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Assessing The Impact of Airlines' Strategic Decisions in Fleet Planning on Profitability by Implementing Panel Data Analysis

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Abstract: This study investigates the impact on airline profitability of different aircraft types that airlines choose as a strategic decision for their flight operations. Datasets were gathered from the MIT Airline Data Project for ten airlines operating in the USA for the five-year period between 2015 and 2019. Three different panel data models- Pooled, Fixed Effects, and Random Effects- were employed to examine the effects of aircraft types (small narrow-body, large narrow-body, and wide-body) on profitability. The plm package of R language was used to create panel data models. In conclusion, the Fixed Effects Panel Data Model proved to be the most successful in explaining profit variation in all datasets. Variables determining airline profits change according to the airline specifications and are not time-dependent.

Keywords: Airline, profitability, aircraft type, strategic management, strategy, panel data model

1. Introduction

Due to the fragile nature of the airline industry, which can easily face financial crises, profitability stands out as the main factor for airlines to survive in their competitive environments. Political turmoil, outbreak of regional clashes, terrorist attacks, global pandemics, etc. create immediate economic fluctuations which firstly affect the operations of aviation industry [1]. Therefore, the airlines have had difficulty coming up with creative strategies to increase revenue. Furthermore, one of the key elements influencing profitability is the fierce and even unfair competition among airline businesses.

Statistics and firsthand knowledge from top airlines with varying business strategies in the aviation industry demonstrate that outsourcing business operations during a global pandemic has enabled carriers to better manage the negative effects of the external logistics environment, adapt quickly to changes in customer demand, and optimize costs based on workload [2]. All strategic decisions of airlines, from route planning to fleet formation, are aimed at increasing the profitability of the business and ensuring its survival. The profitability of airlines varies depending on many different factors. In the scope of this research, it is aimed to assess the impact of fleet structure, which is one of the most significant strategic decisions of the airlines, on profitability by applying different panel data models.

Forming the fleets of the airlines is a part of strategic management. One of the most important elements in the prosperity and profitability of an airline is effective fleet utilization [3]. The fleet structure of Full Service Carriers (FSCs) is different from that of Low Cost Carriers (LCCs) since LCCs operate short distance. According to MIT Airline Data Project, the aircraft in these fleets are three categories [3]:

- Wide-body (WB): Two-aisle configuration
- Large Narrow-body (LN): Typically, 151 seats or more in a two-class configuration (e.g. Boeing 737-800/900/Max 8/Max 9, Boeing 757, Airbus A321/A320 NEO/A321NEO)

• Small Narrow-body (SN): Typically, 150 seats or less in a two-class configuration (e.g. Boeing 737-700, Airbus A319)

The research question of this study: Are aircraft types and airline profitability significantly correlated statistically?

2. Literature review

Reference [4] searched how airlines raise their profitability towards liberalization. According to the findings of this research, profitable airlines have younger, more efficient fleets, high passenger load factors, and a small percentage of capacity-related costs. They also add freight to their passenger loads. Reference [5] indicated that labor productivity was the most important determinant of the profitability while on-time performance had no impact on profitability. According to their research, the average annual maintenance cost, labor productivity, gas price, and employee wage are all important indicators of profitability.

Reference [6] searched the influential factors on three largest Chinese airlines' (Air China, China Southern Airlines, and China Eastern Airlines) profitability between 2006 and 2019 by applying LASSO model. In the conclusion, the influential factors on airline profitability emerged as crude oil prices, exchange rate, volume of the passenger transportation while Chinese airlines' profitability did not rise in tandem with rises in GDP and per capita disposable income. Reference [7] examined the financial performances of sixteen airlines between 2004 and 2017 to determine the factors on profitability of Low Cost Carriers (LCCs) by employing panel data analysis. The results demonstrated that profitability is influenced by growth prospects, asset structure, and degree of debt. Reference [8] investigated the factors that contributed to Copa Airlines' long-term financial stability and profitability while other Latin American airlines experienced losses. Based on this research, five factors contributed to Copa Airlines' profitability: the airline's geographic location, which allows it to use narrow body aircraft throughout America; operations similar to low-cost carriers (LCCs) with a single aircraft; low market concentration of competitors on its routes; a cooperative and productive relationship with its hub airport; a dollarized domestic economy with strong GDP growth.

The relationship between service quality and profitability in airlines has been the subject of many academic studies and the effect of service quality on profitability has been analyzed. Reference [9] concluded that there is no meaningful correlation between customer rankings on SkyTrax (The World Airline and Airport Star Rating programme classifying airlines and airports by the quality of product and staff service standards) and operating profit margins for airlines. Thus, an airline that experiences high levels of customer satisfaction could also have low profit margins, and vice versa. This implies that airlines' short-term profit-oriented decision-making process may place a low value on service and customer satisfaction. Load factors and yields have even greater effects on airline profit margins, because they are mutually dependent. Reference [10] firstly studied the quality-profitability relationship in the US airline business by depending on Airline Quality Rating (AQR) Index. The study's findings demonstrate the AQR's considerable impact on US airlines' profitability. The profitability is also highly impacted by customer complaints, mishandled baggage, and on-time performance; on the other hand, the AQR component's denied boarding has a negligible impact on profitability. Then reference [10] showed and validated the positive and significant impact of service quality on the return on investment (ROI) of US airline companies, while quality was found to have a non-significant effect on airline passenger revenues by utilizing all four quality related indexes (American Customer Satisfaction Index-ACSI; Airline Quality Rating-AQR; JD Power Airline Satisfaction Index; Net Promoter Score-NPS) applied in the US airline industry.

Reference [12] searched the impact of global alliances on the profitability increase of founding member airlines by employing a difference-in-difference analysis; however, they couldn't find any proof that the establishment of international alliances increased the profitability of the founding member airlines or gave them a competitive advantage over non-founding members. Reference [13] conducted an empirical investigation of the combined benefits of code-sharing agreements and global alliances on airline profitability using a sample of 81 airlines between 2007 and 2012. The findings indicated that an airline's profit margin increases from code-sharing when a larger percentage of its code-sharing partners are members of the same global alliance. However, there was no discernible correlation between profit margin and the percentage of comprehensive code-sharing partnerships to total partnerships.

Reference [14] examined the airline profitability change by using panel dataset consisted of 53 airlines in the 1983-2010 period. They demonstrated that technical development has been a consistent primary driver of productivity change since 1990s. Additionally, over the past ten years, changes in input prices have mostly determined changes in profitability and have followed a similar pattern to changes in output prices. The fact that the increase in output prices is less than the increase in input prices when productivity growth is present suggests that some productivity benefits are passed on from airlines to customers.

Reference [15] investigated the operational performance and profitability of nine U.S. airlines between 2015 and 2019 by applying a two-stage network data envelopment analysis (DEA) model and a truncated regression. The results of this study demonstrated that airline companies may evaluate their resource allocation strategies regarding revenue structures, cost management, and the availability of various funding choices in order to improve efficiency at the profitability stage. Airlines using the low-cost business model outperformed their full-service counterparts in terms of efficiency. Although the size of an airline has an advantageous impact on operating efficiency, having more full-time employee equivalents has a negative impact on efficiency results, highlighting the significance of improving labor efficiency among carriers.

Reference [16] examined the impact of outsourced maintenance on eight U.S. passenger airlines' profitability by utilizing the datasets from Air Carrier Financial Reports between 1995-2019. employing four panel data methods: POLS, an individual fixed effects model, a two-way fixed effects model, and a time fixed effects model. They concluded that there was no meaningful correlation between airline profitability and outsourced maintenance.

3. Methodology

Data for this research is in a panel data format as shown in Table 1. It was gathered from MIT Airline Data Project website in xlsx format. The dataset consists of a balanced panel, which means it contains data for 10 airlines (cross-sectional units) over 5 years (time periods). In total, there are 50 observations.

Table 1. Data Sample

Airline	Year	Operating Income (loss) (millions USD)	SN Aircraft in Fleet	LN Aircraft in Fleet	WB Aircraft in Fleet
Alaska Airlines	2015	1,298	41	88	0
Alaska Airlines	2016	1,349	33	115	0
Alaska Airlines	2017	1,260	22	132	0
…	…	…	…	…	…

Income and fleet data were gathered for the operational airlines in the United States namely Alaska Airlines, Allegiant Air, American Airlines, Delta Airlines, Frontier Airlines, Hawaiian Airlines, Jetblue Airways, Southwest Airlines, Spirit Airlines and United Airlines between the 2015-2019 period.

Using natural logarithm of income (log(income)) as a dependent variable and small narrow-body (SN_Aircraft_in_Fleet), large narrow-body (LN_Aircraft_in_Fleet) and wide-body (WB_Aircraft_in_Fleet) aircraft numbers as independent variables, several panel data models were created using R's plm package.

4. Analysis

We would like to understand the effects of fleet size on the incomes of airlines. In particular, we would like to know how incomes change over time and across US airlines and how fleet size relates to this change.

4.1. Pooled Model

We start with a general pooled regression model where the coefficients of the regression equation are assumed to apply for all airlines for all years. Regression coefficients are displayed in Table 2. The intercept (5.79) is the estimated log income when all other variables are zero. In this context, it doesn't have a practical interpretation but serves as a reference point. A one-unit increase in the number of small narrow-body aircraft in the fleet is associated with an approximately 0.36% increase in income. Airlines with more small narrow-body aircraft tend to have higher incomes. A one-unit increase in the number of large narrow-body aircraft in the fleet is associated with approximately a 0.24% increase in income. This suggests that having larger narrow-body aircraft is positively related to airline income. Airlines with a greater number of widebody aircraft in their fleet tend to have higher incomes. A one-unit increase in widebody aircraft is associated with approximately a 0.53% increase in log income. All the coefficients are statistically significant with p-values less than 0.01, indicating a strong relationship between the number of aircraft in each category and airline income. The R-squared value of 0.852 suggests that the model explains approximately 85.2% of the variation in log-transformed income, indicating a good fit for the data. This means that the model captures a substantial portion of the variation in income explained by the number and type of aircraft in the fleet. The F-statistic is highly significant (p-value < 0.001), indicating that at least one of the independent variables is relevant in explaining log income. The model, as a whole, is statistically significant.

Table 2. Pooled Model Coefficients

	Estimate	Std. Error	t value	Pr(|>t|)
(Intercept)	5.792677743	0.111252711	52.06774474	1.53075E-42
SN_Aircraft_in_Fleet	0.003648559	0.000449679	8.113700519	2.01162E-10
LN_Aircraft_in_Fleet	0.002363979	0.000777106	3.042027123	0.00387397
WB_Aircraft_in_Fleet	0.005268682	0.001952085	2.699002076	0.009695056

4.2. Fixed Effects Models

In the fixed effects within model, individual-specific (airline-specific) effects are taken into account by calculating the differences within each airline over time. Regression results are displayed in Table 3. Examining the coefficients, the relationships between the number and type of aircraft in an airline's fleet and its log-transformed income are less pronounced compared to the pooled model. The number of small narrow-body aircraft in an airline's fleet is associated with a marginal increase of about 0.16% in log income, but this effect is not statistically significant. Similarly, the number of widebody aircraft in the fleet has a minimal impact on log income, with a coefficient that is not statistically significant. The number of large narrow-body aircraft, while showing a negative relationship with log income, is also statistically insignificant. The model, as indicated by the low R-squared value of 0.12174 and an F-statistic that is not statistically significant, suggests that the fixed effects within this context might not adequately capture the dynamics of the data, as the adjusted R-squared even becomes negative, raising concerns about its appropriateness.

Table 3. Fixed Effects Within Model Coefficients

	Estimate	Std. Error	t value	Pr(|>t|)
SN_Aircraft_in_Fleet	0.001596986	0.003001682	0.532030413	0.597885333
LN_Aircraft_in_Fleet	-0.00201158	0.001783633	-1.127799243	0.266665197
WB_Aircraft_in_Fleet	0.00514338	0.014442256	0.356134108	0.723762868

On the other hand, in the fixed effects between model, individual-specific (airline-specific) effects are captured by including a fixed effect for each airline. Regression results are displayed in Table 4. The model considers the differences between airlines but does not capture time-specific effects. Examining the coefficients, we find that the number of small narrow-body aircraft in an airline's fleet has a statistically significant positive effect on log income, with an estimated coefficient of approximately 0.35%. This suggests that for each additional small narrow-body aircraft in the fleet, the log-transformed income tends to increase. However, the number of large narrow-body aircraft and widebody aircraft in the fleet do not show statistically significant effects on log income. The model, as indicated by the R-squared value of 0.91095, explains a substantial portion of the variation in log income. The adjusted R-squared is also relatively high at 0.86642, indicating that the model provides a good fit to the data. The F-statistic is statistically significant, suggesting that the overall model is a good fit for the data. In this context, the Between Model appears to capture a more relevant and robust relationship between aircraft fleet composition and log-transformed income for the dataset, especially concerning the number of small narrow-body aircraft.

Table 4. Fixed Effects Between Model Coefficients

	Estimate	Std. Error	t value	Pr(|>t|)
(Intercept)	5.753380169	0.236072669	24.3712252	3.13747E-07
SN_Aircraft_In_Fleet	0.003473405	0.000972053	3.573266357	0.011737893
LN_Aircraft_In_Fleet	0.00303367	0.00180633	1.679466208	0.14406443
WB_Aircraft_In_Fleet	0.003849919	0.004417283	0.87155827	0.416955641

4.3. Random Effects Model

In this model, individual-specific (airline-specific) effects are captured as random effects. The model estimates two types of effects: idiosyncratic and individual. Idiosyncratic Effects: These represent the unexplained variation within individuals (airlines) over time. Idiosyncratic effects explain 35.5% of the total variation. These idiosyncratic effects capture unobservable airline-specific factors that influence income and are not accounted for by the variables in the model. Individual Effects: These common effects, which can be thought of as shared industry-wide factors, explain about 64.5% of the total variation in log income. The estimated theta parameter of 0.6849 indicates the proportion of the total variation that can be attributed to these common effects. A higher θ suggests that individual-specific differences play a more significant role in explaining the variation in the dependent variable, while a lower θ indicates that random fluctuations within individuals have a greater impact. Our result indicates that approximately 68.49% of the total variance in the operating income is attributed to systematic differences between individual airlines, while the remaining 31.51% is due to random fluctuations or idiosyncratic effects within each airline.

Coefficients of the random effects model are displayed in Table 5. We find that the number of small narrow-body aircraft in an airline's fleet has a statistically significant positive effect on log income. Each additional small narrow-body aircraft in the fleet is associated with an average increase of around 0.35% in income. In other words, expanding the fleet with small narrow-body aircraft tends to lead to higher log income. However, the number of large narrow-body aircraft and widebody aircraft in the fleet does not appear to have a statistically significant impact on log income, similar to the findings in the fixed effects between Model. The model overall explains a moderate portion of the variation in log income, as indicated by the R-squared value of 0.56739. This value suggests that a substantial part of the variation is still unexplained, and other factors beyond the variables included in the model are influencing income. The adjusted R-squared value of 0.53918, which is slightly lower, accounts for the number of model parameters and penalties for model complexity, providing a more conservative estimate of model fit. The chi-squared statistic is statistically significant, supporting the overall goodness of fit for the model. This Random Effect Model with Swamy-Arora's transformation allows us to consider both individual-specific and shared industry-wide effects when analyzing the relationship between log income and the composition of airline fleets. It highlights the importance of small narrow-body aircraft in influencing airline income, while also acknowledging the existence of individual-specific and unobservable factors that impact income variations among airlines.

Table 5. Random Effects Model Coefficients

	Estimate	Std. Error	z value	Pr(|>z|)
(Intercept)	5.926263658	0.223039203	26.5705023	1.4887E-155
SN_Aircraft_In_Fleet	0.003943312	0.000842003	4.683252815	2.82358E-06
LN_Aircraft_In_Fleet	0.000581265	0.001022091	0.568701937	0.569558433
WB_Aircraft_In_Fleet	0.00894311	0.003057269	2.925195458	0.003442399

4.4. Testing for Heteroscedasticiy and Serial Correlation

In the context of panel data analysis, the presence of heteroscedasticity and serial correlation can significantly affect the validity of our regression models. These issues were meticulously examined in the pooled, fixed effects, and random effects models to ensure the reliability of our findings.

In the pooled model, a Breusch-Pagan test was employed to test for heteroscedasticity. The results revealed no significant evidence of heteroscedasticity, as indicated by a p-value exceeding the conventional significance level of 0.05. This finding suggests that the assumption of constant error variance across observations is likely met. Consequently, the coefficients of the pooled model are robust and remain interpretable, enhancing the credibility of our analysis. Turning our attention to the fixed effects model, the Breusch-Pagan test revealed no statistically significant heteroscedasticity (p-value > 0.05). This implies that the variances of the idiosyncratic errors do not systematically vary with the predictor variables, and the assumption of constant variance holds for this model. Similarly, in the random effects model, the Breusch-Pagan test found no compelling evidence of heteroscedasticity (p-value > 0.05). These results indicate that the variances of the idiosyncratic errors across different groups (individuals) and time periods remain approximately constant. This reassures us that the assumptions underlying the random effects model are satisfied.

To scrutinize serial correlation, we utilized the Breusch-Godfrey/Wooldridge test for all three models. Remarkably, none of the models displayed statistically significant serial correlation (p-value > 0.05). This outcome supports the assumption that there is no autocorrelation in the idiosyncratic errors over time. The absence of serial correlation implies that the observations at different time periods are independent, reinforcing the reliability of our models.

Overall, the results of these tests offer strong reassurance regarding the integrity of the pooled, fixed effects, and random effects models. The absence of both heteroscedasticity and serial correlation underscores the suitability of our models for the panel data at hand. Consequently, the results and coefficients derived from these models are more likely to accurately reflect the underlying economic relationships, contributing to the robustness and trustworthiness of our panel data analysis.

5. Conclusion

In this study, we investigated the impact of fleet size on airline incomes, employing various panel data models to capture diverse effects across US airlines over the period of 2015-2019. Our analysis began with a pooled model, revealing significant positive relationships between income and the number of small narrow-body, large narrow-body, and wide-body aircraft in the fleet. The high R-squared value (0.852) indicated a strong model fit. Moving to Fixed Effects Models, the within model demonstrated limited significance in the relationships, questioning its appropriateness. Conversely, the between model highlighted a strong positive relationship for small narrow-body aircraft, suggesting it as a more robust representation of the dataset dynamics.

The Random Effects Model incorporated both idiosyncratic and individual effects, revealing that approximately 68.49% of the total variance in operating income is attributed to systematic differences between individual airlines. This model emphasized the significance of small narrow-body aircraft in influencing airline income. Additionally, we conducted thorough tests for heteroscedasticity and serial correlation across all models. The absence of significant findings in these tests enhances the credibility of our results, affirming the reliability of our models in reflecting the true economic relationships.

Our findings suggest that the fixed effects between model and the random effects model are more suitable for understanding the relationship between fleet composition and airline income. We recommend further exploration into airline-specific characteristics and strategies that contribute to the observed variations. Additionally, future research could delve into the potential impact of external factors, such as economic conditions or industry regulations, on airline profitability. The results also underscore the importance of considering both individual-specific and shared industry-wide effects in analyzing airline income dynamics.

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