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Pricing and Market Characteristics: A Case Study of Airlines on the Denver – Los Angeles Route

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Abstract

This study examines the factors that determine airfare pricing on the route from Denver (DEN) to Los Angeles (LAX), including the return trip. This is a pair of cities with distinct economic backgrounds. We analyze a dynamic panel dataset spanning 22 years from 2002 to 2023 to examine how various firm-level, industry-level, and macroeconomic indicators affect airfare. The country's major carriers, Delta Airlines and Southwest Airlines, employ a unique pricing strategy that enhances fare competitiveness on this route, as evidenced by the influence of HHI (i.e., Herfindahl-Hirschman Index). Although this market is an oligopoly and conventional wisdom suggests that higher concentration would lead to higher prices, we observe this effect only partially. We also observe evidence of unique characteristics of airlines.

Keywords: Airfare, Airline Industry, Economic Factors, Market Power

1. Introduction

Airfare pricing is not merely a reflection of supply and demand but a result of the dynamic interaction of several economic factors, both macro and firm-level. Consideration is given to operational costs, passenger demand, market structure, and strategic positioning. Simultaneously, economic growth, regulation, and trends in travel and tourism are considered to be vital factors. The US air carrier market structure is oligopolistic. However, intense competition still exists in many sectors. This study aims to deepen the understanding of pricing and its relation to market power. Different routes have different characteristics regarding the number of passengers who travel on them and the prices charged. Airlines often try to leverage that to secure financial sustainability and market share. For example, all four major US carriers added special flights for the Super Bowl. An American Airlines spokesperson told a popular news outlet in February 2024, “The excitement surrounding this year’s sporting events has never been greater.” Both one-off events and seasonal events affect the way airlines operate in given sector routes.

This research analyzes economic determinants—jet fuel costs, passenger numbers, regional economic activity (GDP), and competition (measured by the Herfindahl-Hirschman Index (HHI)) — to examine their impact on airfares. While passenger numbers and economic activity drive demand, HHI and competition levels, as well as crude oil prices, effect resource prices and, in turn, supply. Fuel and labor are among the most significant expenses for airlines. Labor costs are determined from wages and the state of the economy. Higher volatility in resource prices leads to greater uncertainty, in availability and pricing. Figure 1 *below* shows the trend and fluctuations in the price of one such resource - jet fuel, from 2002 to 2023. Its associated volatility is measured as the standard deviation of 500 weekly price observations (FRED, 2025). Some notable moments observed in Figure 1 include the volatility in jet fuel prices right before the 2008 crash and in 2022 due to Russia’s invasion of Ukraine. Volatility is calculated as the rolling standard deviation of the log (ratio of intertemporal fuel prices) and indicates the level of uncertainty or risk in fuel prices. Such fluctuations can significantly impact operational costs in the aviation sector.

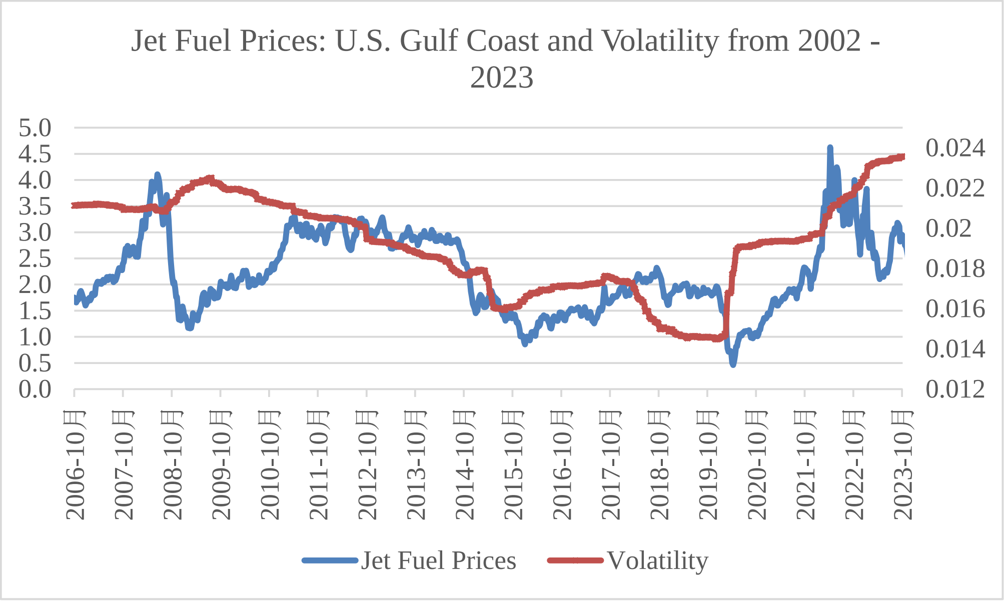

Figure 1. Jet Fuel Price and Volatility (standard deviation) with time.

Source: U.S. Energy Information Administration, Kerosene-Type Jet Fuel Prices: U.S. Gulf Coast *(FRED, 2025)*

In this paper, we focus on the route connecting Denver (DEN) to Los Angeles (LAX), considering passenger travel in both directions over the period 2002 - 2023. Each city exhibits distinct operational characteristics: Denver boasts a balanced presence of legacy carriers and low-cost carriers (LCCs) (such as United, Delta, American, and Southwest), alongside ultra-low-cost carriers (ULCCs) like Frontier and Spirit. This diversity fosters a robust competitive environment for airlines operating at Denver. Figure 2 depicts the share of passengers by each airline at Denver International Airport in December 2019. One can observe that Southwest and United accounted for nearly 60% with Frontier capturing another 13% of the passenger share.

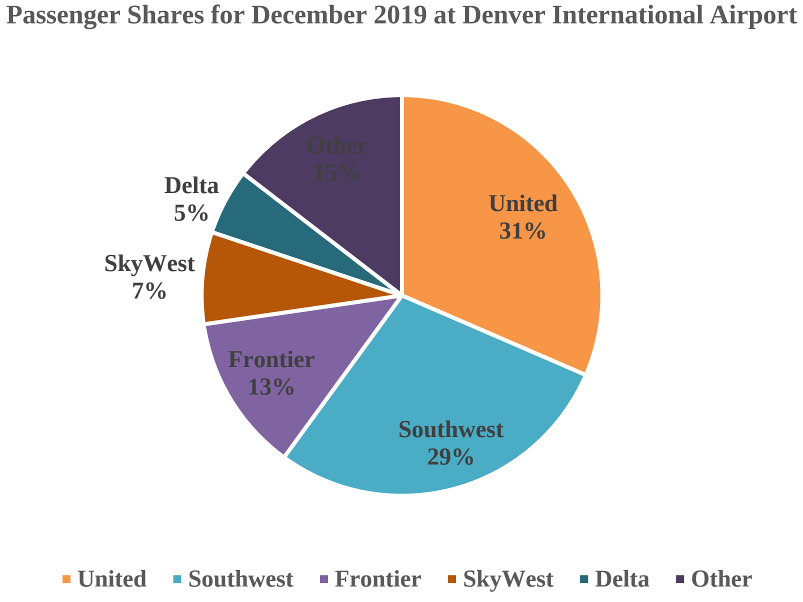

Figure 2. Percentage Passenger Shares by Each Airline Type for DEN in December 2019
(Source: Bureau of Transportation Statistics)

Contrastingly, the Los Angeles market is characterized by the dominance of the top 4 US carriers — American, Delta, United, and Southwest — and by somewhat higher entry barriers. Figure 3 Illustrates the distribution of passenger shares by airline at Los Angeles International Airport (LAX). The consumer base at LAX is considerably more diverse than that at Denver, thereby resulting in a different competitive landscape and somewhat unique pricing dynamics, which is a key rationale for focusing on this route. Unlike a hub such as Atlanta (ATL), where Delta Airlines holds a commanding presence, the Denver–Los Angeles route offers greater diversity in carrier competition, thereby enabling a richer examination of market dynamics and pricing effects.

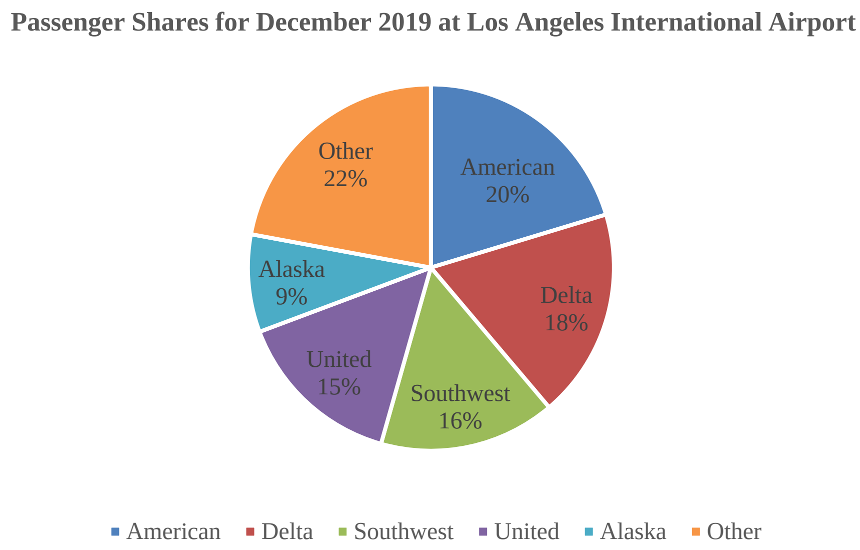

Figure 3. Percentage Passenger Shares by Each Airline Type for LAX in December 2019

(Source: Bureau of Transportation Statistics)

In an era where economic resilience is paramount, carriers are compelled to adapt to market volatility, including fluctuations in fuel costs, regulatory changes, and dynamic competitive pressures that shape fare structures. The unique contribution of this paper is that it analyzes a dataset spanning the years before, during, and after the COVID-19 pandemic—a period marked by unprecedented disruptions. Throughout this timeline, airlines faced diverse challenges, leading some to reduce or suspend operations temporarily, others to cut capacity, and yet others to lay off workers. Adding to this was the steep rebound in air travel, particularly for leisure, that followed the pandemic. The analytical model developed herein explicitly accommodates these anomalies, providing a timely perspective on how airlines recalibrated their pricing strategies in response to fundamental shifts in route characteristics and the evolving "new normal."

Our research aims to provide actionable, data-driven insights to industry participants, regulators, and policymakers to optimize fare structures, enhance consumer welfare, and foster a competitive, sustainable aviation industry. This paper significantly enriches the literature on airline economics by closely examining airfare pricing mechanisms, a vital aspect of the industry's strategic success.

2. Background

The U.S. airline industry, emblematic of intense competition and high volatility, sits at the heart of the nation's economic infrastructure. The strategic maneuvers in this sector have far-reaching implications for many stakeholders, including passengers, government agencies, airlines, and regulatory bodies, as well as regional economies. Airline pricing strategies are intricately tied to the company's internal decision-making processes, particularly in revenue management and cost reduction. However, these strategies are also profoundly influenced by three major external factors that significantly impact the formulation of air ticket prices: market structure, customer demand, and operational factors (Hospodka & BEng, 2013). Airlines operate within a complex framework of operational costs, consumer demand, competitive pressures, and regulatory oversight. The pricing of airfares, especially on high-traffic routes such as Denver to Los Angeles, is a key strategic tool that can influence a carrier's competitive edge. The ability to navigate these factors and set optimal prices is more than a seasonal or financial imperative—it determines an airline's ability to grow, capture market share, and sustain operations.

In the airline industry, the primary cost factors for carriers are salaries and fuel expenses. This cost component is susceptible to market fluctuations and often reflects broader economic trends. A 2017 comparison between full-service and low-cost carriers for a typical narrow-body aircraft shows that full-service carriers incur higher costs in both these areas. Full-service carriers have an average cockpit crew salary of $120,000 with a 35% benefit load, compared to $100,000 with a 25% benefit load for low-cost carriers. Similarly, fuel expenses are slightly higher for full-service carriers at $820 per block hour, as opposed to $800 for low-cost carriers (McKinsey & Company, 2017). These disparities in salaries and fuel costs contribute significantly to the overall cost per available seat kilometer, with full-service carriers averaging 8.19 cents compared to 4.71 cents for low-cost airlines, reflecting the different operational efficiencies and market strategies of the two business models.

When demand for air travel is robust, airlines find it easier to absorb variable costs, as higher passenger revenue generally offsets these costs even with thinner margins. However, this balance is disrupted by the inflexible nature of airline schedules. Airline capacity often accounts for a substantial portion of an airline's overall costs, as fixed costs cannot be easily adjusted in the short term. Conversely, variable costs — such as airport charges, security fees, catering, distribution, and marginal fuel costs—constitute a relatively minor share of the financial burden. This contrast between fixed and variable costs underscores the critical importance of strategic capacity management and pricing decisions. (Grimme, Maertens, & Bischoff, 2011).

A deep understanding of pricing dynamics is vital for airline executives and researchers alike, as it plays a critical role in decisions related to capacity management, route selection, and the development of targeted marketing campaigns. Market forces such as size, level of economic activity, standard of living, and degree of concentration are significant factors shaping an airline's pricing strategy. Additionally, the pricing disparities between full-service carriers (FSCs) and low-cost carriers (LCCs) are essential considerations that reflect differing business models and value propositions. The regulatory role of flagship airlines on routes can serve as a benchmark, influencing ticket prices across the board (Kiarashrad, Pasandideh, & Mohammadi, 2020). It is vital to explore these intricacies through a real-case analysis, offering practical insights that could enhance our understanding of the pricing power of commercial airlines in domestic markets. The route we have chosen for this purpose fits that requirement.

Figure 4 shows the Domestic market share of leading U.S. airlines from February 2022 to January 2023. Sales dipped after the COVID-19 pandemic but bounced back relatively quickly after restrictions were lifted. Furthermore, the leisure travel rebounded more quickly than business travel, as captured in our study of the Los Angeles-Denver route. Market share and pricing power are two factors that are integral to an airline's success, with the former reflecting competitive status and ability to influence fares—both are pivotal in determining the company's financial robustness and strategic dominance. In the post-pandemic era, the U.S. airline industry is at crossroads of making strategic decisions about immediate recovery and long-term resilience.

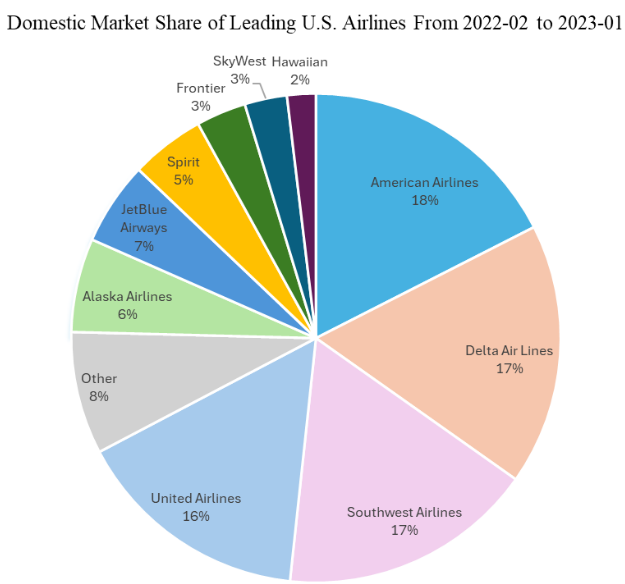

Figure 4. Domestic market share of leading U.S. airlines from 2022-02 to 2023-01 (Source: *(Statista , 2023)*)

Airports in North America recovered from the shocks of COVID-19 faster than those in Europe (Oliver Wyman, 2022). The elements influencing airfare pricing on specific routes highlight the broader challenges and opportunities that airlines face in this new landscape. As such, this study does not merely seek to identify the factors affecting airfare; it also endeavors to interpret the evolution of an airline's pricing strategy, keeping in mind the idiosyncratic nature of a route and its characteristics. Our analysis focuses on a route with no dominant players. Market share is distributed between legacy and low-cost carriers, between hub and non-hub destinations, and in a notable decision by a low-cost carrier to exit the market altogether. It is for this reason that the city pair of DEN (Denver) and Los Angeles (LAX) has been picked as a representative case for such analysis, which, to the best of our knowledge, has not been studied in the past.

3. Determinants of Air Transportation Demand and Supply

Previous studies on the determinants of airfare pricing have reflected the complexity of the airline industry's operational, strategic, and economic dimensions. These studies have focused on demand-related factors such as income, nature of travel, and flier demographic characteristics at origin and destination, but also supply factors, such as the number of airlines operating in a market, fuel price, employee wages, and market structure, as well as the extent and influence of competition. Early investigations, such as the seminal work in 1989 by Borenstein scrutinized how market dynamics shape fare levels and variance (Borenstein, 1989), uncovering a relationship between an airline's market control and higher fares. Subsequent analyses suggest that additional factors, including passenger composition and aircraft capacity, must be considered. (Lee & Luengo-Prado, 2005) and (Gerardi & Shapiro, 2009). An examination of price premiums in response to competition from budget airlines further expanded this (Hofer, Windle, & Dre, 2007). This study found that the occurrence of such premiums among consumers decreased following the entry of budget carriers into the market. However, none of these have examined a market in which a legacy carrier has actively sought to grow its market share.

Demand estimation is typically based on utility maximization of a representative consumer (Garrow, 2007) and (Ben-Akiva & Lerman, 1985). In this process, the relevant variables that are used to identify with air traffic demand on that route or sector for a given period of time are categorized into three main groups (Vandermotten & Dobruszkes , 2022). Macroeconomic factors such as GDP, population size, and trade volumes determine the extent of air travel in an economy. Consumer-specific variables, such as demographic data, social and economic characteristics, including GDP per capita, distribution of skilled workers, age, and rural/urban population, are often used to determine demand (Abel, Dey, & Gabe, 2012). The third set of variables includes geographical attributes, such as climate, seasonality, proximity to alternative major airports, and availability of alternative modes of transport, such as high-speed rail and road transportation, which can also determine the extent of air-travel preference on a given route (Wang, Zhang, & Zhang, 2018). While this framework is widely accepted, recent studies have sought to broaden its scope by incorporating additional elements, such as intermodal competition, cultural factors, and supply-side attributes, including service frequency and competitor fare levels. (Wang, Xia, Zhang, & Zhang, 2018). Our contribution to this study is to incorporate the evolution of a general equilibrium model by studying demand and supply characteristics, conditioning on route and traveler type.

Airlines frequently employ yield management techniques to boost profits (Siegert & Ulbricht , 2020). This approach is particularly popular for understanding sectors driven by seasonal demand, such as tourism, seasonal goods, and the fashion industry. In these sectors, goods are perishable, and capacity is determined in advance. In aviation, the costs prior to the departure of a flight are significantly higher than the costs after a flight’s departure, because the airline’s choice variables are narrowed down to fuel and operating costs. An effective pricing model can significantly enhance revenue, potentially by 2.0 - 5.0% (Zhao & Zheng, 2000). The structure of optimal pricing in aviation has been the focus of various studies~~,~~ addressing demand for a product that cannot be sold after a specific time~~.~~ (Gallego & Van Ryzin, 1994) and management of demand with inventory and price monotonicity, which applies to the perishability of the product once the aircraft has taken off (Zhao & Zheng, 2000).

Addressing the operational aspects, it is noted that the absence of economies of scale, stage length, and fleet commonality affects operating costs. Interestingly, newer fleets may not necessarily lead to lower costs due to higher ownership expenses (Zuidberg, 2014). This introduces a complex dimension to the cost-benefit analysis of fleet modernization. During the early 2000s, the U.S. airline industry was tumultuous, marked by heightened price sensitivity and a distinct consumer preference for nonstop flights (Berry & Jia, 2010). The structural shifts in demand and supply during this era elucidated the intricate balance airlines must navigate to remain profitable. The granularity of market segmentation and dynamic pricing mechanisms is highlighted in subsequent studies that explain airlines' multifaceted approach to discriminating prices based on various factors, including purchase timing and their own market power at a given airport and route. This segmentation allows airlines to capitalize on late-market consumers, showcasing the strategic use of dynamic pricing to optimize revenue (Gu, 2022).

While many factors may affect fares, it is found that advance-purchase days, city-direct distance, market size, market structure, and number of tickets sold are among the most crucial pricing factors. Specifically, airlines first segment their markets into multiple periods (i.e., early versus late) and further split the market by city-direct distance and demographics (i.e., age, income, destination natural features). Price discrimination is also based on the day of purchase identified, suggesting that airlines adjust prices to target the more price-elastic leisure travelers who tend to book on weekends (Puller & Taylor, 2012). This behavior underscores the airlines' agility in responding to consumer purchasing patterns to maximize profits. The impact of the internet on airline pricing also garners attention, with findings suggesting that online purchasers benefit from lower fares (Sengupta & Wiggins, 2014). Yield management in e-commerce sheds interesting light on access to and control over key resources, leading to market power. (Gabor, Kardos, & Oltean, 2022) study the importance of strategic pricing and resource control in attracting customers at the right time. This phenomenon has only grown in importance amid the challenges posed by the COVID-19 pandemic.

The trends in global service connectivity and air passenger flows underscore the critical role of connectivity measures, aligning closely with the findings that stress on the role of airline networks and passenger volume in determining airfare pricing (Taylor, Derudder, & Witlox, 2013). In our research, we explore the idea of cities being "underserved" or "over-visited" by airlines, analyzing these conditions through market concentration using the Herfindahl-Hirschman Index (HHI) to assess airline dominance at a given point in time. We then assess how concentration impacts fare levels, reinforcing the intricate relationship between supply, demand, and the dynamics of network society in the air travel industry. In addition, the gravity model identifies the pivotal role of low-cost carriers (LCCs) and ethnic links in enhancing demand for air travel (Boonekamp, Zuidberg, & Burghouwt, 2018). After accounting for demand, competitive pressure from LCCs has a positive impact on passenger demand.

All the factors discussed above can be amalgamated into gravity models (Krugman, Obstfeld, & Melitz, 2021), wherein a Cobb-Douglas specification is used to transform structural equations of demand and supply into a reduced form (Wang et al., 2018). The development of gravity models also focuses on economic activity (GDP) and region-specific geographical characteristics such as catchment, distance, and travel time, (Tobias, Rothlauf, & Heinzl, 2007). Similar results were also obtained for the geographical region of Turkey (Sivrikaya & Tunç, 2013). Another important determinant is income growth and how income growth has contributed to the growth in passenger demand (Valdes, 2015). Even in smaller markets, the role of market size and proximity of major hub airports is crucial in determination of passenger volumes (Goff, 2005).

Furthermore, analysis of the US feeder airline industry structure and the partnerships between full-service and regional carriers provides empirical evidence on the operational strategies and network organization that underlie models’ focus on airline-specific impacts (e.g., United, Frontier, American, Delta) on airfare levels (Reynolds-Feighan, 2018). Market structure and function are fundamental in shaping airline scheduling and service delivery, playing a pivotal role in strategic competition and cooperation among airlines. These elements influence fare structures, especially when exploring legacy carriers' outsourcing decisions and focusing on competitive effects arising from such partnerships, particularly in response to route competition from LCCs, and on the competitive dynamics between legacy and regional airlines. The lower airfares on outsourced routes resonate with fare impacts driven by airline business models and market competition (Tan, 2019).

4. Model

The model we base this study on is similar to the one described by (Berry, Levinsohn, & Pakes, 1995). The demand specification is based on the utility derived by the customer traveling on airline ‘i' at time ‘t’ given as:

$$u_{i,t} = f\left(P_{i,t}, Inc_t, P_{-i,t}\right) \tag{1}$$

Where,

$\boldsymbol{P_{i,t}}$**:** Price paid by a consumer

$\boldsymbol{Inc_t}$**:** Income of the consumer

$\boldsymbol{P_{-i,t}}$**:** Price charged by substitute airline for the same route derived from the utility of an outside good.

This allows us to use the structural airline demand and supply framework with price (airfare) and quantity (PAX) as the standard variables.[1]

4.1 Demand Analysis

The demand for air transport for airline ‘i' during period ‘t’, represented as Q_{it-D}, is considered to be affected by the airfare $FARE_{i,t}$, the gross domestic product of the origin/ destination state of Colorado or California ($COGDP_t$ or $CAGDP_t$ respectively), and the real disposable income INC_t. It is expected that a decrease in airfare $FARE_{i,t}$ would typically lead to an increase in flight demand, *ceteris paribus*. An increase in either or both of Colorado's GDP at time ‘t’ ($COGDP_t$) or California GDP at time ‘t’ ($CAGDP_t$) would reflect a stronger economy, potentially translating to a higher demand for flights due to the procyclical nature of travel activity. Also, for the same reason, a higher real disposable income at time ‘t’ (INC_t) should similarly increase demand, giving consumers greater capacity to allocate spending to air travel.

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[1] This can also be used empirically to be estimated as 2-stage least squares model, which we will discuss in the results section

From this framework, we estimate a demand model as follows: (need to be consistent for ‘i' and ‘t’)

$$\boldsymbol{Q_{i,t-D} = F(FARE_{i,t}, COGDP_t, CAGDP_t, INC_t)} \tag{2}$$

Seasonality, or the time of year, also plays a role in air travel, particularly on this route, as Denver serves as a popular destination for winter recreation.

4.1 Supply Analysis

The supply of airline seats at time ‘t’ (Q_{it-S}) also adjusts simultaneously to economic incentives and market conditions. But for now, we will consider it separately for theoretical purposes. As jet fuel prices at time ‘t’ denoted as $JFUEL_t$[2] rise, airlines tend to adjust their supply by reducing flight frequency or by raising airfares to offset heightened operational expenses. Airline-specific market share[3] at time ‘t’ ($PaxShare_{i,t}$), and market concentration as measured by Herfindahl-Hirschman Index (HHI) market concentration at time ‘t’ (HHI_t) are also critical determinants of ways in which airlines respond to the dynamic market conditions and adjust the availability of seats and that are not linked directly with passengers (demand). An airline's dominance in market share suggests its capacity to supply more seats, raise prices, or leverage economies of scale to drive prices down. Meanwhile, a higher HHI, indicating less competition, may lead to less price-sensitive supply, allowing airlines with significant market power to maintain higher fares without significantly altering supply levels. It may also encourage airlines to merge to realize greater economies of scale and lower prices. This leads us to create a supply function as follows:

$$\boldsymbol{Q_{it-S} = F(FARE_{i,t},\ JFUEL_t, PaxShare_{i,t}, HHI_t)} \tag{3}$$

This equation suggests that the number of seats an airline sells at any time is influenced by a mix of market conditions (economic health and competition), operational costs (fuel prices), and the airline's specific circumstances (market share). The model may predict how changes in these factors would affect seat sales, which is essential for strategic planning in the airline industry.

5. Empirical Model

As discussed previously, gravity models allow us to simultaneously use demand and supply functions within a general equilibrium framework. This enables us to use a Cobb-Douglas specification based on maximizing consumer utility and minimizing producer costs (Oum, Waters, & Yong, 1992). More specifically, Wang, Zhang, and Zhang (2018) use the reduced form of the Cobb-Douglas specification to illustrate the own-price, cross-price, and income elasticities.[4] This also allows us to determine the sensitivity of parameters to price for our sample with this empirical specification.

The empirical specification that can be used in reduced form to be estimated is as follows:

$$\boldsymbol{lFARE_{i,t} = \widehat{\beta}_0 + \widehat{\beta}_1 lPAX_{i,t} + \widehat{\beta}_2 lJFUEL_{i,t} + \widehat{\beta}_3 lCAGDP_t + \widehat{\beta}_4 lCOGDP_t + \widehat{\beta}_5 lINC_t +}$$

$$\boldsymbol{\widehat{\beta}_6 lACCD_t + +\widehat{\beta}_7 lHHI_t + \widehat{\beta}_8 lF_{legacy_t} + \widehat{\beta}_9 lF_{lcc_t} + \sum_{j=1}^{7} \delta_j A_{j,t} + \sum_{k=1}^{3} Q_k} \tag{4}$$

This regression model is designed to estimate a Cobb-Douglas relationship between the logarithm of average airfare ($FARE$) and several explanatory variables that are believed to influence it, where:

$lFARE_{i,t}$: The dependent variable is the natural log of the average airfare.

$lPAX_{i,t}$: Logarithm of passenger volume per day. This could reflect demand: more passengers might lead to higher prices, or it could indicate economies of scale that reduce prices.

$lJFUEL_{i,t}$: The logarithm of jet fuel price. Fuel costs could lead to higher airfares as airlines pass them on to consumers.

$lCAGDP_t$The logarithm of real GDP of California. Economic health could influence airfare prices through demand.

[2] We used Real Jet Fuel Price (Kerosene Type) deflated to 2023 dollars

[3] Market share is defined as percentage of number of passengers that flew with a given airline as a ratio of total number of passengers that flew on the same route for that period of time

[4] Our specification is different from (Wang, Zhang, Zhang, 2018) in the sense that instead of using geometric mean of origination-destination GDP (O-D) pair we instead isolate the effects of these variables to determine if these have differing effects.

$lCOGDP_t$: The logarithm of real GDP of Colorado. A healthier economy might stimulate demand for air travel, potentially boosting prices.

$lINC_t$: Logarithm of real disposable income. The significance of disposable income is that income could increase or decrease the demand for air travel, potentially affecting airfare prices.

$lACCD_t$: Logarithm of employment rate in the accommodation sector, capturing the influence of the travel and lodging industry's health on airfare pricing by reflecting the sector's demand for travel services and associated economic activity.

lF_{legacy_t}: Logarithm of Average fare index for U.S. legacy carriers, capturing the pricing trends and competitive positioning of established airlines within the market. This was calculated using the weighted average of fares paid by passengers who traveled using legacy carriers during that period.

lF_{lcc_t}: Logarithm of average fare index for low-cost carriers, indicating how price competition and cost-effective operational models of these airlines influence airfare levels. This was calculated using the weighted average of fares paid by passengers who traveled using low-cost carriers during that period.

$lHHI_t$: The logarithm of the Herfindahl-Hirschman Index for market concentration calculated using market shares from below.

$A_{j,t,}$: The market share of each airline (j) at time 't', represented by different airlines such as United Airlines (UA), Frontier Airlines (F9), American Airlines (AA), Delta Air Lines (DL), Spirit Airlines (NK), and Southwest Airlines (WN). These terms capture the individual market-share impact of each airline on airfare prices, calculated from passenger data over a given period.

UA**:** United Airlines market share j=1

$F9$**:** Frontier Airlines market share j=2

AA**:** American Airlines market share j=3

DL**:** Delta Air Lines market share j=4

NK Spirit Airlines' market share j=5

WN**:** Southwest Airlines market share j=6.

AS**:** Alaska airlines market share j=7

US**:** US airways market share j=8

Q_k: dummy variable for the requisite quarter (k=1…4)

6. Data and Summary Statistics

The empirical analysis in this study is supported by a comprehensive dataset from January 1, 2002, to September 1, 2023, encompassing 474 observations. Some of these observations were for different classes on the same airline and were averaged based on the number of passengers who paid that price. The data have been collated from multiple sources. Passenger share and fare data are sourced from the DIIO Cirium (DIIO Mi, 2023) website, which allows us to calculate each airline's (UA, F9, AA, DL, AS, NK, WN) market share on the Denver (DEN) to Los Angeles (LAX) route, along with corresponding airfares. Thus, market share is defined as the number of passengers traveling with a given airline during a given period, divided by the total number of passengers who traveled on that route during that period. Operational cost data, including jet fuel prices, alongside GDP figures for Colorado (COGDP) and California (CAGDP) were obtained from the database of the Federal Reserve Bank of St. Louis (Federal Reserve Bank of St. Louis, 2023), (FRED).[5] HHI was calculated using the market shares obtained above.

[5] All price-related (dollar valued) data—jet fuel prices, disposable income, COGDP, and CAGDP—have been adjusted for inflation.

Table 1a illustrates the descriptive statistics of our dataset for US carriers from DEN to LAX from 2002 to 2022. Table 1b does the same for the route LAX – DEN. ACCD represents employment data from the Traveler Accommodation sector under the North American Industry Classification System[6] (BLS, 2024) from Q1 2002 to Q2 2023. In examining the dynamics of airfare pricing, ACCD offers employment and unemployment trends within the hospital, travel, tourism, and accommodation industry, sourced from both employer and national household surveys. Given the connections between the health of the travel sector and airline pricing strategies, analyzing workforce statistics from this segment shows how fluctuations in employment within the travel accommodation sector may influence airfare levels. The Legacy and LCC fare indices provide a weighted average of the price paid by revenue-paying passengers for US legacy and low-cost carriers, respectively, from Q1 2002 to Q2 2023. Both indices serve as crucial indicators of how shifts in the pricing approaches of these distinct airline categories affect the overall airfare landscape for the DEN-LAX city pair and how average fares influence consumer fare options.

Table 1a. Descriptive Statistics dataset from Denver to Los Angeles, 2002 – 2022

Statistic	N	Mean	St. Dev.	Min	Max
PAX	474	239.4	190.4	3.1	797.9
FARE	474	177.4	59.5	24.4	398
COGDP	474	391,806	60,788	304,444	514,223
CAGDP	474	3,047,827	472,011	2,240,362	3,884,718
INC	474	16,388	2,141	12,055	18,157
JFUEL	474	2.6	1	0.9	5.1
ACCD	474	12,030	1,304	8,875	14,289
UA	474	0.4	0.1	0.2	0.6
F9	474	0.2	0.1	0	0.4
AA	474	0.1	0.05	0.03	0.2
DL	474	0.1	0.1	0.004	0.2
AS	474	0.01	0.01	0	0.03
NK	474	0.03	0.04	0	0.1
US	474	0.01	0.01	0	0.1
WN	474	0.2	0.2	0	0.4
HHI	474	0.3	0.04	0.2	0.4
F_legacy	474	210.8	45.8	90	329.7
F_lcc	474	162.8	54.4	62.9	346.2

Source: DIIO Mi, Federal Reserve Bank of St. Louis, Bureau of Labor Statistics: Accessed 2024

Table 1b. Descriptive Statistics of dataset Los Angeles to Denver, 2002 – 2022

Statistic	N	Mean	St. Dev.	Min	Max
PAX	471	250	196.5	6.9	819.2
JFUEL	471	2.6	1	0.9	5.1
FARE	471	167.7	61.8	17.8	362.3
CAGDP	471	3,061,612	466,691	2,240,362	3,884,718
COGDP	471	393,594	60,260	304,444	514,223
INC	471	16,353	2,143	12,055	18,157
ACCD	471	12,077	1,282	8,875	14,289
UA	471	0.4	0.1	0.2	0.6
F9	471	0.2	0.1	0	0.4
AA	471	0.1	0.05	0.03	0.2
DL	471	0.1	0.1	0.004	0.2
AS	471	0.01	0.01	0	0.03
NK	471	0.03	0.04	0	0.1
US	471	0.01	0.01	0	0.1
WN	471	0.2	0.1	0	0.4
HHI	471	0.3	0.04	0.2	0.4
F_legacy	466	160.5	25.5	79.4	204.1
F_lcc	461	119.2	26.9	54.9	205

Sources: DIIO Mi, Federal Reserve Bank of St. Louis, Bureau of Labor Statistics: Accessed 2024

[6] Workforce employment statistics are obtained from the accommodation subsector under Traveler Accommodation with Workforce Employment Statistics retrieved from the North American Industry Classification System (NAICS) 7211.

Table 2 (parts a & b) illustrate the correlation coefficients of variables in this study. ***Table 2a*** highlights the coefficient for variables on the DEN–LAX route. There is a high correlation (70-73%) between overall prices and fares charged by legacy and low-cost carriers. Prices charged by both legacy and low-cost carriers have a strong correlation with the Herfindahl-Hirschman Index (69% and 78% respectively). This suggests intense price competition faced by legacy carriers on this route. Finally, there is a high correlation of 90% between the fare indices of legacy (F_legacy) and low-cost carriers (F_lcc), indicating that changes in the other closely mirror fare changes in one category of carriers.

Table 2a. Correlation Coefficients of variables under study for the Denver to Los Angeles Route

	PAX	JFUEL	FARE	COGDP	CAGDP	INC	ACCD	UA	F9	AA	DL	AS	NK	US	WN	HHI	F_legacy	F_lcc
PAX	1	0.02	0.02	0.2	0.22	-0.1	0.28	-0.22	-0.21	-0.13	0.11	-0.19	0.24	-0.07	0.24	-0.22	-0.16	-0.21
JFUEL	0.02	1	0.15	-0.06	-0.05	0.03	0.1	-0.06	0.15	-0.31	-0.3	-0.02	-0.29	0.43	0.25	0.03	0.16	0.04
FARE	0.02	0.15	1	-0.62	-0.63	0.46	-0.42	0.49	0.51	0.36	-0.53	0.39	-0.49	0.18	-0.48	0.57	0.71	0.73
COGDP	0.2	-0.06	-0.62	1	0.98	-0.84	0.72	-0.45	-0.85	-0.44	0.83	-0.5	0.57	-0.2	0.59	-0.56	-0.79	-0.84
CAGDP	0.22	-0.05	-0.63	0.98	1	-0.76	0.76	-0.53	-0.83	-0.42	0.78	-0.53	0.63	-0.17	0.62	-0.62	-0.79	-0.87
INC	-0.1	0.03	0.46	-0.84	-0.76	1	-0.48	0.13	0.7	0.4	-0.85	0.3	-0.21	0.28	-0.34	0.28	0.66	0.58
ACCD	0.28	0.1	-0.42	0.72	0.76	-0.48	1	-0.47	-0.78	-0.41	0.45	-0.48	0.67	-0.06	0.65	-0.51	-0.45	-0.62
UA	-0.22	-0.06	0.49	-0.45	-0.53	0.13	-0.47	1	0.31	0.47	-0.17	0.55	-0.56	-0.22	-0.81	0.86	0.5	0.7
F9	-0.21	0.15	0.51	-0.85	-0.83	0.7	-0.78	0.31	1	0.42	-0.72	0.41	-0.67	0.27	-0.58	0.38	0.62	0.67
AA	-0.13	-0.31	0.36	-0.44	-0.42	0.4	-0.41	0.47	0.42	1	-0.26	0.36	-0.2	-0.28	-0.79	0.32	0.35	0.47
DL	0.11	-0.3	-0.53	0.83	0.78	-0.85	0.45	-0.17	-0.72	-0.26	1	-0.3	0.41	-0.41	0.23	-0.38	-0.73	-0.63
AS	-0.19	-0.02	0.39	-0.5	-0.53	0.3	-0.48	0.55	0.41	0.36	-0.3	1	-0.42	-0.04	-0.55	0.52	0.42	0.53
NK	0.24	-0.29	-0.49	0.57	0.63	-0.21	0.67	-0.56	-0.67	-0.2	0.41	-0.42	1	-0.26	0.49	-0.63	-0.51	-0.64
US	-0.07	0.43	0.18	-0.2	-0.17	0.28	-0.06	-0.22	0.27	-0.28	-0.41	-0.04	-0.26	1	0.24	-0.04	0.27	0.12
WN	0.24	0.25	-0.48	0.59	0.62	-0.34	0.65	-0.81	-0.58	-0.79	0.23	-0.55	0.49	0.24	1	-0.61	-0.46	-0.69
HHI	-0.22	0.03	0.57	-0.56	-0.62	0.28	-0.51	0.86	0.38	0.32	-0.38	0.52	-0.63	-0.04	-0.61	1	0.69	0.78
F_legacy	-0.16	0.16	0.71	-0.79	-0.79	0.66	-0.45	0.5	0.62	0.35	-0.73	0.42	-0.51	0.27	-0.46	0.69	1	0.9
F_lcc	-0.21	0.04	0.73	-0.84	-0.87	0.58	-0.62	0.7	0.67	0.47	-0.63	0.53	-0.64	0.12	-0.69	0.78	0.9	1

Table 2b highlights the correlation coefficients for variables on the LAX – DEN route. Of note is a positive correlation of only 59% between overall fares and those charged by low-cost carriers, indicating a more substantial divergence in fares on this route between legacy and low-cost carrier strategies, which we will explore in this paper. Conversely, a negative correlation of almost 70% between Colorado's and California’s GDP and fares charged by low-cost carriers suggests that, even as the economies of both states improved, price competition put pressure on these airlines on this route. Overall, this tells us that each route and its legs have their own characteristics. While we can make broad conclusions about demand for air travel, the idiosyncrasies associated with each route is a fascinating subject of attention and detailed analysis.

Table 2b. Correlation Coefficients of variables under study for the Los Angeles to Denver Route

	PAX	JFUEL	FARE	COGDP	CAGDP	INC	ACCD	UA	F9	AA	DL	AS	NK	US	WN	HHI	F_legacy	F_lcc
PAX	1	0	0.22	0.16	0.18	-0.07	0.28	-0.15	-0.2	-0.04	0.08	-0.16	0.22	-0.09	0.16	-0.16	-0.03	-0.13
JFUEL	0	1	0.17	-0.08	-0.06	0.04	0.07	-0.06	0.18	-0.32	-0.32	-0.01	-0.32	0.42	0.24	0.04	0.42	0.26
FARE	0.22	0.17	1	-0.5	-0.5	0.37	-0.32	0.37	0.42	0.19	-0.43	0.28	-0.42	0.17	-0.32	0.49	0.46	0.59
COGDP	0.16	-0.08	-0.5	1	0.98	-0.82	0.74	-0.46	-0.86	-0.37	0.81	-0.5	0.58	-0.2	0.56	-0.58	-0.35	-0.7
CAGDP	0.18	-0.06	-0.5	0.98	1	-0.74	0.78	-0.53	-0.84	-0.35	0.76	-0.53	0.64	-0.18	0.6	-0.64	-0.34	-0.73
INC	-0.07	0.04	0.37	-0.82	-0.74	1	-0.45	0.14	0.68	0.34	-0.83	0.29	-0.19	0.29	-0.31	0.3	0.36	0.45
ACCD	0.28	0.07	-0.32	0.74	0.78	-0.45	1	-0.51	-0.76	-0.36	0.43	-0.49	0.66	-0.06	0.65	-0.54	0.02	-0.44
UA	-0.15	-0.06	0.37	-0.46	-0.53	0.14	-0.51	1	0.34	0.47	-0.17	0.57	-0.58	-0.21	-0.82	0.86	0.16	0.65
F9	-0.2	0.18	0.42	-0.86	-0.84	0.68	-0.76	0.34	1	0.35	-0.7	0.41	-0.67	0.29	-0.57	0.41	0.22	0.53
AA	-0.04	-0.32	0.19	-0.37	-0.35	0.34	-0.36	0.47	0.35	1	-0.17	0.34	-0.14	-0.3	-0.78	0.3	-0.11	0.23
DL	0.08	-0.32	-0.43	0.81	0.76	-0.83	0.43	-0.17	-0.7	-0.17	1	-0.28	0.4	-0.41	0.17	-0.4	-0.55	-0.58
AS	-0.16	-0.01	0.28	-0.5	-0.53	0.29	-0.49	0.57	0.41	0.34	-0.28	1	-0.42	-0.03	-0.56	0.53	0.12	0.45
NK	0.22	-0.32	-0.42	0.58	0.64	-0.19	0.66	-0.58	-0.67	-0.14	0.4	-0.42	1	-0.28	0.47	-0.64	-0.3	-0.66
US	-0.09	0.42	0.17	-0.2	-0.18	0.29	-0.06	-0.21	0.29	-0.3	-0.41	-0.03	-0.28	1	0.24	-0.02	0.42	0.24
WN	0.16	0.24	-0.32	0.56	0.6	-0.31	0.65	-0.82	-0.57	-0.78	0.17	-0.56	0.47	0.24	1	-0.6	0.06	-0.48
HHI	-0.16	0.04	0.49	-0.58	-0.64	0.3	-0.54	0.86	0.41	0.3	-0.4	0.53	-0.64	-0.02	-0.6	1	0.46	0.79
F_legacy	-0.03	0.42	0.46	-0.35	-0.34	0.36	0.02	0.16	0.22	-0.11	-0.55	0.12	-0.3	0.42	0.06	0.46	1	0.72
F_lcc	-0.13	0.26	0.59	-0.7	-0.73	0.45	-0.44	0.65	0.53	0.23	-0.58	0.45	-0.66	0.24	-0.48	0.79	0.72	1

7. Empirical Results

7.1 Regression Results for DEN – LAX and LAX – DEN

When we examine the interplay between quantity and price derived from the reduced-form equation, the airline seats available versus the price paid by consumers provides insights into market dynamics. As discussed before, solving for the utility function leads us to use log-log models to analyze pricing in the reduced-form gravity equation. The log-log specification allows for examining elasticity, revealing how percentage changes in passenger volume, jet fuel prices, and economic conditions proportionally affect airfares. This approach offers insight into the interplay among customer characteristics, market competition, and macroeconomic conditions, thereby providing valuable guidance on optimal pricing strategies and market dynamics in this sector.

We use different models to progressively incorporate a broader spectrum of variables to capture the multifaceted nature of air travel demand and pricing. The main model captures the effects of quantity (number of passengers) and jet fuel prices on airfare paid. Gross Domestic Product for California (CAGDP) and Colorado (COGDP) offer insights into the economic backdrop influencing travel behaviors and fare structures. Additionally, the inclusion of all employees in the accommodation and food services sector (ACCD) underscores the vitality of the leisure and hospitality industry. It serves as a proxy for a supply factor in the empirical equation. The GDPs of Colorado (COGDP) and California (CAGDP) also serve as proxies for the financial health of the airline's operational and customer bases, respectively.

Similarly, higher disposable income among consumers can lead to increased demand for air travel, prompting airlines to charge higher fares, as these consumers are willing to pay more for their tickets. These economic indicators have conflicting influences on airfares. On the one hand, a higher GDP/income level may signal increased consumer spending power and travel demand, potentially leading to higher fares. On the other hand, economic stabilizers such as higher wages and interest rates could also reduce supply on this route due to cost considerations. However, stabilizer effects take longer to kick into an economy. Additionally, on the supply side, greater competition tends to drive prices down. However, these effects are ambiguous due to interactions among companies in an oligopoly.

Table 3 describes the results of OLS regressions for the route DEN – LAX. In particular, Table 3a uses models 1 – 7. Across models 1-7, we observe that passenger volume is positively correlated with fare. As observed from models 3, 4, and 5, the explanatory power improves relative to models 1 and 2, and the effect of passengers on fare becomes statistically significant at the 1% level. However, this relationship is inelastic. This correlation is confirmed as we added more variables to models 8-14, shown in Table 3b, where passengers and jet fuel are the most significant determinants of ticket prices, consistently across all 14 models for both routes (DEN–LAX–DEN). We show the results for models 1 – 7 for the route LAX – DEN (return route) in Table 4a. We also show models 8 – 14 for the route LAX – DEN (return route) in Table 4b. Going back to models 8 – 14 for DEN-LAX, the relationship between JFUEL and fare is also positive, indicating that while airlines want to pass on the higher fuel costs to the passengers, they are hindered somewhat by the market dynamics and competition. Therefore, this relationship suggests some absorption effects of changes in Jet Fuel prices by airline companies themselves (coefficient < 1), possibly indicating evidence of the presence of strong competition on the route as well as the nature of the industry in general.

Table 3a. Regression Results with heteroskedasticity robust White's standard errors obtained by using independent variables for Denver to Los Angeles (DEN – LAX) Route (Models 1 – 7)

	Dependent variable:						
	lFARE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lPAX	-0.002	-0.004	0.057^{***}	0.052^{***}	0.058^{***}	0.018	0.034^{**}
	(0.018)	(0.017)	(0.014)	(0.014)	(0.014)	(0.016)	(0.017)
lCAGDP			-1.764^{***}		-2.138^{***}		
			(0.105)		(0.586)		
lCOGDP				-1.765^{***}	0.389		
				(0.109)	(0.600)		
lINC						1.308^{***}	
						(0.126)	
lJFUEL		0.240^{***}	0.263^{***}	0.236^{***}	0.268^{***}	0.230^{***}	0.334^{***}
		(0.051)	(0.040)	(0.040)	(0.041)	(0.045)	(0.048)
lACCD							-1.601^{***}
							(0.181)
Constant	5.098^{***}	4.896^{***}	30.896^{***}	27.339^{***}	31.458^{***}	-7.875^{***}	19.663^{***}
	(0.092)	(0.100)	(1.547)	(1.387)	(1.774)	(1.238)	(1.674)
Observations	449	449	449	449	449	449	449
R^2	0.00003	0.048	0.418	0.402	0.419	0.233	0.190
Adjusted R^2	-0.002	0.044	0.415	0.398	0.414	0.227	0.185

Residual Std. Error (df)	0.437 (447)	0.426 (446)	0.334 (445)	0.339 (445)	0.334 (444)	0.383 (445)	0.394 (445)
F Statistic	0.013 (1; 447)	11.29*** (2; 446)	106.73*** (3; 445)	99.55*** (3; 445)	80.05*** (4; 444)	44.96*** (3; 445)	34.831*** (3; 445)
Note:					*p<0.1; **p<0.05; ***p<0.01		

Table 3b. Regression Results with heteroskedasticity robust White's standard errors obtained by using independent variables for the Denver to Los Angeles (DEN – LAX) Route (Models 8 – 14)

	Dependent variable:						
	lFARE						
	(~~1~~ 8)	(~~2~~ 9)	(~~3~~10)	(~~4~~ 11)	(~~5~~12)	(~~6~~ 13)	(~~7~~ 14)
lPAX	0.056***	0.063***	0.061***	0.060***	0.060***	0.075***	0.074***
	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
lJFUEL	0.207***	0.247***	0.135***	0.111***	0.111***	0.087	0.063
	(0.042)	(0.043)	(0.039)	(0.038)	(0.038)	(0.054)	(0.056)
lF_legacy			0.947***		0.238		
			(0.079)		(0.164)		
lF_lcc				0.838***	0.665***		
				(0.064)	(0.135)		
lACCD		-0.601***	-0.428***	0.038	-0.051	1.004***	1.041***
		(0.185)	(0.162)	(0.165)	(0.176)	(0.286)	(0.287)
UA						-2.204**	-1.503
						(1.023)	(1.111)
F9						-1.245	-0.919
						(0.834)	(0.870)
AA						-1.526	-1.030
						(1.020)	(1.070)
DL						-3.358***	-3.200***
						(0.776)	(0.792)
AS						3.736	2.800
						(2.882)	(2.966)
NK						-2.363**	-2.183**
						(0.954)	(0.962)
US						2.850	3.295*
						(1.774)	(1.804)
WN						-2.403***	-1.944**
						(0.826)	(0.878)
lHHI	1.578***	1.377***	0.434***	0.151	0.167	1.152***	1.057***
	(0.111)	(0.126)	(0.135)	(0.142)	(0.142)	(0.256)	(0.262)
Q1							-0.009
							(0.044)
Q2							0.013
							(0.043)
Q3							0.074*
							(0.044)
Q4							
Constant	6.640***	11.957***	4.206***	0.326	0.780	-1.350	-2.295

	(0.148)	(1.646)	(1.575)	(1.658)	(1.685)	(2.674)	(2.735)
Observations	449	449	449	449	449	449	449
R^2	0.347	0.362	0.517	0.540	0.542	0.500	0.505
Adjusted R^2	0.343	0.357	0.512	0.535	0.536	0.487	0.488
Residual Std. Error (df)	0.354 (445)	0.350 (444)	0.305 (443)	0.298 (443)	0.297 (442)	0.313 (436)	0.312 (433)
F Statistic	78.872*** (3; 445)	63.050*** (4; 444)	94.851*** (5; 443)	103.983*** (5; 443)	87.223*** (6; 442)	36.386*** (12; 436)	29.412*** (15; 433)
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 4a. Regression Results with heteroskedasticity robust White's standard errors obtained by using independent variables for Los Angeles to Denver (LAX - DEN) Route (Models 1 – 7)

	Dependent variable:						
	lFARE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lPAX	0.058***	0.058***	0.113***	0.108***	0.113***	0.079***	0.111***
	(0.021)	(0.020)	(0.018)	(0.018)	(0.018)	(0.019)	(0.020)
lCAGDP			-1.818***		-2.276***		
			(0.130)		(0.733)		
lCOGDP				-1.815***	0.476		
				(0.135)	(0.749)		
lINC						1.335***	
						(0.152)	
lJFUEL		0.220***	0.258***	0.230***	0.265***	0.212***	0.328***
		(0.058)	(0.049)	(0.050)	(0.050)	(0.054)	(0.055)
lACCD							-2.000***
							(0.213)
Constant	4.730***	4.539***	31.358***	27.637***	32.055***	-8.498***	22.967***
	(0.107)	(0.117)	(1.923)	(1.715)	(2.216)	(1.486)	(1.970)
Observations	466	466	466	466	466	466	466
R^2	0.017	0.046	0.329	0.316	0.330	0.183	0.198
Adjusted R^2	0.015	0.042	0.325	0.311	0.324	0.178	0.193
Residual Std. Error (df)	0.508 (464)	0.501 (463)	0.420 (462)	0.425 (462)	0.421 (461)	0.464 (462)	0.460 (462)
F Statistic (df)	7.910*** (1; 464)	11.164*** (2; 463)	75.545*** (3; 462)	71.035*** (3; 462)	56.686*** (4; 461)	34.482*** (3; 462)	38.100*** (3; 462)
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 4b. Regression Results with heteroskedasticity robust White's standard errors obtained by using independent variables for Los Angeles to Denver (LAX - DEN) Route (Models 8 – 14)

	Dependent variable:						
	lFARE						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
lPAX	0.108***	0.124***	0.130***	0.126***	0.128***	0.130***	0.129***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
lJFUEL	0.188***	0.243***	0.103**	0.072	0.063	0.051	0.029
	(0.050)	(0.051)	(0.052)	(0.052)	(0.052)	(0.067)	(0.069)

lF_legacy			1.049^{***}		0.443^{**}		
			(0.140)		(0.210)		
lF_lcc				1.085^{***}	0.768^{***}		
				(0.132)	(0.200)		
lACCD		-0.920^{***}	-1.522^{***}	-0.979^{***}	-1.215^{***}	0.820^{**}	0.874^{**}
		(0.226)	(0.229)	(0.212)	(0.239)	(0.367)	(0.373)
UA						-3.555^{***}	-3.037^{**}
						(1.285)	(1.368)
F9						-0.966	-0.647
						(1.053)	(1.095)
AA						-2.453^{*}	-2.032
						(1.286)	(1.336)
DL						-2.619^{***}	-2.403^{**}
						(0.989)	(1.008)
AS						1.385	0.388
						(3.659)	(3.777)
NK						-3.312^{***}	-3.234^{***}
						(1.212)	(1.218)
US						1.070	1.403
						(2.242)	(2.278)
WN						-2.523^{**}	-2.136^{*}
						(1.038)	(1.091)
lHHI	1.721^{***}	1.415^{***}	0.592^{***}	0.019	0.081	1.844^{***}	1.810^{***}
	(0.131)	(0.149)	(0.179)	(0.220)	(0.221)	(0.324)	(0.329)
Q1							-0.010
							(0.055)
Q2							0.035
							(0.055)
Q3							0.058
							(0.055)
Q4							
Constant	6.510^{***}	14.632^{***}	14.013^{***}	8.386^{***}	9.953^{***}	1.515	0.574
	(0.181)	(2.008)	(1.899)	(2.025)	(2.151)	(3.461)	(3.592)
Observations	466	466	466	466	466	466	466
R^2	0.305	0.329	0.402	0.415	0.420	0.405	0.408
Adjusted R^2	0.300	0.323	0.395	0.408	0.413	0.390	0.388
Residual Std. Error (df)	0.428 (462)	0.421 (461)	0.398 (460)	0.394 (460)	0.392 (459)	0.400 (453)	0.400 (450)
F Statistic (df num; den)	67.528^{***} (3; 462)	56.468^{***} (4; 461)	61.755^{***} (5; 460)	65.161^{***} (5; 460)	55.445^{***} (6; 459)	25.744^{***} (12; 453)	20.646^{***} (15; 450)
Note:							*p<0.1; **p<0.05; ***p<0.01

In models 3, 4, and 5 in tables 3a and 4a, for both routes we observe that a 1% increase in California GDP results in a decrease of almost 2% in fares on this route. The effect of Colorado's GDP is more ambiguous but similar, possibly due to the high correlation of the two variables with each other as seen in Table 2. In Model 4, on both routes, a 1% increase in Colorado GDP results in a nearly 2% decrease in fares. Income, on the other hand, is positively correlated with fare, with a 1% increase in income leading to a 1.3% increase in fares on both routes (model 6) due to strong demand-side effects.

We used employment in accommodation as an index to measure the level of economic activity in the tourism and hospitality industry. The accommodation index (ACCD) is negatively correlated with fares (models 7, 9, and 10), but the effects are ambiguous in models 11 and 12. As we add more explanatory power through models 13 and 14, the accommodation index has a positive, significant (at 1%) but mildly inelastic relationship with the fare. These results are robust across both routes. Comparing models 3, 4, 5, and 7, we observe that, due to the correlation between ACCD and COGDP and CAGDP (Table 2), the ACCD variable behaves similarly to COGDP and CAGDP in terms of its effect on the percentage change in fare (i.e., the coefficients are strongly and negatively associated with prices).

Jet fuel has a strong effect on prices, both directly and indirectly, through demand and supply-side effects. On the demand side, it reduces disposable income, thereby reducing the propensity to fly, assuming a high correlation with gasoline prices, as seen in Wood and Gokhale (2017). On the supply side, there is a direct positive correlation, provided the supply is not inelastic. In our examination, the jet fuel price generally shows a positive, significant (at least 10% in most models) correlation with the fare. In fact, in model 7, a 1% rise in fuel prices generally increases fares by 0.2% to 0.3%, ceteris paribus, possibly picking up the airline-specific effects, which we discuss in empirical specifications in models 10 – 14.

As we add airline specific fixed effects (i.e. market share of each airline as the regressor) to increase explanatory power, the effect of jet fuel on fares becomes weaker. In contrast, the effect of market power (HHI) remains stable, positive, and significant, particularly on the LAX-DEN side (Table 4b vs Table 3b). Some of those effects in earlier models (1-12) seem to capture airline-specific fixed effects, which, when accounted for in models 13 and 14, provide a clearer picture of the correlation between this index and fare, which, although positive, is not statistically significant at 5%. This underscores again the importance of firm behavior in an oligopolistic market structure and the influence it exerts on each other's pricing strategies.

Most of the airline-specific fixed effects are negative and significant at the 10% level, implying that, after accounting for all other variables, airlines tend to keep their fares low, with all majors involved in this activity (models 13 and 14). In particular, we notice that Delta appears to be trying to gain market share by flying its passengers at a lower average fare, particularly on the DEN-LAX route.[7] Spirit, as it is popularly known for low fares, is not far behind, and it is aggressive on fares on both sides of the route. The others include Southwest and Frontier. On the other hand, firm-specific fixed effects for US Airways on the DEN–LAX route are positive. This result should be analyzed carefully because the airline operated in a different environment. However, the effect was passed on to American Airlines, whose firm-specific fixed effect is not significantly different from zero. Coming back to US Airways, our results indicate that when the airline operated, it flew at fares above average, placing it in the category of legacy carriers during its period of operation.[8]

Next, when examining market power, the variable of interest is the HHI. The HHI coefficient indicates the effect of market power on fares on the route. The coefficient is positive and significant at the 1% level, and it is greater than 1. We can interpret this to mean that an increase in market power (an increase in HHI) leads to higher prices charged to customers. This is robust across all models (8 - 14), across both routes, and ties in with our previous discussion on why jet fuel prices were not impacting prices nearly as much as HHI.

Another important observation is the price interplay effects of legacy and low-cost carriers (models 10, 11, and 12). From Table 2, we observe that both legacy and low-cost carriers have a positive correlation with overall market fares. However, the coefficient is not greater than 1, meaning 1% change in the price of either legacy or low-cost carrier leads to less than 1% change in overall fare in the market, thereby implying that while these airlines tend to keep their prices low, they also have a significant effect on each other's prices, cutting across sectors. This is more pronounced on the LAX–DEN route, underscoring the effect of multiple alternatives available to passengers at LAX. Although cross-sector effects are generally relatively small, some airlines, such as Frontier, Spirit, Delta, and Southwest, have tried to lead this route by keeping prices low to maintain their market share.

Next, we analyze variance inflation factors (VIFs) of the 14 specifications. These are shown in Table 5. These are highly similar. Therefore, we will discuss those together. We find that the economic variables jet fuel, accommodation index, income, and number of passengers are stable and do not exhibit collinearity. Fares of legacy and low-cost carriers are variable. On their own, they do not show collinearity, but together they show collinearity. Hence, it is best to

[7] We did a coefficient comparison test in model 13 to find that the difference between the coefficients of Delta and American and Frontier as well as Southwest and Frontier and found that Delta and Southwest are indeed trying to gain market share by cutting fares

[8] It must be noted that US airways eventually merged with American in 2013 and US airways specific fixed effects existed before that time

consider only one. Similarly, Colorado and California GDP and income show strong collinearity when used together, especially with the accommodation index, as they all reflect economic growth, and the accommodation index is based on an industry that is strongly procyclical.

Table 5. Summary of Variance Inflation Factors for Models 1 - 14

Model Type	**VIF Range (DEN-LAX)**	**VIF Range (LAX-DEN)**	**Conclusion**
Initial Models (Models 2-11)	1.0 to 3.56	1.0 to 3.56	Excellent stability in both directions.
Models with lCAGDP and lCOGDP (Model 5)	33.2 to 33.5	33.1 to 33.4	Strong collinearity in both directions.
Models with Individual Airline Dummies (13 & 14)	1.7 to 80.9	1.63 to 77.4	Very high collinearity in both directions, particularly WN and UA.
Model with quarterly dummies	< 2	< 2	Seasonality patterns do not show a collinearity pattern

We use this information to create three more models, 15 to 17. In model 15, we use California GDP rather than Colorado GDP, and we use HHI rather than airline market shares. Then, in model 16, we use Colorado GDP, but not California GDP. Similarly, we use airline market shares but not HHI. Finally, in model 17, we use Colorado GDP with HHI, but drop the substitute fares. This model produces stable VIFs in both directions, with VIFs ranging from 1.11 to 2.43 (DEN-LAX) and 1.1 to 2.83 (LAX-DEN). Model 17 seems to produce the most optimal results, including key economic drivers (lJFUEL, lPAX, lCOGDP, lHHI, quarterly dummies) without redundant terms. Hence, model 17 seems best specified. We present the regression results from models 15–17 for both routes in Table 6 below.

Table 6a presents the results of regressions after accounting for VIFs for the DEN-LAX route. These models confirm the previous results. The effects of jet fuel prices and accommodation index labor costs are inelastically passed on to customers through fares. Competition affects prices strongly.

Table 6a. Regression results for Models 15 – 17 from Denver to Los Angeles

Heteroskedasticity-Robust Regression Results for Models 15 to 17			
	Dependent variable:		
	DEN-LAX lFARE		
	(15)	(16)	(17)
lPAX	0.06^{***}	0.06^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)
lJFUEL	0.14^{***}	0.07	0.17^{***}
	(0.04)	(0.05)	(0.03)
lACCD	0.06	0.15	0.74^{**}
	(0.38)	(0.38)	(0.33)
lCAGDP	-0.62^{**}		
	(0.31)		
lF_legacy	0.73^{***}		
	(0.15)		
lHHI	0.45^{***}		1.01^{***}
	(0.15)		(0.13)
lCOGDP		0.18	-1.55^{***}
		(0.42)	(0.22)
lF_lcc		0.77^{***}	
		(0.14)	
UA		0.64	
		(0.51)	
F9		0.30	
		(0.49)	
AA		0.86	
		(0.79)	

DL		-0.25	
		(0.73)	
AS		2.25	
		(1.54)	
NK		0.12	
		(0.81)	
US		3.38**	
		(1.42)	
WN		0.24	
		(0.50)	
Q1	-0.02	0.03	-0.03
	(0.04)	(0.04)	(0.04)
Q2	-0.01	0.04	-0.02
	(0.04)	(0.04)	(0.04)
Q3	-0.01	0.04	0.04
	(0.04)	(0.04)	(0.04)
Constant	10.09***	-3.35	18.84***
	(2.92)	(5.11)	(1.65)
Observations	449	449	449
R^2	0.53	0.55	0.48
Adjusted R^2	0.52	0.53	0.47
Residual Std. Error	0.30	0.30	0.32
F Statistic	54.09***	32.86***	51.20***
Note:		*p<0.1 **p<0.05 ***p<0.01	

Table 6b presents the results of regressions after accounting for VIFs for LAX-DEN route. These models also confirm our previous observations. The index of accommodation, which is a proxy for labor costs and jet fuel prices, influences average fares. However, there is also a statistically significant effect of the competition measure, as reflected in market shares and HHI.

Table 6b. Regression results for Models 15 – 17 from Los Angeles to Denver

Heteroskedasticity-Robust Regression Results for Models 15 to 17			
		Dependent variable:	
		lFARE	
	(15)	(16)	(17)
lPAX	0.13***	0.13***	0.12***
	(0.02)	(0.02)	(0.02)
lJFUEL	0.11**	-0.02	0.18***
	(0.05)	(0.07)	(0.04)
lACCD	-0.60	-0.40	0.41
	(0.45)	(0.51)	(0.41)
lCAGDP	-0.83***		
	(0.27)		
lF_legacy	0.83***		
	(0.20)		
lHHI	0.52***		1.15***
	(0.19)		(0.16)

lCOGDP		0.09	-1.36***
		(0.61)	(0.26)
lF_lcc		1.05***	
		(0.20)	
UA		0.21	
		(0.63)	
F9		1.16*	
		(0.61)	
AA		0.37	
		(0.98)	
DL		0.10	
		(0.93)	
AS		1.63	
		(1.93)	
NK		-0.09	
		(1.00)	
US		1.27	
		(2.02)	
WN		0.37	
		(0.57)	
Q1	-0.03	0.05	-0.03
	(0.05)	(0.06)	(0.05)
Q2	-0.05	0.01	0.01
	(0.05)	(0.05)	(0.05)
Q3	-0.02	0.001	0.03
	(0.05)	(0.05)	(0.05)
Constant	18.85***	1.58	19.32***
	(2.24)	(6.51)	(2.04)
Observations	466	466	466
R^2	0.42	0.43	0.39
Adjusted R^2	0.41	0.41	0.38
Residual Std. Error	0.39	0.39	0.40
F Statistic	36.46***	20.96***	36.26***
Note:			*p<0.1 **p<0.05 ***p<0.01

When we compare model 17 for DEN – LAX and the return route, we find that HHI plays a strong role in determining fares. Moreover, this effect is significant. Wage pressures (measured by accommodation index) are more statistically significant on average from the DEN – LAX side than the other way around. However, fuel costs influence prices on both routes. Fares respond vigorously to changes in passenger numbers. COGDP has a negative influence on prices, indicating unaccounted-for adverse supply-side effects associated with perceived higher economic activity. Also, some of the procyclical influence has been captured by the ACCD index, which could make the effects of COGDP slightly confounding, *ceteris paribus*. However, evidence of intense competition on the route suggests that the pass-through from both passengers and fuel on fares, although positive, is inelastic.

Interpretation of results:

HHI: Market concentration and desire for market power are consistent determinants of fares. The elasticities of HHI on both sides are statistically significant.

ACCD: Accommodation index is a proxy for supply-side cost pressures and the ability to provide the best possible services to passengers. This cost is a statistically significant determinant of ticket fares in the DEN–LAX route, but not vice versa.

COGDP: Over time, as GDP grew, supply-side competitive forces and fierce competition for market share likely led to excess capacity and/or lower fares, or both. We see that in Figures 6 and 7 next.

Figure 6 and Figure 7 show the correlation of fare and market share for selected airlines for both routes. From Figure 6 we can see that all three airlines (Delta, Spirit, and Frontier) were forced to cut prices for specific periods to gain a larger share of customers on the DEN–LAX route. We show this relationship for Delta in Figure 6a below, for Spirit in Figure 6b, and for Frontier in Figure 6c.

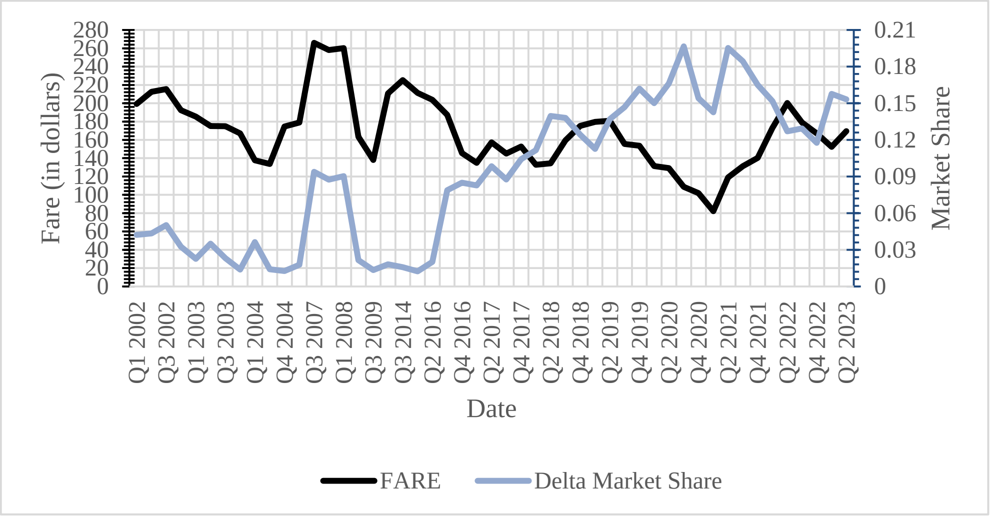

Figure 6a. Market share and Fare versus time for Delta Airlines DEN – LAX (Q1, 2002 - Q2, 2023)

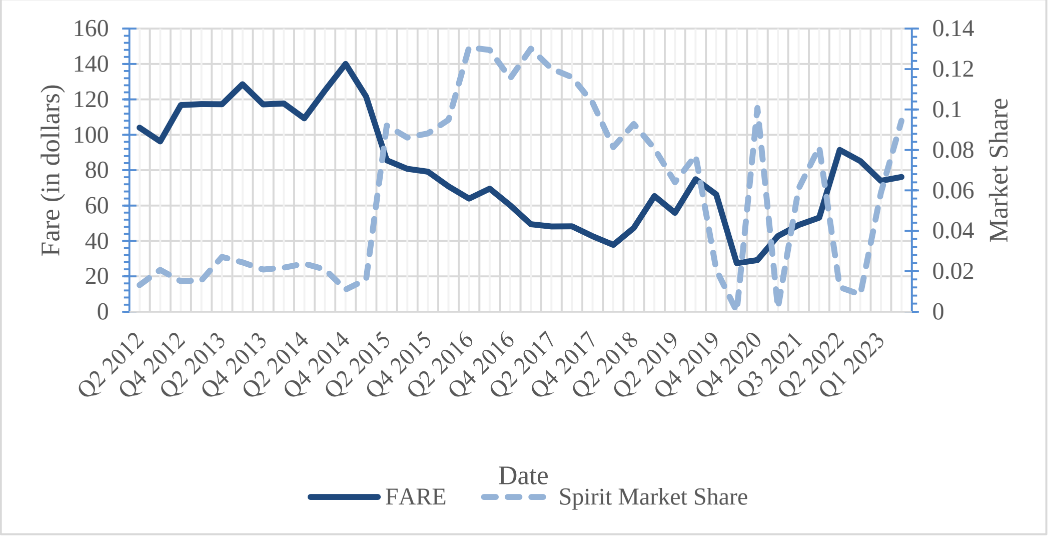

Figure 6b. Market share and Fare versus time for Spirit Airlines DEN – LAX (Q2, 2012 - Q2, 2023)

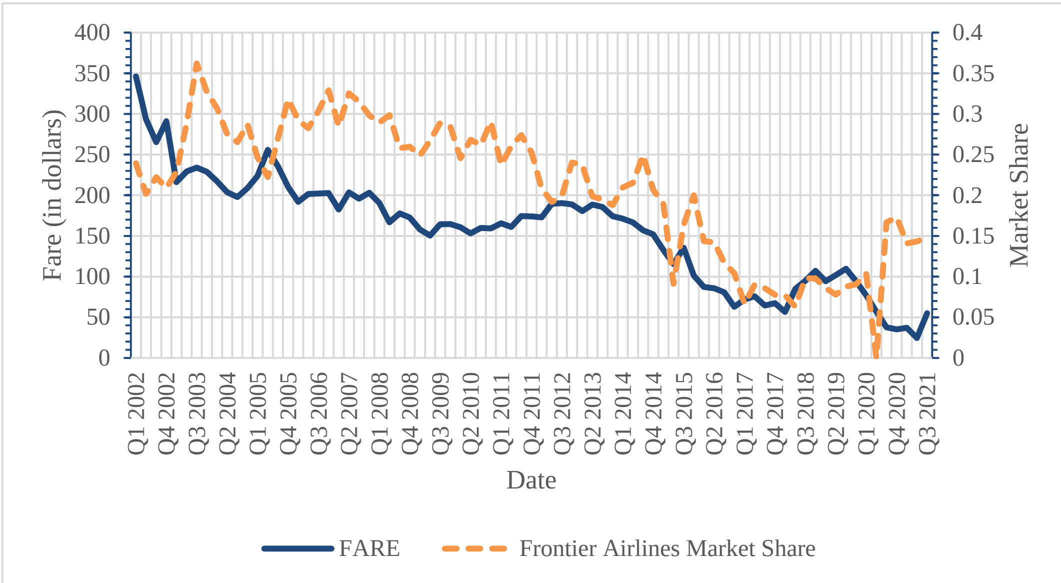

Figure 6c. Market share and Fare versus time for Frontier Airlines DEN – LAX (Q1, 2002 - Q3, 2021)

Figure 7 below shows similar pressures for the route LAX–DEN (return route). Figure 7a shows the inverse correlation between Delta Airlines' prices and market share.

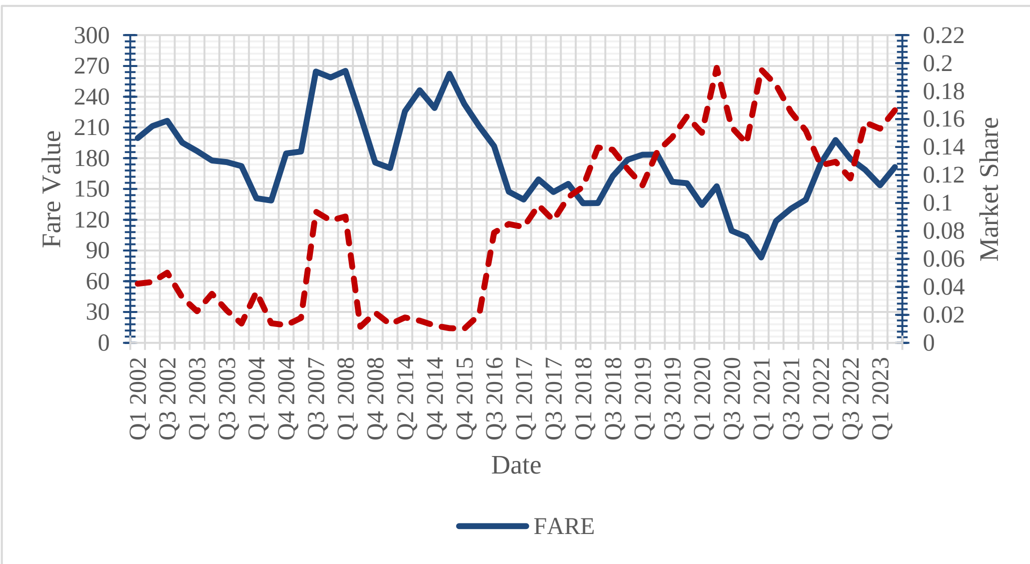

Figure 7a. Market share and Fare versus time for Delta Airlines LAX - DEN (Q1, 2002 - Q2, 2023)

Figure 7b displays Spirit Airlines' market share and price relationship for the period under study.

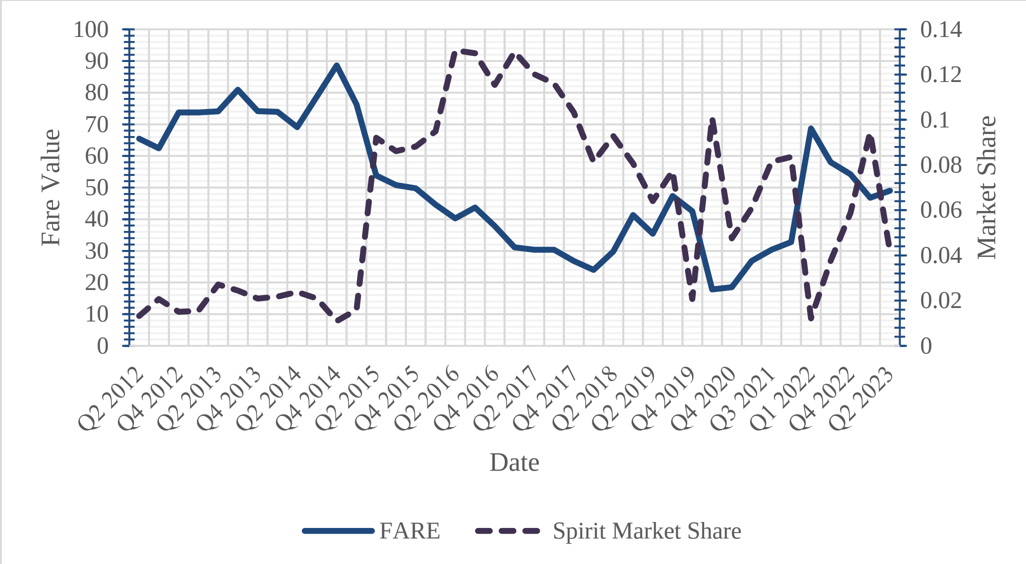

Figure 7b. Market share and Fare versus time for Spirit Airlines LAX – DEN (Q2, 2012 - Q2, 2023)

We observe the same inverse correlation between price and market share as described above (for Delta and Spirit) in figure 7c below for Frontier, which showcases the intense competition for passenger share via aggressive ticket prices.

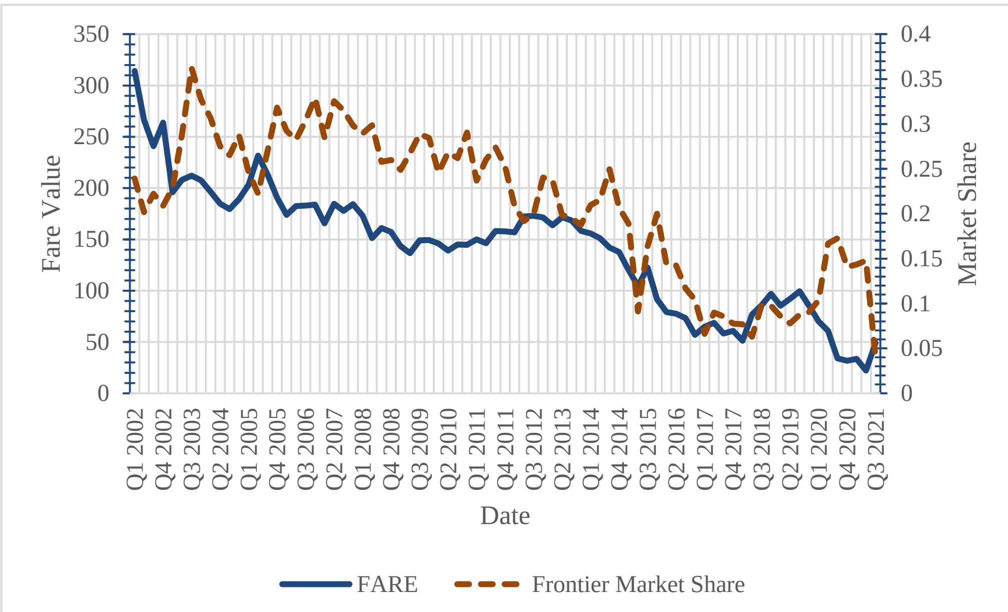

Figure 7c. Market share and Fare versus time for Frontier Airlines LAX – DEN (Q1, 2002 - Q3, 2021)

Even though the broader pattern of price competition to gain market share shows a broadly similar trend across airlines in Figures 6 and 7, our regression results reveal slight differences among these airlines. This is evidenced not only by the market share variables representing airline-specific fixed effects for Delta (2009 – 2014), Spirit (2015 - 2019), and Frontier (2005 – 2012) for the route DEN - LAX. Further, this is also seen from the evidence for Delta (2015 – 2018) and Spirit (2015-2019) for the route LAX to DEN.

Finally, we include quarterly fixed effects to account for seasonality in model 14 for each route (Tables 3b and 4b). In general, we did not find significant seasonality effects on fares across both routes; this may be due to airlines' aggressive pricing policies to gain market share, particularly on the DEN-LAX route. In model 14, the only significant finding is a small positive correlation between Q3 and fare (at 10%), possibly due to residents traveling out of Colorado to the West Coast for summer travel.

7.2 Robustness Checks

To assess the robustness of our models, particularly Models 13 and 14, which include airline-specific fixed effects, we first conduct ablation studies. To do this, we divided our variables into core economic variables which are based on theory of demand and supply (number of passengers, jet fuel prices and employees hired within the hospitality industry), market structure variables airline market shares and HHI) and seasonality variables (quarterly dummies) and performed both the test of joint significance as well as compared the values of R^2, the coefficient of determination.

For the LAX route, the base model used airlines as clusters, yielding an R^2 of 50% (62% within and 61% between). When the main economic variables were removed and the regression was rerun, R^2 dropped to 36% with 41% as within groups and 64% between groups. The joint test of significance yielded an F-statistic of 46.9, which was highly significant at the 0.01% level, indicating that the variables are jointly highly significant. Similarly, after ablating airline market share variables, R^2 dropped to 41% within, 65% between, and overall 35.7%. The F-statistic was 5712 and indicated strong joint significance at the 0.01% level. Finally, after ablating seasonality, R^2 dropped slightly to an overall 48.7%, 61.5% within, and 61.6% between. The F-statistic was 7.8, and the joint significance was still at 1%. Overall, all variable groups were significant and explained a large amount of variation in the fare dependent variable.

For the LAX–DEN route, the base model was also created using airlines as clusters, yielding an R^2 of 35%, decomposed as 64.5% within and 20.9% between. When the main economic variables were removed and the regression was rerun, R^2 dropped to 30.5% with 59% as within groups and 30.5% between groups. The joint test of significance yielded an F-statistic of nearly 32, with the model variables significant at the 0.1% level. Similarly, after ablating airline market share variables, R^2 dropped to 45.7% within, 29.2% between, and overall 28.6%. The F-statistic was 2923 and showed very strong joint significance at the 0.01% level. Lastly, we also ablated seasonality, *ceteris* paribus, and found that R^2 dropped to an overall 44.3%, 63.7% within, and rose slightly to 22.1% between. The F-statistic was 9.9 and still joint significance at 1%. Overall, all variable groups were significant for the return route as well.

To test this further and establish the veracity of our models, we examined the AIC and BIC for all our models, as shown in Tables 5a and 5b below. Table 5a shows the results for DEN – LAX, while Table 5b shows the same for LAX – DEN. In Table 5a, we notice that the best models with the least AIC and BIC are models 10 – 14, which include most of the regressors.

Table 5a. Regression Results with AIC/BIC for DAN – LAX Route

DEN–LAX: GLM results with AIC/BIC														
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
AIC	552	531	292	311	292	422	447	354	340	209	199	191	227	229
BIC	564	547	313	332	317	443	467	375	365	239	228	224	285	300
Log Likelihood	-273	-261	-141	-151	-141	-206	-218	-172	-164	-98	-93	-87	-99	-98
Deviance	87.8	83.6	50.3	52.4	50.1	66.2	69.7	57.4	55.4	41.9	41.0	40.1	42.2	41.9
Num. obs.	474	474	474	474	474	474	474	474	474	474	474	474	474	474

As we saw earlier, Table 5a helps us select models 10 – 14. Similarly, for the LAX-DEN return route, in Table 5b, we notice that models 10 – 14 have relatively lower values of AIC and BIC. This ties in with our previous results of the joint test of significance results obtained from ablation studies.

Table 5 b. Regression Results with AIC/BIC for LAX – DEN Route

LAX–DEN: Results with AIC/BIC														
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
AIC	699	687	528	537	530	617	609	540	526	467	451	447	487	492
BIC	712	703	549	557	555	638	630	560	551	496	480	480	546	562
Log Likelihood	-347	-339	-259	-263	-259	-303	-299	-265	-257	-227	-218	-216	-230	-228
Deviance	120	116	83	84	82	100	98	85	82	72	70	69	73	73
Num. obs.	471	471	471	471	471	471	471	471	471	466	461	461	471	471

We used the Poisson Pseudo-Maximum Likelihood estimator because this dataset contains a log-linear specification. Because it is a panel dataset, heteroskedasticity may be observed in the regressions. We used two methods to correct that. We used White's correction, and we compared the results using the PPML estimator. We find that there is no change in the overall significance of the parameters estimated for the models in Table 3a and 3b (DEN-LAX route). For the return route results in tables 4a and 4b, we find that airline-specific fixed effects become slightly more statistically significant.

Finally, we also performed the Fisher-type Phillips-Perron test for panel unit roots to check whether we need to worry about spurious regression, whether the variables are non-stationary, and whether further action is needed to correct that.

Our results reject the null of a unit root at the 0.1% significance level for both sides of the route, thereby confirming the presence of panel cointegration among economic variables, airline market shares, and even seasonality factors. This suggests a stable long-term relationship between the chosen empirical specifications.

8. Conclusion and Policy Implications

Our investigation of the Denver-Los Angeles air travel has explored several factors shaping airfare pricing, highlighting the significance of a diverse array of elements that come to the forefront well beyond passenger counts and seasonal trends. While jet fuel prices – an essential component of operating costs – do play a role in fare determination, the HHI Index, which captures the level of market competition, has a more significant influence on pricing strategies. We observed that Delta made sustained efforts over several years to gain market share, consistently trying to attract passengers through its pricing and, likely, through promotional strategies as well. Notably, peer pricing strategies and competitor response are particularly prominent. Consistent with economic theory, passenger volume significantly influences airfare pricing, as does broader economic activity, such as GDP and consumer income.

Overall, these empirical findings show that economic conditions continue to influence airfare levels significantly. More importantly, it should be underscored that each route has its own characteristics, as this study demonstrates. It is pertinent to examine route-specific characteristics rather than draw blanket conclusions about pricing strategies for the country or an economic region as a whole. This is our contribution to the research by examining this critical route, which amalgamates both low-cost and legacy carriers even during a crisis such as the COVID-19 pandemic. Moreover, when examining the impact of airline business models, we observe a landscape in which both legacy and low-cost carriers determine fares, challenging the prevailing notion that LCC entry causes a downward effect on the overall price structure in a city pair.

The route we studied between DEN and LAX has distinct characteristics: there is no single dominant airline, and both legacy and low-cost carriers serve it. There is no indication that any carrier, regardless of cost structure, commands significant market power. However, oligopolistic conditions coexist alongside active price competition and a hunger for market share. Price competition is intense, as seen in airline-specific fixed effects. At the same time, a mix of legacy and low-cost carriers operating on the route makes some interesting conclusions. There are very few markets that exhibit the dynamic blend of business, tourism, and international connectivity as seen at airports such as LAX and DEN. LAX serves as a key hub for global flag carriers linking to the US. In contrast, DEN, despite its inland location, serves as a strategic connecting point for legacy carriers, bridging East and West Coast traffic. Market concentration, competitive strategies, and seasonal fluctuations each play a unique role in price determination. This suggests a need for airlines to adopt flexible pricing strategies that adapt to prevailing market conditions, as well as a closer look at each route to assess its characteristics, especially if it has a strategic impact on the airline’s business goals.

While network planners and analysts might assume that the economic factors influencing travel on a route are identical to those affecting its return segment, our study does not find empirical support for this assumption. While most explanatory variables yielded similar insights into fare determination, certain factors – such as the level of competition and airline-specific fixed effects – proved particularly noteworthy. Additionally, even among the factors that seemed comparable across models and airlines, the impact was in opposite directions. Delta, Frontier, and Southwest airlines all had highly significant coefficients on the DEN-LAX portion of the trip. However, for the LAX-DEN portion of the trip, these coefficients were less negative and not statistically significantly different from 1 in absolute value. So, while we can think of these fixed effects as similar across airlines, there is evidence of an intense price war to gain market share, and these effects differ on each leg of the journey. This is visible by comparing the coefficients of American, Delta, and Southwest airline-specific fixed effects across Tables 3(b) and 4(b).

Through this study, we add to the literature by focusing on a single route and contributing to a broader understanding of pricing mechanisms in the airline sector. Our study also lays the groundwork for strategic and policy-oriented advancements within airlines and regulators alike, showing that addressing competitive dynamics and enhancing consumer welfare need not follow a blanket approach. Several sector-specific attributes are often overlooked when decision makers generalize and implement broad policy measures for airline passengers. Future studies could deepen understanding of what drives airline pricing and profitability by incorporating additional revenue metrics into their analysis. Assessing the precise impact of aircraft leasing on airline financial performance would provide valuable insights into the dynamics of network performance and revenue management.

Declaration of Generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work, the author(s) used Copilot and Grammarly in order to perform modifications, if any, in the areas of spellcheck and grammar corrections. After using this tool/service, the author(s) reviewed and edited the content as needed and took full responsibility for the publication's content.

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Authors' contributions

Ms. Chen and Dr. Gokhale were responsible for study design and revising. Ms. Chen was responsible for data collection. Ms. Chen drafted the initial manuscript and Dr. Gokhale revised it. All authors read and approved the final manuscript. There are no special agreements concerning authorship.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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Appendix A. Regression Results with Report on AIC and BIC

DEN–LAX: GLM results with AIC/BIC

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
(Intercept)	5.07^{***}	4.82^{***}	6.54^{***}	6.50^{***}	6.52^{***}	3.33^{***}	6.37^{***}	3.24^{***}	4.15^{***}	3.70^{***}	3.61^{***}	3.60^{***}	4.88^{***}	4.49^{***}
	(0.03)	(0.06)	(0.11)	(0.11)	(0.11)	(0.14)	(0.17)	(0.12)	(0.25)	(0.22)	(0.22)	(0.22)	(0.67)	(0.71)
PAX	0.00	0.00	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{*}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}	0.00^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JFUEL		0.10^{***}	0.08^{***}	0.08^{***}	0.09^{***}	0.09^{***}	0.12^{***}	0.09^{***}	0.10^{***}	0.06^{***}	0.08^{***}	0.07^{***}	0.05^{*}	0.04
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
CAGDP			-0.00^{***}		-0.00^{***}									
			(0.00)		(0.00)									
COGDP				-0.00^{***}	0.00									
				(0.00)	(0.00)									
INC						0.00^{***}								
						(0.00)								
ACCD							-0.00^{***}		-0.00^{***}	-0.00^{*}	0.00	0.00	0.00^{***}	0.00^{***}
							(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HHI								5.41^{***}	4.58^{***}	1.34^{**}	0.29	0.38	3.91^{***}	3.62^{***}
								(0.37)	(0.42)	(0.45)	(0.49)	(0.49)	(0.87)	(0.89)
F_legacy										0.01^{***}		0.00^{**}		
										(0.00)		(0.00)		
F_lcc											0.01^{***}	0.00^{***}		
											(0.00)	(0.00)		
UA													-2.38^{*}	-1.74
													(0.96)	(1.05)
F9													-1.43	-1.11
													(0.73)	(0.77)
AA													-1.42	-0.98
													(0.90)	(0.95)
DL													-3.53^{***}	-3.36^{***}
													(0.67)	(0.69)
AS													2.99	2.20
													(2.63)	(2.71)
NK													-2.76^{**}	-2.55^{**}
													(0.85)	(0.86)
US													2.74	3.19
													(1.66)	(1.69)
WN													-2.46^{***}	-2.04^{*}
													(0.73)	(0.79)
Q1														0.00
														(0.04)
Q2														0.02
														(0.04)
Q3														0.07
														(0.04)
AIC	551.92	530.59	292.24	311.20	292.11	421.90	446.45	354.08	339.50	209.43	198.91	190.71	226.68	229.30
BIC	564.41	547.23	313.05	332.00	317.08	442.70	467.25	374.89	364.47	238.56	228.04	224.00	284.94	300.04
Log Likelihood	-272.96	-261.29	-141.12	-150.60	-140.06	-205.95	-218.22	-172.04	-163.75	-97.71	-92.45	-87.36	-99.34	-97.65
Deviance	87.80	83.58	50.34	52.39	50.11	66.18	69.69	57.35	55.38	41.91	40.99	40.12	42.20	41.90
Num. obs.	474	474	474	474	474	474	474	474	474	474	474	474	474	474

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

LAX–DEN: Results with AIC/BIC

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
(Intercept)	4.73***	4.53***	30.89***	27.29***	31.45***	-8.39***	22.71***	6.51***	14.43***	13.36***	7.33***	9.10***	1.06	0.13
	(0.11)	(0.12)	(1.92)	(1.71)	(2.21)	(1.48)	(1.96)	(0.18)	(1.99)	(1.93)	(2.09)	(2.21)	(3.45)	(3.58)
lPAX	0.06**	0.06**	0.11***	0.11***	0.11***	0.08***	0.11***	0.11***	0.12***	0.13***	0.12***	0.13***	0.13***	0.13***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
lJFUEL		0.22***	0.26***	0.23***	0.27***	0.21***	0.33***	0.19***	0.25***	0.10*	0.08	0.07	0.05	0.03
		(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
lCAGDP			-1.79***		-2.16**									
			(0.13)		(0.73)									
lCOGDP				-1.79***	0.39									
				(0.13)	(0.75)									
lINC						1.32***								
						(0.15)								
lACCD							-1.97***		-0.90***	-1.44***	-0.81***	-1.09***	0.80*	0.85*
							(0.21)		(0.22)	(0.23)	(0.22)	(0.25)	(0.37)	(0.37)
lHHI								1.72***	1.42***	0.64***	0.18	0.22	1.87***	1.84***
								(0.13)	(0.15)	(0.18)	(0.22)	(0.22)	(0.32)	(0.33)
lF_legacy										1.04***		0.47*		
										(0.14)		(0.21)		
lF_lcc											1.03***	0.70***		
											(0.13)	(0.19)		
UA													-2.89*	-2.38
													(1.24)	(1.32)
F9													-0.28	0.03
													(1.00)	(1.04)
AA													-1.70	-1.28
													(1.23)	(1.28)
DL													-1.94*	-1.73
													(0.93)	(0.95)
AS													2.14	1.11
													(3.63)	(3.76)
NK													-2.63*	-2.56*
													(1.16)	(1.17)
US													1.68	1.99
													(2.21)	(2.25)
WN													-1.84	-1.46
													(0.98)	(1.04)
Q1														-0.01
														(0.06)
Q2														0.03
														(0.05)
Q3														0.06
														(0.05)
AIC	699.28	686.54	528.18	536.61	529.91	617.03	608.75	539.60	525.75	467.09	450.63	447.27	487.34	491.61
BIC	711.75	703.16	548.96	557.38	554.84	637.80	629.53	560.38	550.68	496.10	479.57	480.34	545.51	562.24
Log Likelihood	-346.64	-339.27	-259.09	-263.30	-258.96	-303.51	-299.38	-264.80	-256.87	-226.54	-218.32	-215.63	-229.67	-228.81
Deviance	120.17	116.47	82.86	84.36	82.81	100.06	98.32	84.89	82.08	72.14	69.59	68.79	73.13	72.86
Num. obs.	471	471	471	471	471	471	471	471	471	466	461	461	471	471

***p < 0.001; **p < 0.01; *p < 0.05

Table 5a. Variance Inflation Factor for variables in models 2-14 for the DEN – LAX route

Var	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
lACCD						1.13		1.49	1.5	1.63	1.85	4.46	4.5
lCAGDP		1.07		33.5									
lCOGDP			1.06	33.2									
lINC					1.02								
lJFUEL	1	1	1	1.05	1	1.05	1	1.09	1.16	1.18	1.18	2.08	2.25
lPAX	1	1.07	1.06	1.07	1.02	1.07	1.08	1.1	1.1	1.1	1.1	1.15	1.16
AA												10.4	11.5
AS												1.7	1.81
DL												10.3	10.8
F9												29.2	31.8
NK												7.5	7.64
Q1													1.67
Q2													1.64
Q3													1.7
UA												43.9	51.8
US												2.03	2.1
WN												71.4	80.9
lF_lcc										2.7	12.1		
lF_legacy									1.93		8.59		
lHHI							1.09	1.44	2.18	2.54	2.55	7.46	7.81

Table 5b. Variance Inflation Factor for variables in models 2-14 for the LAX – DEN route

Variable	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
lACCD						1.14		1.53	1.74	1.53	1.96	4.46	4.58
lCAGDP		1.06		33.4									
lCOGDP			1.05	33.1									
lINC					1.02								
lJFUEL	1	1	1	1.05	1	1.05	1	1.08	1.24	1.28	1.29	2.03	2.18
lPAX	1	1.05	1.05	1.06	1.02	1.09	1.05	1.1	1.1	1.1	1.1	1.13	1.13
AA												10.4	11.1
AS												1.7	1.8
DL												10.4	10.8
F9												29.4	31.7
NK												7.56	7.61
Q1													1.63
Q2													1.67
Q3													1.63
UA												42.4	47.9
US												2.01	2.06
WN												70.3	77.4
lF_lcc										3.31	7.65		
lF_legacy									1.91		4.42		
lHHI							1.05	1.41	2.27	3.5	3.56	7.36	7.56