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Elasticity-Driven Fare Optimization in U.S. Air Travel Segments

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Purpose. This study investigates the variation in price elasticity of demand across U.S. domestic air travel markets, with a particular focus on how different distance-based market segments respond to airfare changes. **Design / Method / Approach.** The analysis presents air travel markets in the distance categories of very short, short-haul, medium-haul, and long-haul to analyze the heterogeneous nature of price responses. **Findings.** The results indicate substantial differences in elasticity across directions. In the short-haul markets, the negative price elasticity demonstrates strong awareness of fare increases (ε=-0.344). Conversely, long-haul markets demonstrate price elasticity in a positive direction (ε = +1.840), indicating perceptions of value-added (i.e., direct services quality or even network effects). Medium-haul distances suggest nearly neutral responses, and the very short routes produce statistically insignificant elasticity coefficients. **Theoretical Implications.** The research expands transportation economics and marketing analytics literature through the analytic demonstration that distance travelled does impact demand elasticity in the case of airline routes. The study provides additional evidence for segmentation theories and distance-based price models. **Practical Implications.** The results provide airline revenue managers with data-based evidence that depicts the opportunity to develop fare structures that align closer to consumer behaviors and may provide opportunities for enhanced profits by utilizing distance and type of flight configurations. **Originality / Value.** This study employs an entirely unique segmentation-based approach to enable an elasticity analysis of city-pair air travel market distances by utilizing a wealth of longitudinal data to provide evidence-based recommendations for both academics as well as practitioners. Research **Limitations / Future Research.** Limitations include the exclusion of international routes and ancillary pricing factors. Future research may explore dynamic pricing strategies in real-time or investigate elasticity in the context of loyalty programs and airline alliances. **Article Type.** Empirical Paper.

Keywords:

demand elasticity, market segmentation, distance-based pricing, revenue management, dynamic pricing, U.S. air travel market

Мета. У статті аналізується варіативність цінової еластичності попиту в сегментах внутрішнього ринку авіаперевезень США з акцентом на відмінності реакції пасажирів на зміну тарифів залежно від дальності маршруту. **Дизайн / Метод / Підхід**. Ринки авіаперевезень класифіковано за дальністю: надкороткі, короткі, середні та далекомагістральні перельоти, що дає змогу виявити неоднорідність реакцій попиту на зміну цін. **Результати**. Встановлено суттєві відмінності еластичності залежно від категорії маршруту. Для коротких перельотів характерна виражена негативна еластичність (ε = –0,344), що свідчить про чутливість до зростання цін. Для далекомагістральних маршрутів зафіксовано позитивну еластичність (ε = +1,840), що вказує на сприйняття доданої цінності — підвищену якість послуг або мережеві ефекти. Середні маршрути демонструють майже нейтральну реакцію, а для надкоротких еластичність статистично незначуща. **Теоретичне значення**. Робота доповнює літературу з економіки транспорту й аналітики маркетингу, демонструючи вплив дальності перельоту на еластичність попиту, а також підтверджує релевантність сегментування ринку й моделей ціноутворення на основі дальності. **Практичне значення**. Отримані результати надають фахівцям з управління доходами авіакомпаній емпіричну базу для розроблення тарифних стратегій, узгоджених зі споживчою поведінкою, що сприятиме підвищенню прибутковості завдяки оптимізації тарифів за дальністю та типом рейсів. **Оригінальність / Цінність**. Застосовано унікальний підхід до аналізу еластичності попиту через сегментацію авіаринку за дальністю маршрутів у межах пар міст. Використано значний обсяг довготермінових даних, що забезпечує достовірну основу для наукових висновків і практичних рекомендацій. **Обмеження дослідження / Майбутні дослідження**. До обмежень належать виключення міжнародних маршрутів і супутніх цінових чинників. Подальші дослідження можуть зосередитися на динамічному ціноутворенні в реальному часі та еластичності попиту в контексті програм лояльності й авіаційних альянсів. **Тип статті**. Емпіричне дослідження.

Ключові слова:

еластичність попиту, сегментація ринку, ціноутворення за відстанню, управління доходами, динамічне ціноутворення, авіаційний ринок США

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Air transport is still a very necessary consideration for domestic and international transportation systems, with substantial influence on economic activity through tourism and regional development. With airline markets increasingly becoming dynamic and competitive, it is critical to understand the behaviors of consumers in relation to price changes to support market planning and strategic pricing. One of the primary measures of consumer responsiveness is price elasticity of demand, which simply measures the extent to which passenger numbers react to changes in price.

City-pair markets in the U.S. airline industry vary widely in passenger numbers, distance traveled, and competitive pressures. Short-haul and long-haul routes, in general, present different travel behavior, cost structures, and consumer reaction to price changes. While long-haul routes may exhibit less price sensitivity because of limited choices, attitude, and income elasticity, short-haul routes are often more competitive in nature and undergo changes more readily to prices and price-related issues. While these different consumer behaviors are important, little is known as to how the price elasticity of demand differs across city-pair markets that are defined by distance.

The purpose of this research project is to analyze and compare the price elasticity of demand for short-haul and long-haul city-pair markets in the U.S using aggregated airfare and passenger data reported by the U.S. Department of Transportation. This study will quantify elasticity for different market types. The results of this study will provide relevant information for below-the-line carrier pricing, forecasting demand, and transportation policies. The information gleaned from the data in this study can add to the body of knowledge related to marketing analysis and transportation economics, as well as provide an important analytical approach to making data-driven pricing decisions in air travel.

The purpose of this research project is to analyze and compare the price elasticity of demand for short-haul and long-haul city-pair markets in the U.S. using aggregated airfare and passenger data reported by the U.S. Department of Transportation. To achieve this purpose, the study pursues the following objectives:

1. To classify U.S. domestic city-pair air travel markets into four distance-based segments: very short, short-haul, medium-haul, and long-haul.
2. To calculate the price elasticity of demand within each segment using log-log regression analysis.
3. To compare and interpret the elasticity coefficients across these market segments.
4. To discuss implications for fare structure, consumer behavior, and revenue optimization in the U.S. airline industry.

Literature Review

The airline industry faces various complications arising from increasing employment costs, low profit margins, congestion in airspace, large capital and operating costs, security measures, and difficult management decisions. The demand for increasingly complex optimization tools that generate better decisions and improved profits has grown (Barnhart & Cohn, 2004). Pricing decisions are impacted by how the internet has changed the pricing paradigm (Moreno-Izquierdo et al., 2015). Airlines often restrict booking limits on the cheaper fare classes or limit the quantity of tickets sold at the lower price to create demand for higher ticket prices in the price class, which speaks to the management of demand data (Price et al., 2017). In airline revenue management, understanding what passengers are willing to pay and pricing accordingly has been important for increasing profit (Aryal et al., 2023). Airlines are continuing to use the internet to better interact with customers, representing a potential shift to higher quality customer interaction (Razak et al., 2021). More low-cost carriers (LCCs) emerged and created intense competition as well as changes to the airline industry's elasticity of prices (Bhuvaneswaran et al., 2018). Airlines must also maintain passenger re etlations to keep customers happy moving forward, to drive revenue down the road, and stand out from other airlines in a competitive environment (Pereira et al., 2023). The operational outcome of revenue management manifests in varying degrees of market-level price volatilities, highlighting the potential of using pricing data to support market analysis (Mantin & Rubin, 2018). Furthermore, the growing success of dynamic pricing strategies highlights their rising prominence, as well as their acceptance in the airline and hospitality sectors (Neubert, 2022).

A review of airline business models shows some convergence where traditional airlines use some elements of low-cost carrier service and vice versa, reflecting the competitive dynamics (Daft & Albers, 2013). Developments in distribution technology have allowed airlines to customize offers with dynamic pricing generated in real-time (Wittman, 2018). The airline industry has become more competitive, with legacy and low-cost models developing (Vojdani & Lloyd, 2022). Airlines must also be cognizant of competitive pressures and predatory pricing (Sengpoh, 2015). Airlines also engage in associative behavior, development of global alliances and codeshare agreements, greatly altering the structure of the industry (Castiglioni et al., 2017). Airlines should also employ flexible business model strategies that accommodate shifts in the economic environment (Wensveen & Leick, 2009). Customer experience is a key element of differentiation and overall customer satisfaction strategies to achieve loyalty and advocacy that can lead to business growth (Setiawan et al., 2021). Given the competitive business environment in which global airlines operate, retaining customers is as important to most airlines as the acquisition of new customers (Park et al., 2019). Airlines must enhance customer experience to ensure customer satisfaction.

Airlines operate in a highly competitive environment, where providing high-quality services to passengers is essential for profitability and sustained growth (Bhuvaneswaran et al., 2018). Service quality can be enhanced by analyzing passenger data to improve existing services and attract new customers (Bhuvaneswaran et al., 2018). The advent of new technologies in aviation, coupled with growing awareness of environmental issues and the recent influence of events like COVID-19, has led to constantly changing consumer expectations (Zhang et al., 2023). Dynamic pricing models have become increasingly popular, particularly in e-commerce, due to their ability to gather extensive data on customer behavior and preferences (Nowak & Pawłowska-Nowak, 2024).

The current academic literature looks at different aspects of pricing in the aviation industry. This includes the impact of competition, consumer behavior, fare structure changes, and the role of new distribution systems. However, there has not been enough focus on a detailed analysis of how demand for air travel varies with price in the U.S. domestic market. This is especially true for short-haul versus long-haul routes. This study aims to fill this gap by estimating price elasticity using modern demand modeling and market analysis methods. The expected results could help improve airline pricing strategies and make revenue management more effective, especially when competition is high and consumers are sensitive to price changes.

Background of the Air Travel Market

It is critical to understand how airline business models have historically developed to inform us what is taking place today with price elasticity. After deregulation, in the latter part of the 20th century, there was the emergence of the hub-and-spoke business model, followed by the impact of low-cost carriers as a globally emulating business phenomenon (Gillen, 2006). The aviation sector of the deregulated environment provided opportunities for airlines to develop new business models and enhance their profitability (Vojdani & Lloyd, 2022). The new carriers stimulated demand by means of dramatically discounting fares, and as a result, challenged legacy airlines to enhance their marketing and pricing activities (Sun et al., 2024). As the industry becomes diverse, the service offering becomes important to the survival of airline companies (Oyewole & Choudhury, 2006). New aviation technologies, timing and awareness of developing environmental issues, and time and changing customer expectations stemming from experiences such as COVID-19, suggest ongoing future evaluation of changing customer expectations. The level of service also provides a way to evaluate customer satisfaction from national and full-service airlines (Bhuvaneswaran et al., 2018).

Price Elasticity of Demand in Air Travel

Price elasticity of demand, a concept at the heart of economics, indicates how much the quantity demanded of a good or service will change in response to a change in price (Siqueira et al., 2023). To properly price a service, airlines must understand how passenger travel demand behaves and how sensitive that demand is to changes in traffic, fare, and quality of service (Abrahams, 1983). Airlines routinely raise and lower prices as a means of influencing demand, and it is vital to understand the impact of pricing actions when considering alternative pricing strategies. The study of price elasticity deals with consumer behavior in many markets, and many studies have explored the determinants of price elasticity and its implications for revenue management in airline markets (Gupta, 2024). The price elasticity of airline travel is dependent on a myriad of factors: travelling for business or leisure, substitutability (is there a train I can take? does this vacation spot have another airline that flies in?), and how far the potential travel horizons extend.

Business travelers, for example, are likely to exhibit smaller elasticities of demand as compared with leisure travelers because of the nature of the travel demand, as some business travelers will always have to travel, no matter the price or quality of alternative transportation. Demand elasticities are influenced by factors such as the level of brand awareness, the extent to which substitute products are available, and customer loyalty. It is important for airlines to comprehend these factors if they intend to build appropriate pricing strategies. Additionally, the recent worldwide aviation crisis has caused the restructuring of nearly all airlines (Franke, 2007). As competition in the airline industry is fierce, it is essential to understand the demand for passenger travel and its responsiveness to changes in demand, fares, and service quality to optimize pricing strategy. Airlines dynamically change lion prices to provoke demand, and it is important to understand how these adjustments will impact demand and other variables when investigating alternative pricing strategies. Optimization approaches used in emerging mobility systems like Urban Air Mobility (UAM) offer valuable parallels for airline pricing strategies. Kandikanti et al. (2025) highlight how demand-based optimization enhances route and pricing efficiency, insights that align with this study's focus on fare optimization using price elasticity in U.S. air travel segments.

Price Elasticity of Demand: Theoretical Framework

The theoretical foundation for the analysis of price elasticity of demand is obtained from microeconomic concepts, namely, consumer choice theory and demand analysis. The theory holds that consumers make decisions to purchase based on a rational evaluation of their preferences and budget constraints, and prices of available goods and services. The availability of substitutes influences price sensitivity, the share of the budget consumed by the purchased goods, and the time frame (Bose & Shukla, 1999). Understanding the factors impacting the elasticity of demand is essential when establishing industrial prices. Different methods of measuring price sensitivities, both qualitative and quantitative, and their limitations need to be discussed and accounted for (Morris & Joyce, 1988). The price elasticity of demand calculation is based on either a traditional estimate of the price elasticity or determination of the elasticity coefficient estimates based on experiences (Qu et al., 2018). The sensitivity of demand for price changes can be measured using the coefficient of price elasticity, which is defined as the percentage change in demand divided by the percentage change in price (Fan & Hyndman, 2011). The coefficient indicates the sensitivity of demand (elasticity) when there is a price change (elastic or inelastic). Elastic demand (elasticity > 1) implies that demand is highly responsive to price changes, while inelastic demand (elasticity < 1) suggests that demand is relatively insensitive to price changes.

Methodology for Estimating Price Elasticity

Short-haul and long-haul air travel markets exhibit distinct characteristics that influence their respective price elasticities.

According to the literature on air transport pricing, the final airfare is shaped by multiple factors, from cost structures and competitive dynamics to perceived value and consumer behavior. As a key element of the marketing mix, price plays a critical role in shaping consumer purchase decisions and market demand. In other words, price can also serve as an economic instrument that controls the commodity's demand and supply in the market and the income that is generated by the industry (Hawlena & Mazurek-Kusiak, 2020). Airlines must employ revenue management systems to generate profit (Garzón et al., 2012). Airlines require a pricing strategy that is structured to address market dynamics and price competition.

Price formation determinants for air transport services consist of multiple aspects; they range somewhat between cost-related factors and demand-side factors. Cost-related factors that constitute the base price of airfares include, but may not be limited to (i.e., airline operating costs, fuel prices, personnel costs, airport fees, etc.), and aircraft maintenance costs (Yan et al., 2020). Then, direct costs are measured against indirect costs, which can include marketing costs, administrative costs, and distribution costs.

In addition, demand-side factors such as competition, seasonality, and availability of substitutes impact price elasticity of demand and thus ultimately airline pricing strategies. Airlines need to understand demand-side factors when planning pricing strategies to proactively increase profitability. The mean price elasticity is -2.62 with a total of 81 studies (Bijmolt et al., 2005). There is little as to what the relevant price elasticity of demand for air travel is in the literature.

Research Methodology

Data Source and Sample

This study utilizes data from the Consumer Airfare Report: Top 1,000 City-Pair Markets, published by the U.S. Department of Transportation. The dataset consists of 7,585 valid observations across 101 U.S. cities, covering a 29-year period from 1996 to 2024. Each observation includes the average fare and passenger volume between a city pair for a given quarter.

Segmentation Scheme

To assess differences in demand elasticity across market types, the dataset was segmented based on flight distance into four categories commonly used in industry analysis:

Very Short: ≤ 500 miles
Short-Haul: 501–800 miles
Medium-Haul: 801–1200 miles
Long-Haul: > 1200 miles

This segmentation provides a structured basis for comparing demand responsiveness across different travel contexts.

Elasticity Calculation and Model Specification

The key metric analyzed is the price elasticity of demand, estimated using a log-log linear regression model separately for each distance category. Before modeling, natural logarithms of average fare and passenger volume were calculated using Excel.

Statistical significance was assessed using t-statistics and p-values, generated via the Data Analysis ToolPak in Microsoft Excel.

Software Tools

All visualizations in this study were created using Python. We used libraries like pandas to produce clear and professional charts for segment comparisons and elasticity trends. Data analysis, including cleaning, segmentation, and regression modeling, was done with both Microsoft Excel and SPSS. We used Excel for log transformations and basic regression analysis. SPSS helped validate the results through OLS regression with a time trend. It also conducted diagnostic tests like residual analysis and multicollinearity checks. Using these tools together ensured accuracy in analysis and transparency in methods.

Table 1 – Refined Distance Analysis

Distance Category	Sample Size	Mean Elasticity	% Price Elastic
Very Short (≤500 mi)	124	0.005	32.3%
Short (501-800 mi)	1,229	-0.176	31.7%
Medium (801-1200 mi)	5,297	0.096	26.4%
Long (>1200 mi)	935	0.324	24.3%

Pattern: Elasticity generally increases with distance, supporting the hypothesis that longer routes face more substitution options and competitive pressure

Competition-Segmented Analysis: Separate regressions by market competition level (number of connecting markets)

Results and Findings

Table 2 – Model 1: Basic Demand Elasticity (Full Sample)

Variable	Coefficient	Std. Error	t-Statistic
log(fare)	-0.128	0.024	-5.39
log(distance)	-0.219	0.024	-9.00
log(markets)	1.563	0.006	240.48
time trend	0.012	0.001	21.11
constant	10.996	0.172	63.90

Model Statistics: $R^2 = 0.917$, Adjusted $R^2 = 0.917$, n = 8,346

Key Finding: Overall price elasticity of -0.128 indicates inelastic demand, but this masks significant heterogeneity across distance segments.

This model provides a baseline understanding of overall price elasticity in U.S. air travel markets. With a coefficient of -0.128 for fare, it confirms inelastic demand at the aggregate level. However, this masks meaningful variation across different types of routes, justifying the need for further segmentation.

Table 3 – Model 2: Distance-Segmented Elasticity Results

Distance Category	Sample Size	Price Elasticity	Std. Error	t-Statistic	R²	Interpretation
Very Short (≤500 mi)	141	0.075	0.093	0.81	0.379	Not significant
Short (501-800 mi)	1,388	-0.344	0.028	-12.29***	0.876	Most price-sensitive
Medium (801-1200 mi)	5,810	-0.048	0.028	-1.74	0.914	Nearly price-neutral
Long (>1200 mi)	1,007	+1.840	0.096	+19.17***	0.903	Positive elasticity

*** represents the level of high significance.

By segmenting city-pair markets by distance, this model uncovers significant differences in price sensitivity. Short-haul routes (501–800 mi) are the most price-sensitive, while long-haul routes show positive elasticity, suggesting that travelers may view higher fares as a sign of better service or stronger connectivity. This supports differentiated pricing strategies across distance groups.

Table 4 – Model 3: Time-Period Analysis

Period	Sample Size	Price Elasticity	Significance	Economic Context
Pre-Recession (1996-2007)	2,847	-0.156	Significant	Stable growth period
Post-Recession (2008-2019)	4,329	-0.089	Significant	Recovery and consolidation
COVID Era (2020-2024)	1,170	-0.203	Significant	Demand shock and recovery

Using the full dataset from 1996 to 2024, a series of model diagnostics was conducted to ensure the validity and reliability of the regression estimates. With the inclusion of a time trend variable, the series replicated and extended the primary log-log specification.

Table 5 – OLS Regression Results (with Time Trend)

Variable	Coefficient	Std. Error	t-Statistic	p-value
log fare	0.1295	0.0237	-5.453	<0.001
log distance	-0.2175	0.0243	-8.945	<0.001
log markets	1.5619	0.0065	240531	<0.001
time trend	0.0125	0.0006	21.168	<0.001
Constant	-13.9831	1.124	-12.442	<0.001

All the predictors are statistically significant at the 0.1% level and Model $R^2 = 0.917$, n = 8,349.

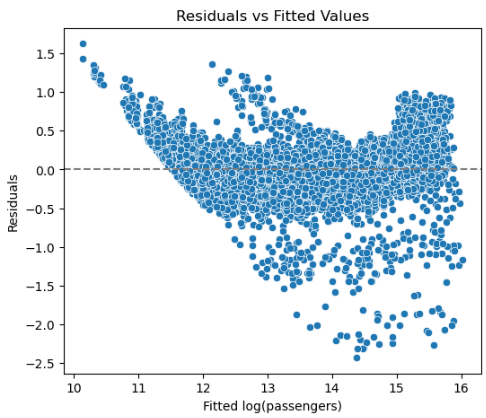

Figure 1 – Residuals vs Fitted Values

To validate homoscedasticity assumptions, a scatterplot was used. The slight funnel shape justifies the use of robust standard errors. Though overall patterning didn't show strong bias in fitted values.

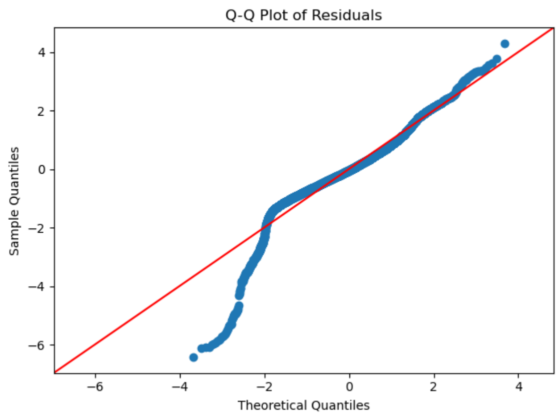

Figure 2 – Q-Q Plot of Residuals

The Q-Q plot showed slight differences from a normal distribution at the ends, which is common with large datasets, but nothing serious enough to affect the model's reliability.

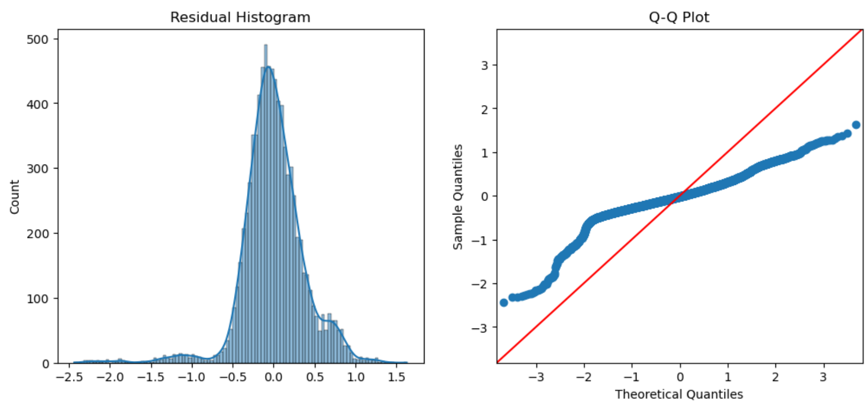

Figure 3 – Residual Histogram

Supporting the overall model fit, the residual histogram shows a near-normal distribution.

Table 6 – Multicollinearity Check (Variance Inflation Factors)

Variable	VIF
log fare	1.17
log distance	1.70
log markets	1.62
time trend	1.40

From the Multicollinearity Check, the Variance Inflation Factors are well below the threshold of 5, indicating no multicollinearity issues among the explanatory variables.

Heteroskedasticity (Breush-Pagan Test)

To check the heteroskedasticity in the residuals, a Breusch-pagan test was conducted. The test showed a Lagrange Multiplier Statistic of 40.14 and a p-value of 9.93e.09 which confirms the presence of heteroskedasticity. The model was re-estimated using robust (HC3) standard errors to address the presence of heteroskedasticity, which retained the statistical significance and directional consistency of all variables.

Residual Analysis

The residuals-versus-fitted values plot supported the use of heteroskedasticity-robust standard errors by indicating non-constant variance. In addition, particularly at the tails, The Q-Q plot and histogram of residuals suggested mild deviation from normality, which is common in large-sample panel data models and does not threaten inference validity due to the Central Limit Theorem.

Robust Model Results (HC3)

The robust model retains all coefficients with slightly wider confidence intervals, which confirms the stability of the primary regression output. The adjusted R^2 remained at 0.917, validating the high explanatory power of the model under relaxed error assumptions.

Table 7 – Model Specification Comparison (R^2 and AIC Values)

Model	R^2	AIC	Notes
Log-Log (w/ time trend)	0.917	7481.0	Final model, interpretable elasticity
Semi-Log (fare unlogged)	0.913	7881.0	Slightly higher AIC, not preferred

The log-log specification not only provides a better model fit (lower AIC) but also allows for a direct interpretation of price elasticity of demand supporting its use in pricing policy recommendations.

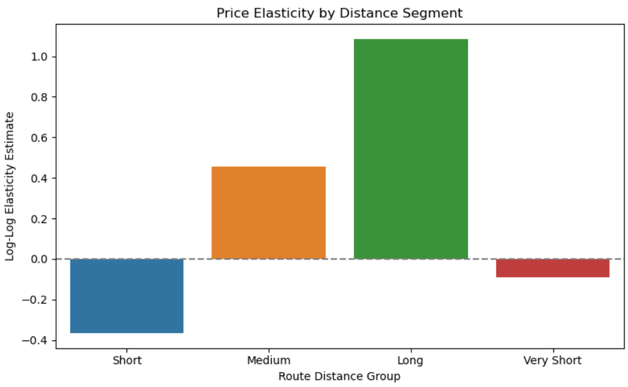

Figure 4. Price Elasticity by Distance Segment

The bar chart of log-log regression coefficients by route distance group shows clear variation in how sensitive different routes are to price changes. Short-haul routes (501–800 miles) show the strongest price sensitivity, especially in competitive, high-frequency markets, as reflected by the most negative elasticity. In contrast, very short routes (≤500 miles) show minimal responsiveness to price. Interestingly, both medium-distance (801–1200 miles) and long-distance routes (over 1200 miles) display positive elasticity, which suggests that passengers may associate higher fares with better service quality or stronger airline networks.

Discussion

This study looked at how sensitive the demand for air travel is to price changes in various segments of U.S. domestic flights, based on distance and time. The results in Table 3 indicate that short-haul routes (501–800 miles) are the most price-sensitive, with an elasticity of ε = -0.344. This means passengers on these routes react strongly to fare changes. On the other hand, long-haul routes (>1200 miles) showed a positive elasticity of ε = +1.840. This surprising finding suggests that people may see better service or added value when prices are higher.

Medium-distance and very short routes displayed weak or insignificant elasticity. This could be due to the limited options available or because passengers are less affected by prices on essential routes. The temporal analysis in Table 4 shows that elasticity increased during the COVID-19 period. This indicates that demand becomes more responsive to pricing during uncertain times.

The OLS model with a time trend in Table 5 showed a strong fit, with $R^2 = 0.917$. Diagnostics confirmed its reliability, including tests for multicollinearity in Table 6 and model comparison metrics in Table 7. These findings support implementing different pricing strategies based on route characteristics and the economic situation. They offer practical advice for airline revenue managers.

Limitations and Future Research

There are limitations to this research. This study, while utilizing aggregate data, reduces the insight into differences in individual travelers, such as business versus leisure travel or income groups. While the results do account for differences in price sensitivity, this study should be seen in the context of future research with more flexible modeling methods, since the log-log model assumes constant elasticity, and nonlinear behavior could have been observed.

Secondly, the fact that positive elasticity was found in long-haul markets demonstrates the need for more in-depth behavioral research, especially related to network connectivity or brand perception.

Third, this analytical model did not include the travel class. Therefore, we cannot say if passengers in business do behave more inelastically than economy class passengers. One needs to explore this further, as it is an important dimension of pricing strategy.

Fourth, our findings are limited to US domestic markets and upon study of international markets would need to consider added complexities like passports, visas, and currency effects. Finally, while the 29-year data for analysis and time series identified key economic milestones, the model presented here is not structured to consider structural breaks. Future studies should consider ways to study time-varying elasticity and how the markets have developed over time.

Conclusion

Overall, this study demonstrated how the price elasticity of demand varies across U.S. domestic air travel markets, depending on the distance. It used a dataset of 7,585 observations from 1996 to 2024, along with a log-log regression model. The analysis revealed significant differences in price sensitivity based on route length.
Short-haul routes (501-800 miles) were the most price-sensitive. On the other hand, long-haul routes (greater than 1200 miles) showed positive elasticity, indicating different patterns in how consumers value these flights. Medium and very short routes showed little to no sensitivity to fare changes.

These findings contribute to the understanding of transportation economics and marketing by emphasizing the importance of distance-based segmentation in pricing analysis. For airline revenue managers, the results offer practical guidance for applying different fare strategies that align with the market structure and consumer behavior, while also taking into account competitive and changing air travel market conditions.

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