by the number of passengers from origin to destination.

[e] The Herfindahl index is calculated by summing the squares of the individual segment market share of passengers of all ticketing carriers at origin–destination market.

[f] The number of carrier's passengers divided by total passengers at origin.

[g] The observed carrier's own hub airports. The hub airports are Dallas-Fort Worth International (DFW), Lambert-St. Louis International (STL), Miami International (MIA), and O'Hare International (ORD) for American Airlines. For United Airlines, the hub airports are Denver International (DEN), Los Angeles International (LAX), O'Hare International (ORD), San Francisco International (SFO), and Washington Dulles International (IAD). For Delta Airlines, they are Cincinnati/Northern Kentucky International (CVG), Hartsfield-Jackson Atlanta International (ATL), John F. Kennedy International (JFK), and Salt Lake City International (SLC). For Continental Airlines, they are Antonio B. Won Pat International (GUM), Cleveland Hopkins International (CLE), George Bush Intercontinental (IAH), and Newark Liberty International (EWR). Finally, Detroit Metropolitan Wayne County (DTW), Memphis International (MEM), and Minneapolis-Saint Paul International (MSP) are the hub airports for Northwest Airlines.

[h] The slot-controlled airports are O'Hare International (ORD), Laguardia (LGA), JFK International (JFK), and Ronald Reagan National airports (DCA).

[i] Served as an operating carrier.

to lower operating costs per passenger, which leads to much lower airfares. The price model includes market power (e.g., Herfindahl index and market share) and market competition variables (e.g., LCC and multiple airports) to test the perfect contestability theory in the domestic city-pair markets. Additional variables included in the model are the carriers' interactions with the selected market conditions that may be related to carrier's pricing strategies (hub airport, LCC, market share, Herfindahl index, and tourism area variables). The carriers' interactions can provide insight into the carriers' pricing strategies under market conditions. For example, when an LCC enters the market that was previously dominated by two carriers, one existing carrier

Table 2
Multivariate diagnostic tests for heteroskedasticity and endogeneity in the price model in 2000 and 2005[a].

Diagnostic test	2000	2005
Heteroskedasticity[b]		
Breusch–Pagan test	$F(33, 647{,}782) = 3274^{**}$	$F(33, 772{,}176) = 4411^{**}$
	[0.001]	[0.001]
White test	$F(2, 647{,}813) = 48{,}946^{**}$	$F(2, 772{,}207) = 78{,}484^{**}$
	[0.001]	[0.001]
Endogeneity[c]		
Load factor		
Origin	−0.031**	−0.019**
	[0.001]	[0.001]
Destination	−0.029**	−0.023**
	[0.001]	[0.001]
Frequency		
Origin	0.020**	0.015**
	[0.001]	[0.001]
Destination	0.018**	0.012**
	[0.001]	[0.001]
Herfindahl index		
Origin	0.003**	0.006**
	[0.001]	[0.001]
Destination	0.009**	0.011**
	[0.001]	[0.001]
Market share		
Origin	0.003**	0.005**
	[0.353]	[0.001]
Destination	0.003**	0.004**
	[0.001]	[0.001]

* Significant at the 5% level.
** Significant at the 1% level.
[a] The paper uses the semi-log form of OLS estimation. *p*-Values are presented in parentheses.
[b] The null hypothesis of homoskedasticity is used.
[c] Parameter estimates of residual are presented. The null hypothesis of exogeneity is used.

may change its pricing strategies and follow the LCC's low airfares, while the other carrier may keep its strategies for high airfares. Thus, this paper examines whether carriers' pricing strategies and market conditions interact.

4. The econometric procedures

This paper performs a diagnostic test for multicollinearity, heteroskedasticity, and endogeneity to produce a robust and unbiased model. First, based on the correlation matrix of the variables, the paper does not detect high correlation between the explanatory variables that results in the multicollinearity problem. Second, it employs the Breusch–Pagan (Breusch and Pagan, 1979) and the White (White, 1980) tests to check for heteroskedasticity in the model. Table 2 shows the results of the diagnostic tests for heteroskedasticity. The null hypothesis of homoskedasticity can be rejected at the 5% significance level, indicating that heteroskedasticity exists in the model, and therefore the Ordinary Least Squares (OLS) is no longer asymptotically efficient (Wooldridge, 2006). Third, the Hausman test (Hausman, 1978) is conducted to check for possible endogenous explanatory variables (load factor, frequency, the Herfindahl index, and market share variables). A variable is endogenous if a change in the variable affects airfares, and the airfares also result in a change in the variable. For example, load factor and frequency variables may all be endogenous because increases in these variables may reduce airfares per passenger, and the lower airfares in turn increase the demand, which also affects the values in these variables. Similarly, the Herfindahl index and market share variables may be endogenous because increases in these variables are likely to increase airfares, which may result in inducing a new entry to the high-revenue markets, thereby decreasing airfares. The test results show that the null hypothesis of exogeneity can be rejected at the 5% level for all the variables, indicating that they are endogenous (Table 2).

Therefore, we employ the estimation[9] that combines the Feasible Generalized Least Squares (FGLS) and the Instrumental Variable (IV) techniques to correct heteroskedasticity and endogeneity problems. The estimation procedures are: (1) divide all variables in Eq. (4) by the estimated error; (2) regress each of the endogenous variables on all exogenous variables in Eq.

[9] An alternative may be the estimation of a system of multiple equations. However, our goal is to examine the impacts of the proposed variables on airfares and therefore we specify the single equation (Eq. (4)) rather than a system of multiple equations, which include airfare, load factor, capacity, and frequency functions.

(4) and lagged load factor, frequency, Herfindahl index, and market share, and obtain the estimated endogenous variables; (3) replace the endogenous variables with the estimated endogenous variables; and (4) estimate the model specified in step (3).

5. The results

This paper reports the results of two models: the model with variables associated with operating cost, demand, and market power characteristics (model 1) and the model with the carriers' interactions with the market condition variables in addition to the variables used in the model 1 (model 2).

5.1. Estimated models

The results of the model 1 in 2000 and 2005 are shown in Table 3. Overall, most of the estimated coefficients are statistically significant at the 5% significance level. More importantly, many coefficients have the expected or acceptable signs in the price model.

Average segment distance ($AVGDIST_{ij}$), capacity ($ORICAP_i,\ DESCAP_j$), and load factor ($ORILOAD_i,\ DESLOAD_j$) have negative impacts on airfares by influencing operating costs. This indicates that increases in these variables are found to lead to lower operating costs per passenger, and thereby decrease airfares. Although these variables may influence demand for air-passenger service in some cases, their impacts on the operating costs are more dominant. On the other hand, total distance ($DIST_{ij}$) and service frequency ($ORIFREQ_i,\ DESFREQ_j$) are shown to have positive influences on airfares in 2000. As distance increases, the substitution effect between air travel and other transportation modes (e.g., bus and car) becomes smaller. This may result in a positive effect of distance on airfares. Similarly, one possible explanation for the positive sign is that the effect of greater flight frequency on demand overshadows its effect on costs. Higher flight frequencies translate into more convenient flight schedules, increasing the desirability of service. In contrast, the negative sign implies that the effect of greater frequency on costs is larger than its effect on demand. The results indicate that the impact of frequency on costs is larger in 2005, while the effect of frequency on demand is larger in 2000.

Market concentration ($ORIHERF_i,\ DESHERF_j$) and carrier's market share ($ORISHARE_i,\ DESSHARE_j$) have the hypothesized positive influences on airfares at both origin and destination, indicating that increases in these variables are likely to increase the carrier's pricing power to set higher airfares. A dominant carrier is able to have pricing power through marketing devices, such as frequent-flyer programs (FFPs), travel agent commission override programs (TACOs), and computer reservation systems (CRSs).[10] In addition, competition with an LCC, tourism areas, and multiple airports at origin and destination cities are found to have negative impacts on airfares, indicating that the existence of these factors is likely to increase market competition and reduce the carrier's pricing power, thereby leading to lower airfares. The impacts of these variables are found to be consistent in the models between 2000 and 2005. Consequently, the results support that perfect contestability[11] is not met for the domestic airline markets, which is consistent with the findings of the previous studies (Graham et al., 1983; Bailey et al., 1985; Call and Keeler, 1985; Morrison and Winston, 1987).

Individual carriers ($AA_{ij},\ UA_{ij},\ DL_{ij},\ CO_{ij},\ NW_{ij}$, and SW_{ij}) play crucial roles in determining airfares by showing that the impacts of the major carriers are all significant at the 1% level in both 2000 and 2005.[12] American, United, Continental, and Northwest tend to charge higher airfares relative to the non-major carriers, while Southwest appears to offer lower airfares. This implies that American, United, Continental, and Northwest may practice pricing strategies that lead to higher prices, whereas Southwest may practice pricing strategies that result in lower prices. Southwest is shown to have an expected negative effect on airfares because it is able to leverage its lower cost structure into substantially lower fares (Ito and Lee, 2003). In examining the annual data of 2000 and 2005, the major carriers, except Delta, have identical impacts on airfares. While Delta is positively associated with airfares in 2000, it is inversely related to airfares in 2005. One possible reason for this is that Delta's managerial decisions have influenced their pricing strategies over the 2000 and 2005 period. Delta announced a restructuring of airfares on January 5, 2005 by removing some restrictions (e.g., saturday-night stays) and lowering restricted airfares (Baggaley, 2005). This is likely to influence its average airfares. Furthermore, the changes in the carrier's pricing strategies may influence the competitors' airfares in the markets. For example, the changes in Delta's pricing strategies may affect AirTrans, Continental, US Airways, and American, which share their markets with Delta. In particular, AirTrans, which has the highest overlap with Delta, could have the largest impact from the change in Delta's pricing strategies. This supports that the carrier's pricing strategy may be a prominent determinant of airfares, and therefore the impacts of individual carriers need to be included in the price model.

It should be emphasized that for completeness, we examine whether a structural change exists between airfares for the period of 2000–2005. The Chow F-test is used to test the null hypothesis of identical coefficients in the price model (H_0: $\alpha_k = \beta_k,\quad k = 1, \ldots, 34$, and $var(\varepsilon_i) = \mathrm{var}(\varepsilon_j)$). The results show that the null hypothesis is rejected at the 5% level

[10] Borenstein (1989) suggests that the FFPs are effective in attracting repeat business by providing free travel or discounts, and the TACOs effectively attach travel agents to a certain carrier through higher commission and bonuses. Similarly, the CRSs may provide biased information to passengers by displaying the information of a certain carrier first, which owns the system. Thus, these marketing devices can enable the dominant carrier to obtain pricing power.

[11] In a contestable market, an existing carrier is constrained from charging high airfares by the threat that charging such high fares will attract new carriers to enter the market and compete with, or replace, existing firms (General Accounting Office, 1991).

[12] This paper also finds that the dummies for carriers are jointly significant in the model ($F_{6,\ 647,782}$ = 3,391 in 2000 and $F_{6,\ 772,176}$ = 4,200 in 2005).

Table 3
Heteroskedasticity-adjusted instrumental variable (IV) estimation (semi-log form) of airfares per passenger-mile in 2000 and 2005.

Variable	Parameter estimate[a]	
	2000	2005
INTERCEPT	0.2939**	0.8283**
	(0.0158)	(0.0142)
$ORICAP_i$	−0.0057**	−0.0035**
	(0.0002)	(0.0001)
$ORILOAD_i$	−0.1987**	−0.2855**
	(0.0058)	(0.0089)
$ORIFREQ_i$	0.0304**	0.0117**
	(0.0009)	(0.0009)
$DESCAP_j$	−0.0057**	−0.0019**
	(0.0001)	(0.0001)
$DESLOAD_j$	−0.2619**	−0.2948**
	(0.0057)	(0.0075)
$DESFREQ_j$	0.0241**	−0.0024**
	(0.0008)	(0.0008)
$DIST_{ij}$	0.0456**	−0.0303**
	(0.0019)	(0.0023)
$AVGDIST_{ij}$	−0.1303**	−0.0594**
	(0.0016)	(0.0017)
$ROUND_{ij}$	−0.0857**	−0.0855**
	(0.0003)	(0.0003)
$TOUR_{ij}$	−0.0124**	−0.0112**
	(0.0005)	(0.0004)
$RESTRICT_{ij}$	−0.1893**	−0.0297**
	(0.0005)	(0.0007)
$AVGPOP_{ij}$	−0.0074**	0.0019**
	(0.0004)	(0.0004)
$AVGINC_{ij}$	0.0366**	−0.0138**
	(0.0017)	(0.0018)
$ORIHUB_i$	0.0102**	0.0260**
	(0.0008)	(0.0010)
$ORISLOT_i$	−0.0012	0.0008
	(0.0009)	(0.0008)
$ORIHERF_i$	0.0062**	0.0054**
	(0.0003)	(0.0003)
$ORISHARE_i$	0.0046**	0.0060**
	(0.0002)	(0.0001)
$DESHUB_j$	0.0125**	0.0196**
	(0.0008)	(0.0008)
$DESSLOT_j$	−0.0013	0.0020*
	(0.0009)	(0.0008)
$DESHERF_j$	0.0111**	0.0107**
	(0.0003)	(0.0003)
$DESSHARE_j$	0.0038**	0.0046**
	(0.0002)	(0.0001)
$LOWCOST_{ij}$	−0.0444**	−0.0302**
	(0.0005)	(0.0005)
$ORIMULTIPLE_i$	−0.0048**	−0.0061**
	(0.0004)	(0.0004)
$DESMULTIPLE_j$	−0.0076**	−0.0055**
	(0.0004)	(0.0004)
AA_{ij}	0.0066**	0.0082**
	(0.0006)	(0.0006)
UA_{ij}	0.0121**	0.0071**
	(0.0006)	(0.0005)
DL_{ij}	0.0089**	−0.0245**
	(0.0005)	(0.0005)
CO_{ij}	0.0208**	0.0256**
	(0.0007)	(0.0007)
NW_{ij}	0.0202**	0.0165**
	(0.0005)	(0.0005)
SW_{ij}	−0.1002**	−0.0842**
	(0.0009)	(0.0007)
Q1	−0.0558**	−0.0551**
	(0.001)	(0.001)
Q2	−0.0110**	−0.0066**
	(0.0004)	(0.0004)

(*continued on next page*)

Table 3 (*continued*)

Variable	Parameter estimate[a]	
	2000	2005
Q3	−0.0122**	−0.0055**
	(0.0004)	(0.0004)
Adjusted R^2	0.5259	0.4104
F-value	21,776	16,291

* Significant at the 5% level.
** Significant at the 1% level.
[a] Standard errors are presented in parentheses.

($F_{34,\ 1419{,}958}$ = 2814), indicating that there is a structural change in the period. This implies that pricing behaviors have changed significantly as a result of the changes in variables associated with operating cost, demand, market power, and firm characteristics in the US airline industry.

This paper further investigates whether the relationship between airfares and the individual carriers depends on the market conditions. If the effect on airfares of individual carriers depends on the value (or the existence) of market conditions, the first-order model (model 1) is not appropriate for predicting airfares (Mendenhall and Sincich, 2003). For this purpose, the interaction terms are created by multiplying the dummies for individual carriers by each of the market condition variables (hub airport, competition with an LCC, tourism areas, market share, and market competition) and added in the model.[13] Using the carriers' interaction terms, the paper examines whether the relationship between airfares and the individual carriers depends on the market conditions.

As shown in model 1, the heteroskedasticity-adjusted IV technique is used to perform the interaction model (model 2) in 2000 and 2005.[14] Overall, most of the estimated coefficients are found to be statistically significant at the 5% level[15], indicating there is sufficient evidence that the carrier effects and the market conditions interact. In 2000, all the carriers' interactions, except Delta interacting with the Herfindahl index at destination ($DL^*_{ij}DESHERF_j$), are significant at least at the 5% significance level. Three interactions ($UA^*_{ij}ORIHUB_i$, $CO^*_{ij}ORIHUB_i$, and $DL^*_{ij}TOUR_{ij}$) are found to be insignificant in 2005. This shows that the interaction model (model 2) tends to be more adequate than the model 1 in estimating airfares. It should be noted that the coefficient of the interaction does not show a change in airfares as a dollar value because the model uses a semi-log function with the interaction terms.

5.2. Estimated carriers' airfares

While the previous section shows that carrier effects and market conditions interact, it does not provide the magnitude of differences in airfares among carriers, given the market conditions. Using the estimated average airfares, we explain the overall impact of the combined effects from carriers and market conditions, instead of the interaction term itself. This may explain whether US air carriers use different pricing strategies depending on market conditions. This approach allows us to obtain three informants: first, it shows the estimated airfare differences among the carriers under the given market conditions. If large differences are found, this suggests that the individual carriers' pricing strategies vary under the same market conditions. Second, it presents estimated airfare differences among different market conditions for the same carrier. If the differences are large, this indicates that the same carrier uses different pricing strategies, depending on market conditions. Third, it shows whether the differences in estimated airfares vary for the period of 2000–2005, indicating whether the carriers' pricing strategies changed over the period.

We use the coefficients from the estimations and mean values from the regression data to estimate average airfares in 2000 and 2005. For example, the mean values from the data include a total distance of 1320 miles, an average segment distance of 700 miles, an average population of 2834,287, an average per-capita income of $35,669, and an average load factor of 72% in 2005 (Table 1).

Table 4 shows the estimated average airfares by carrier, given the mean characteristics of market conditions in 2005. For flights originating from a hub airport ($ORIHUB_i$), the estimated average airfares per passenger-mile are higher for American ($.21), United ($.21), Continental ($.23), and Northwest ($.22) in comparison to the non-major carriers ($.19). This indicates that these carriers may take advantage of pricing power from using their hub facilities, and therefore set higher airfares. On the other hand, Delta uses the pricing strategies that lead to lower airfares than the other non-major carriers ($.18). Similar

[13] We used each of the market factors separately and estimated it with all of the carrier's dummies. This approach produces a simple model with the least number of highly correlated variables and the fewest independent variables. We also include discussion and results of model with all of the interaction terms in Appendix B.

[14] When the interaction terms are included, the carrier dummies were also used. We found that some carrier dummies showed flipping signs and became insignificant. In order to show the overall impact, we combined effects from the carrier dummy and the interaction terms, instead of the interaction term itself.

[15] We compute *F*-statistics to check for joint significance of interaction terms and find that all the interactions, except hub airport at origin for 2005 and hub airport at destination for 2000, are jointly significant at the 5% significance level. Due to a large quantity of tables, the tables are not included in this paper. However, they are available upon request.

Table 4
Estimated average airfare per passenger-mile by carrier in 2005.

Interaction	Estimated average airfare ($)						
	AA	*UA*	*DL*	*CO*	*NW*	*SW*	Others
$ORIHUB_i$	0.21	0.21	0.18	0.23	0.22	N/A[a]	0.19
$DESHUB_j$	0.19	0.19	0.16	0.21	0.20	N/A[a]	0.18
$LOWCOST_{ij}$	0.11	0.11	0.08	0.13	0.13	N/A[a]	0.09
$TOUR_{ij}$	0.15	0.15	0.11	0.17	0.16	0.06	0.14
$ORIHERF_i$	0.17	0.19	0.15	0.21	0.20	0.06	0.20
$DESHERF_j$	0.17	0.17	0.14	0.20	0.19	0.04	0.19
$ORISHARE_i$	0.20	0.21	0.17	0.22	0.23	0.10	0.22
$DESSHARE_j$	0.20	0.21	0.16	0.23	0.22	0.10	0.21

[a] Not applicable because of the non-hub and LCC characteristics of Southwest.

Table 5
Estimated average airfare per passenger-mile by carrier in 2000.

Interaction	Estimated average airfare ($)						
	AA	*UA*	*DL*	*CO*	*NW*	*SW*	Others
$ORIHUB_i$	0.35	0.35	0.35	0.36	0.36	N/A[a]	0.34
$DESHUB_j$	0.34	0.34	0.34	0.36	0.35	N/A[a]	0.33
$LOWCOST_{ij}$	0.16	0.16	0.16	0.18	0.18	N/A[a]	0.14
$TOUR_{ij}$	0.33	0.34	0.33	0.34	0.34	0.22	0.32
$ORIHERF_i$	0.33	0.35	0.34	0.33	0.34	0.20	0.34
$DESHERF_j$	0.33	0.35	0.34	0.33	0.34	0.20	0.34
$ORISHARE_i$	0.31	0.33	0.34	0.33	0.35	0.22	0.34
$DESSHARE_j$	0.33	0.33	0.34	0.34	0.36	0.22	0.34

[a] Not applicable because of the non-hub and LCC characteristics of Southwest.

differences of estimated airfares are found for flights flying to a hub airport ($DESHUB_j$). When competing with an LCC at the markets ($LOWCOST_{ij}$), American, United, Continental, and Northwest are shown to have higher airfares, while Delta appears to have a lower airfare than the other non-major carriers. For the tourism areas ($TOUR_{ij}$), the estimated airfares are higher for American ($.15), United ($.15), Continental ($.17), and Northwest ($.16), compared to the other non-major carriers ($.14). Based on the results, Delta ($.11) and Southwest ($.06) are likely to act as price leaders, which initiate "price wars" in the markets serving tourism areas.

Using the value of market concentration at the origin ($ORIHERF_i$), the estimated airfares are higher for Continental ($.21) and Northwest ($.20) than for the other non-major carriers, while the estimated airfares are lower for American ($.17), United ($.19), Delta ($.15), and Southwest ($.06) in the same comparison. Most carriers have similar differences using the value of market concentration at destination ($DESHERF_j$). In the case of the carrier's market share at both origin and destination ($ORISHARE_i$, $DESSHARE_j$), Continental and Northwest have higher estimated airfares than the other non-major carriers, while American, United, Delta, and Southwest show lower estimated airfares in the same comparison. In particular, Southwest's fares are 53% lower than the non-major carriers that have the given 29% of market share at origin airports. This indicates that the non-major carriers are likely to use pricing strategies that lead to higher airfares, while Southwest does not increase its airfares given the same level of the carrier's market dominance power. Some observers might think that Southwest's origin share would contribute to higher than average prices, but Southwest's low cost structure has allowed it to maintain low airfares.[16]

Furthermore, we test whether carriers have different pricing strategies depending on market conditions. Continental, Northwest, Delta, and Southwest show consistent airfare differences compared to the non-major carriers for all market conditions. Regardless of the market conditions, Continental and Northwest have estimated airfares consistently higher than the other non-major carriers, while Delta and Southwest have estimated airfares consistently lower in the same comparison. That is, the pricing strategies of these carriers do not largely depend on the characteristics of market conditions. However, American and United have changes in the airfare differences, depending upon the market conditions. For example, in comparison to the non-major carriers, the estimated average airfares for these carriers are higher in the markets with the existence of an LCC, whereas they are lower with the mean characteristics of market concentration. Consequently, these carriers may use different pricing strategies depending on the characteristics of the market conditions.

[16] Since 2000, Southwest Airlines has used aggressive fuel hedging resulting in cost savings. Southwest hedged more than 70% of its fuel use and was able to purchase its fuel substantially cheaper than other carriers in 2008. For example, Southwest paid only $1.98 per gallon while American, which had 27% of its fuel hedged, paid $2.74 per gallon on average (Pae, 2008). This enabled southwest to provide lower airfares.

Table 5 shows the estimated average airfares between the carriers in 2000. The results show that the magnitude of the airfare differences to the other non-major carriers tends to be smaller in 2000 than that in 2005. For example, Continental has the largest airfare difference to the non-major carriers (+19%) for flights originating from a hub airport in 2005. However, the airfare difference of Continental (+7%) is smaller in 2000, although it still has the largest airfare difference among the carriers. All carriers, except American and Southwest, have changes in the signs (+/−) of the estimated airfare relative to the non-major carriers between 2000 and 2005. This indicates that these carriers may have changed their pricing strategies over the period in comparison to the other carriers. Continental and Northwest are found to have higher estimated airfares for all the market conditions in 2005, but they have lower estimated airfares for some of the market conditions. Similarly, Delta has lower estimated airfares than the other non-major carriers for all the market conditions in 2005, but it has higher airfares for some of the market conditions in 2000. By contrast, Southwest has consistently lower estimated average airfare than the non-major carriers in both 2000 and 2005. The results support that the carriers' pricing strategies may change over the period as well as market conditions.

6. Summary and conclusions

This paper explores pricing behaviors of the US air carriers by examining average airfares in the domestic markets. Heteroskedasticity-adjusted Instrumental Variable (IV) technique is used to estimate the price models and discuss the individual carriers' pricing strategies.

The contribution of this paper to the literature is to improve our understanding of the differential pricing strategies used by US air carriers. The results show that American, United, Continental, and Northwest tend to charge higher airfares, while Southwest appears to charge lower airfares. In addition, this paper provides insight into carriers' differential pricing strategies given the market conditions of the segment markets. Using the estimated average airfares, the differences in estimated airfares are found to vary among the carriers under given market conditions. For example, for flights originating from a hub airport, American, United, Continental, and Northwest have higher estimated airfares than the non-major carriers, whereas Delta has lower estimated airfares than the non-major carriers in 2005. In examining the airfare differences among the different market conditions for the same carrier, Continental and Northwest have estimated airfares consistently higher than the other non-major carriers, while Delta and Southwest have estimated airfares consistently lower in the same comparison in 2005. Finally, this paper tests whether carriers' pricing strategies change over a period. In examining the estimated airfares for the period of 2000–2005, Continental and Northwest have higher estimated airfares for all market conditions in 2005, but they have lower estimated airfares for some of the market conditions in 2000. By contrast, Southwest has consistently lower estimated average airfares than the non-major carriers in both years.

In sum, we conclude that the individual carrier effects play pronounced roles in determining airfares, indicating that the carriers' unique pricing strategies may affect airfares. The findings suggest that the individual carriers' pricing strategies may vary given the same market conditions, and the same carrier may use different pricing strategies depending on market conditions. Moreover, the results indicate that the carriers' pricing strategies may change over the period. However, the influence of pricing strategies of one carrier to the others in the markets has not been taken into account in this paper. Without further investigation, the interaction among the carriers' pricing strategies for profit maximization or for increasing market share cannot be adequately explained. This issue should be addressed in future research.

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Appendix A. Description of variables and expected signs

We collected all US route data from the DB1B in 2000 and 2005, and eliminated the top and bottom one percents of airfare data to remove outliers (e.g., data input errors). Data used in this paper are one-way route data, which do not combine the city-pair data for AB and BA routes. In addition, we created route-specific variables (e.g., P_{ij}, $DIST_{ij}$, $AVGDIST_{ij}$, $AVGPOP_{ij}$, and $AVGINC_{ij}$) by itinerary, carrier, quarter and other flight characteristics. For airport-specific variables (e.g., $ORICAP_i$, $DESCAP_j$, $ORIHERF_i$, and $DESHERF_j$), they are constructed by airport, carrier, quarter and other flight characteristics. For example, $ORICAP_i$ is the average seat capacity for all flights out of origin i by carrier and quarter. Route-specific variables would be the most appropriate measure to explain airfares on the routes, but route data are not available for capacity, load factor, frequency, Herfindahl index, carrier's market share, and multiple airports. Therefore, we used airport-specific variables for these characteristics.

A.1. Capacity

We used the T-100 Segment data to generate airport-specific capacity variables ($ORICAP_i$ and $DESCAP_j$) because of absence of route data for these characteristics, For example, $ORICAP_{DFW}$ for American Airlines is the average seat capacity for all American Airline flights out of DFW by quarter. Flight capacity may influence not only the carriers' operating costs per passenger but also passengers' demand for air-passenger service. According to Borenstein (1989) and Bitzan and Chi (2006), a large capacity may increase aircraft utilization and reduce operating costs per passenger, which enables the carriers to decrease airfares. Moreover, a large aircraft may increase demand for air-passenger service because of more comfortable seating and therefore increase airfares in some cases. In addition, a larger aircraft is generally considered safer under bad weather conditions, and it may increase the demand. Because the effect of capacity may offset its impact on operating costs and demand, the expected sign is not predetermined.

A.2. Load factor

Similar to capacity, load factor is a measure of aircraft utilization and influences operating costs. Bailey et al. (1985) show that load factor is likely to be positively associated with productivity. On the other hand, load factor may affect demand for air-passenger service. Douglas and Miller (1974) conclude that a load factor is positively related to market density (the number of passengers per day), indicating that a higher load factor may increase demand for air-passenger service and lead to an increase in airfares. Bitzan and Chi (2006) point out that a high load factor may decrease demand due to less comfortable seating, which leads to a reduction in airfares. Based on the offset effects of load factor on operating costs and demand, the expected sign is not predetermined for load factor.

A.3. Service frequency

$ORIFREQ_i(DESFREQ_j)$ is total frequency of all flights by carrier/quarter out of origin i (flying to destination j). As discussed earlier, route-specific variables would be the most adequate measure in the model. However, route data are not available for these variables and therefore airport-specific variables are used. Frequency of service can increase or decrease the airfares depending on its effect on operating costs and demand. A higher frequency of flights is likely to reduce operating costs per passenger, which enables the carriers to decrease airfares. However, frequent flights may increase operating costs, holding the average capacity constant. That is, frequent flights of a given capacity may lead to high operating costs, which result in high airfares. On the demand side, a higher frequency of flights may allow passengers to purchase a ticket for their desired flight schedules and decrease the waiting for the next flight when the reserved flight is cancelled. In addition, a higher frequency of service is likely to occur during an on-peak demand period, which leads to higher airfares. For these reasons, the expected sign of the variable is not predetermined.

A.4. Total distance and average segment distance

Total distance is the total distance of flight from origin to destination, and the average segment distance is the average distance per flight segment. We used the actual flying distance weighted by the number of passengers. Because the weighted average airfare per passenger-mile is used as the dependent variable, distance can be positively or negatively associated with it. As distance increases, a carrier is likely to reduce its unit operating costs, which may lead to lower airfares. However, an increase in distance tends to have a smaller substitution effect between air travel and other transportation modes (e.g., bus and car). This may result in a positive effect of distance on airfares.

A.5. Round travel

The dummy for a round trip ($ROUND_{ij}$) is equal to one if origin and final stop are the same and the itinerary is not circle trips. (e.g., A → B → A, A → B → C → B → A, or A → B → C → D → A). Otherwise, it is set to zero. In other words, the dummy excludes all one-way and circle trips (e.g., A → B or A → B → C → A). Increases in round-trip flights are likely to lead to increases in aircraft utilization (e.g., a good balance of inbound and outbound traffic flows). In addition, business passengers tend to buy one-way tickets disproportionately. Therefore, round trip fares are lower and a negative impact of the round trip is expected in the model.

A.6. Tourism areas

This paper collects a list of 50 tourism areas based on tourism market shares by overseas visitors from the Office of Travel and Tourism Industries (OTTI), US Department of Commerce (Office of Travel and Tourism Industries, 2007). In this paper, we assume that overseas and domestic travelers have the same tourist destinations. If the market share for overseas visitors in 2001 is equal to 0.5% or greater, then the $TOUR_{ij}$ is equal to one. Otherwise, it is equal to zero. A negative relationship is expected between the tourism areas and airfares because most of the tourism areas are likely to have high competition for vacation travelers. Therefore, a negative impact of tourism variable is expected.

A.7. Ticket restrictions

We used the DB1B to create a dummy for ticket restrictions ($RESTRICT_{ij}$). If an observation from the DB1B is recorded as a restricted ticket, then the ($RESTRICT_{ij}$) is equal to one. Otherwise, it is equal to zero. It should be noted that ticket restrictions do not have standard conditions and may vary by carrier. In general, conditions of restricted tickets include non-refundable, $0 value after departure, penalty-applied tickets, and/or specific stay-rules (e.g., minimum or maximum days). Therefore, restricted ticket fares are likely to be lower than non-restricted tickets and a negative sign is expected.

A.8. Population and income

This paper uses the average metropolitan statistical area (MSA) population between origin and destination cities. For small cities/towns, county population is used. Because the per-capita disposable income data are currently not available at the MSA or city level, we use the average per-capita income, which is a good proxy for available personal travel budget. Both population and income are likely to have positive impacts on demand for air-passenger service and lead to higher airfares. However, carriers serving large populated cities generally use bigger aircraft and experience economies of density. In addition, these big cities are likely to have more transportation options and higher competition, which reduce airfares. Thus, the expected sign of the population variable is not determined.

A.9. Hub airport

The dummy for the hub airport at origin ($ORIHUB_i$) is equal to one if the origin airport is the carrier's major hub airport. For example, for United Airlines, if a flight departs from O'Hare International Airport (ORD), the $ORIHUB_i$ is equal to one. This paper also includes a dummy for hub airport hub at destination ($ORIHUB_i$) using the same method. Several studies have investigated the effects of hub airports associated with service quality and airfares. Bailey et al. (1985) argue that average speed and delay rate may vary by markets. Using a simulation model, they show that large hub markets are found to have the smallest delay (40 min) and fastest travel speed (351 mph) among the market categories. Moreover, the carriers using their hub airports may dominate airport facilities and provide better service that saves passengers' ground time and increases demand for service. Borenstein (2005) supports that airfare premium exists on major hub routes by showing 26% of the average premiums in 10 large hub airports. He finds that the hub premia have declined for the last 10 years, but the premium still applied on the hub routes. Based on the previous studies, carriers using their hub airports are likely to have better service quality and higher demand for air-passenger service, which leads to an increase in airfares. Thus, carriers using their own hub airports are expected to have a positive impact on airfares.

A.10. Slot-controlled airports

The dummy for slot-controlled airports accounts for limited capacity at the airport, which may affect both operating costs and demand for air-passenger service. Because carriers that are not "grandfathered" are required to purchase slots to operate their aircrafts to land and take-off, the operating costs are higher for the flights using slot-controlled airports than those using non slot-controlled airports, which may increase airfares. In addition, because the slots are apportioned out to carriers on the basis of availability, they may lead to reduced operating times compared to the normal first come, first served practice at other airports. This may increase demand for air-passenger service at slot-controlled airports, thereby leading to higher airfares. On the other hand, since the slot-controlled airports are likely to be highly congested, passengers may be required to arrive at the airports earlier than other non-congested airports. The longer departure procedure at the slot-control airports may increase full travel costs that include the passengers' time value. This may decrease demand for air-passenger service and lead to a reduction in airfares. Due to the different effect of a slot-controlled airport associated with operating costs and demand characteristics, the expected sign of the variable is not determined.

A.11. Herfindahl index and market share

This paper employs the Herfindahl–Hirschman (Herfindahl) index to measure market concentration at the airport level. As found in Bitzan and Chi (2006), we use the market share of ticketing carriers instead of operating carriers. The market share of non-ticketing and codesharing carriers is added to that of their ticketing carriers. In imperfect competition markets, increases in these variables lead to higher airfares. The Herfindahl index and market share variables are expected to be positively associated with airfares.

A.12. Low-cost carrier (LCC)

We collect a list of low-cost carriers (LCCs) used by Ito and Lee (2003). The LCCs include Air South, Access Air, AirTran, American Trans Air, Eastwind, Frontier, JetBlue, Kiwi, Morris Air, National, Pro Air, Reno, Southwest, Spirit, Sun Country, ValuJet, Vanguard, and Western Pacific. The dummy for low-cost carrier competition is equal to one if LCC service is available on the city-pair route. The LCC dummy uses airport-pair routings instead of city-pair routings based on the assumption that there are differentiated service characteristics by airports. If city-to-city competition is used for the LCC, it does not incorporate different geographic locations of airports, accessibility to other transportation modes at airports, and distance from an airport to origin/destination (e.g., home or hotel). As found in Hess et al. (2007), ground-level distance plays an important role in airport-choice behavior. Therefore, we use airport-to-airport competition for the LCC dummy. In addition, we do not consider the market share of an LCC to incorporate both existing and potential competition with an LCC. Due to the low cost structure of LCCs, competing carriers' prices may be affected by an entry or existence of an LCC regardless of its market share. A low operating cost structure of LCC enables the carrier to provide low airfares and act as a price leader in the markets (Hofer et al., 2008; Daraban, 2007). In addition, other competitors may follow the low airfares in the market. Hence, a "price war" due to the competition with an LCC may reduce airfares of all carriers in the markets, and a negative impact of the variable is expected.

A.13. Multiple airports

If multiple airports are located in the same MSA, then a dummy for multiple airports ($ORIMULTIPLE_i$ and $DESMULTIPLE_j$) is equal to one. Otherwise, it is equal to zero. We use alternative airports in MSA instead of Combined MSA (CMSA) or other nearby cities. For DCA, for example, the dummy for multiple airports is equal to one because IAD is available in the Washington-Arlington-Alexandria, DC-VA-MD-WV MSA. However, for BWI that is not located within the DC-VA-MD-WV MSA and does not have an alternative airport, the dummy for multiple airports is equal to zero. We do not have full information on travelers' airport-choice behaviors and therefore we cannot determine if travelers in one MSA are willing to travel to the other MSA to take their flights. Accessibility to other transportation modes (e.g., rail station), traffic congestion to an alternative airport, distance from an airport to origin/destination, and frequency of flights may all influence consumers' airport-choice behaviors. Therefore, we use the MSA to examine the competition between airports. Because of the competition between airports, a negative sign of the dummy for multiple airports is expected.

A.14. Carrier effects

Carriers may have their own unique operating, marketing, and customer service strategies, which affect demand for air service. We defined the major carriers based on the passenger-miles. The six major domestic carriers (AA_{ij}, UA_{ij}, DL_{ij}, NW_{ij}, CO_{ij}, and SW_{ij}) represent approximately 71% of total domestic revenue passenger-miles in 2005 (Bureau of Transportation Statistics, 2007).[17] That is, the rest of carriers, defined as non-major carriers in this paper have only 29% of total passenger-miles. Because these carriers dominate domestic city-pair markets, the major carriers' pricing strategies are important to us. It would be possible to use a specific carrier instead of the non-major carriers as the base case, but this paper is more interested in comparisons to general characteristics of non-major carriers, rather than unique characteristics of single carrier. We captured the observations for the commuter affiliates as the major carrier observations. For example, if *UA* is a ticketing carrier and XJ is the non-ticketing operating carrier, then we considered this ticket as a *UA* observation. The Air Travel Consumer (ATC) report shows that flight delay, cancellation rates, and complaint rates vary by carrier. For these reasons, the effects of individual carriers are examined in this paper. The expected signs of the dummies for individual carriers are not predetermined.

A.15. Seasonal effect

Dummies for seasonal effects are derived from the demand function. In general, the third quarter shows high demand for air travel and therefore the third quarter may have a positive impact on airfares. The expected impacts of other quarters are not predetermined. Note that this paper does not use a year dummy because we conduct our analysis for 2000 and 2005, separately. This allows us to determine whether the impacts of variables are consistent for the period 2000–2005.

Appendix B. The results of model with all of the interaction terms

This paper reports the results of a model that includes all of the interaction terms in addition to the base model (Tables 6 and 7). When all interactions were included, it created a large number of highly correlated variables and the number of independent variables substantially increased (78 variables = 33 variables in the base model + 45 interaction terms). Eight and nine variables were found to be insignificant at the 5% level in 2000 and 2005, respectively. Tables 6 and 7 show that the differences in estimated airfares by carriers appeared to be bigger than those in Model 2 (Tables 4 and 5) and some estimated airfares were overstated (e.g., Southwest Airlines).

Therefore, we used each of the market factors ($ORIHUB_i$, $DESHUB_j$, $LOWCOST_{ij}$, $TOUR_{ij}$, $ORIHERF_i$, $DESHERF_j$, $ORISHARE_i$, and $DESSHARE_j$) separately and estimated it with all of the carrier's dummies. This approach allowed us to reduce a multicollinearity problem and produce a parsimonious regression model, which has the least number of regressors. Following Der and Everitt (2005), we attempted to build a simpler model by including other variables to the base model, which are essentially useful in estimating airfares.

[17] In addition, all of these carriers have greater than a 5% market share of national total.

Table 6
Estimated average airfare per passenger-mile by carrier using the model with all of the interaction terms in 2005.

Interaction	Estimated average airfare ($)						
	AA	*UA*	*DL*	*CO*	*NW*	*SW*	Others
$ORIHUB_i$	0.14	0.14	0.11	0.20	0.25	N/A[a]	0.20
$DESHUB_j$	0.16	0.19	0.11	0.21	0.25	N/A[a]	0.19
$LOWCOST_{ij}$	0.13	0.13	0.06	0.19	0.23	N/A[a]	0.16
$TOUR_{ij}$	0.15	0.15	0.07	0.23	0.25	0.01	0.19
$ORIHERF_i$	0.13	0.15	0.09	0.21	0.24	0.00[b]	0.20
$DESHERF_j$	0.13	0.14	0.09	0.21	0.24	0.00[b]	0.20
$ORISHARE_i$	0.14	0.15	0.09	0.21	0.24	0.00[b]	0.20
$DESSHARE_j$	0.15	0.16	0.09	0.21	0.24	0.00[b]	0.20

[a] Not applicable because of the non-hub and LCC characteristics of Southwest.
[b] Negative values are truncated by $0. The estimated average fares are −0.03, −0.03, −0.02, and −0.01 for $ORIHERF_i DESHERF_j ORISHARE_i$, and $DESSHARE_j$, respectively.

Table 7
Estimated average airfare per passenger-mile by carrier using the model with all of the interaction terms in 2000.

Interaction	Estimated average airfare ($)						
	AA	*UA*	*DL*	*CO*	*NW*	*SW*	Others
$ORIHUB_i$	0.27	0.33	0.40	0.32	0.38	N/A[a]	0.37
$DESHUB_j$	0.29	0.31	0.40	0.33	0.37	N/A[a]	0.36
$LOWCOST_{ij}$	0.25	0.24	0.36	0.32	0.37	N/A[a]	0.31
$TOUR_{ij}$	0.28	0.28	0.36	0.34	0.37	0.18	0.34
$ORIHERF_i$	0.27	0.30	0.39	0.33	0.38	0.17	0.37
$DESHERF_j$	0.28	0.29	0.40	0.33	0.37	0.17	0.37
$ORISHARE_i$	0.27	0.29	0.39	0.33	0.38	0.18	0.37
$DESSHARE_j$	0.28	0.29	0.39	0.33	0.39	0.19	0.37

[a] Not applicable because of the non-hub and LCC characteristics of Southwest.

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