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Environmental factors governing efficiency of Indian aviation sector: A data envelopment analysis

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Abstract
The Indian aviation industry which is an integral part of Indian transport network, plays a crucial role in connecting people, economies, and cultures. Indian aviation industry is highly competitive in nature. Hence, operational efficiency is of paramount importance to sustain profitability, enhance customer satisfaction, and to maintain a competitive edge. The primary objective of the current study is to explore the efficiency of 6 major airline companies operating in India covering both the full service and low-cost carriers using secondary data drawn from various sources from the financial year 2004-05 to 2018-19 and to analyze the impact of select environmental factors on the efficiency of Indian aviation companies through a regression model. The study initially determined how efficiently the operating cost and its components are utilized by each airline relative to its peers. Based on two inputs and two outputs, a non-parametric approach namely Data Envelopment Analysis (DEA) is used to estimate the Overall Technical Efficiency (OTE) of select airline companies during the period of study. The empirical estimates show that airlines are operating with OTE between 62.2% and 92.7%. It is observed that Jet Airways is the most efficient unit during the period of study. In the second stage of the study, a regression model is developed which proves that majority of the independent variables chosen for the study significantly predicts the OTE score of the select airline companies during the post-reform period.

Keywords: Aviation sector, data envelopment analysis, efficiency, multple linear regression

Introduction

An essential part of a nation's transportation network is its aviation. India is no exception to it. The first commercial flight took place in 1911, and with the nationalisation of airlines in 1953, the industry underwent significant advancements. The 1990 aviation sector reforms opened up the market for private low-cost carriers (LCCs) that altered the industry dynamics. Driven by the rising disposable income of the escalating middle class, the Indian aviation business is among the fastest growing aviation industries globally. Nevertheless, despite its growth, the business still confronts several difficulties that includes poor infrastructure, regulatory barriers and financial volatility. In light of the above circumstances, improving operational efficiency has emerged as the top priority for all airlines looking forward to stay in the business (Cui & Yu, 2021) [16]. The way businesses use their resources to create and provide services is referred to as their efficiency (Chen, 2007) [11]. Thus, any airline's operational productivity depends on their efficiency. An analysis on airline's capacity to enhance their productivity while limiting their resource consumption helps to identify their efficiency (Forsyth *et al*., 1986) [24]. In this study, 6 airlines from India are evaluated against one another based on their operational efficiency and profitability over a period of 15 years from 2005 to 2019[36]. This study investigates the operational efficiency scores of the selected airlines across cost, size, and ownership structures including budget and full-service, private and state-owned, large and small, operating in the country and offering scheduled services on domestic and international routes. The current study makes an attempt to identify the significant determinants governing the efficiency of the companies in the Indian Aviation Sector through a regression model. In the initial model, 10 independent variables (operating and administrative expenses, employee expenses, total expenditure, average weight load factor, passenger-kilometer performed, ton kilometer performed, number of employees, net profit margin, debt-equity ratio, PBIT, return on equity, quick ratio, and reserves) and a dependent variable (Overall Technical Efficiency) are considered. Once the impact of each of the independent variable is determined to predict the dependent variable, the information on the multiple variables can be used to accurately predict the dependent variable. The model assumes that independent and dependent variables create a relationship in the form of a straight line (linear) that best approximates all the individual data points.

Past Studies and Research Gap

DEA was introduced by Charnes, Cooper, and Rhodes (CCR) (1978) [10]. It was a generalization of the Farrell (1957) [22] single-output/single-input measure of technical efficiency to the multi-output/multi-input measure. DEA achieved the objective by constructing a single virtual output and a single virtual input by calculating optimal weights for each output and each input of an operational process. Unlike other methodologies, the weights were not assigned theoretically in an arbitrary manner. Rather, they were optimally determined for each firm through separate linear programming problems so as to maximize the resulting efficiency of each firm. Banker *et al*. (1984) [5]

used CCR ratio of DEA to comprehend both technical and scale inefficiencies based on the optimal value of the ratio form, as obtained directly from the data without prior specification of weights and/or explicit delineation of assumed functional relations between inputs and outputs. Technical inefficiencies were identified with failures to achieve best possible output levels and/or usage of excessive amounts of inputs. Methods for identifying and correcting the magnitudes of these inefficiencies were illustrated in the paper. The authors further introduced a new separate variable that determined whether operations were conducted in regions of increasing, constant or decreasing returns to scale in multiple input and multiple output model.

Schefczyk (1993), Tofallis (1997), Joo & Fowler (2014), Saranga & Nagpal (2016), Kottas & Madas (2018) [27, 28, 38, 39, 41], used the traditional approaches of DEA as discussed above to evaluate the operational performance of the airline companies. Schefczyk (1993) [39], in his study had considered 15 large international carriers for the year 1990. The study used the Constant Returns to Scale (CRS) model to estimate the gross efficiency of each firm. In the second stage of the analysis, a regression model was developed to analyse the relationship between profitability and performance by considering efficiency. The results of the study showed that performance had a positive correlation with profitability. Studies based on the Indian aviation industry by Jain and Natarajan (2015) and Seth *et al*. (2023) [25, 40] also used the traditional DEA approach. Jianfeng (2015) [26] discovered the limitations of the traditional DEA. According to him, traditional DEA considered each Decision-Making Unit (DMU) as a 'black box'. Here, efficiency of each DMU and were assessed in a single operating process by considering only the initial inputs and the final outputs. The internal structure of the operating process was neglected. He, therefore considered it as a faulty process as it was not possible to specify the sources of inefficiency in the assessed DMUs. With a view to overcoming the shortcomings of traditional DEA model, the two-stage DEA approach had been introduced as an up-gradation to the old technique. The new approach had been used to evaluate the performance of a DMU by splitting its operation into two stages. The approach examined each stage separately by studying the effects of intermediating variables on the overall system. Further, this approach also preserved the fact that the two stages of operations were interrelated. In this connection, some other studies concerning airline industry are worth mentioning. Mhlanga (2018) [32] studied ten airlines in southern Africa for the period of 2012 to 2016[18, 31] based on a variety of parameters. A two-stage analysis was carried out. In the first stage, operational efficiencies were estimated using DEA, and in the second stage, factors impacting efficiency were determined using a two-way random effect Generalised Least Square (GLS) regression and Tobit model. The findings revealed that, 'aircraft size', 'seat load factor (SLF)', 'LCC business model' and 'revenue hours per aircraft' had positive and significant impact ($p < 0.05$) on technical and cost efficiency of the airlines. However, 'aircraft families' and 'ownership' negatively impacted airline efficiencies. Mhlanga *et al*. (2018) [32] identified two structural drivers, namely, 'aircraft size' and 'seat load factor', and two executional drivers, namely, 'low-cost business model' and 'revenue hours per aircraft', out of the variables having significant positive influence on airline efficiencies. Cui & Yu, (2021) [16] examined 130 papers published between the period of 1993–2020[30] and summarized the literature involving the special application of DEA models in airline efficiency. The extensive literature review found that the traditional DEA models were not always suitable for efficiency evaluation in complex situations. Hence, authors all over the world had developed a diversity of extended and modified radial DEA, non-radial DEA, network DEA, dynamic DEA, etc. Regression methodologies were often used as the second step following DEA to identify the cause of high or low efficiency based on the correlation between the efficiency scores and the contextual factors. The common regression methods that were combined with DEA models were Tobit regression, bootstrapping, truncated regression, GLS regression, and time-series regression. There had been a growing amount of literature in exploring the efficiency of airline industry using DEA. However, compared to other countries, the studies on efficiency in the Indian aviation sector are rather insufficient since the total market valuation remained relatively low till the early twenty-first century.

It is clear from the literature review that there have not been much in-depth investigations into the Indian civil aviation industry, primarily because Government owned airlines dominated the country's civil aviation market. Moreover, there is a dearth of research on expenditure incurred by the airline businesses towards operations and personnel for the global market. Researches in this area for the Indian market is even less. While quite a few studies, both internationally as well as in India had taken an attempt to evaluate the operational efficiencies of the competing units in the sector, very few of them analysed the impact of select environmental factors on the operational efficiency of the aviation sector. Given this situation, the present study is an attempt, not only to find out the operational efficiency of select Indian airlines in post-reforms era, but also to understand the impact of select environmental variables on the operational efficiencies of the firms.

Objectives of the Study

The objectives of the study are as follows:

1. To estimate the efficiency of select companies in Indian aviation sector (Refer to Section 5.1); and
2. To analyse the impact of select environmental factors on the efficiency of Indian aviation companies (Refer to Section 5.2).

Research Methodology

1. Selection of Decision-Making Units (DMUs) & Data Period

The period of study is 2004-05 to 2018-19. During this long period, several airlines operated in India. Out of these airlines, few exist today while the rest ceases to have their existence. During 2004-05 there were three national passenger carriers (Air India, Indian Airlines, and Alliance Air) and three private passenger airlines (Jet Airways, Sahara Airways, Air Decan) operating in India. While in the year 2018[37]-19, there were three national carriers (Air India, Air India Express, and Alliance Air) and nine private airlines (Jet Airways, Jet Lite, Air Asia, Air Deccan, Air Odisha, Air Heritage, Go Air, Indigo, Spice Jet, Star Air, True Jet, Zoom Air, and Vistara) operating in India (DGCA, 2019a) [20]. However, out of these airlines, only six airlines (Air India, Jet Airways, Spice Jet, Kingfisher Airline, Indigo, and Go Air) have been selected for the current study based on the availability of financial data using convenience sampling method. Out of the selected airlines, Air India is a national carrier and public airline, while the remaining five airlines are private passenger airlines.

2. Selection of Input and Output Variables

The objective of the study is to check the efficiencies of the selected public and private airline companies. Efficiency is typically a function of input and output.

$$\Rightarrow \text{Efficiency} = \text{Output} \div \text{Input}$$

With a view to estimating the efficiency of the competing units, appropriate financial or nonfinancial variables about airline companies are identified. Prior research has shown that operating and administrative expense (Jain & Natarajan, 2015) [25] and the number of employees (Cui & Yu, 2021, Lin & Hong, 2020) [16, 30] are the two most important inputs for estimating efficiency. Whereas, Operating Income (Assaf & Josiassen, 2011) and Ton Kilometre (KM) available (Assaf & Josiassen, 2011, Jain & Natarajan, 2015) [25] are selected as the outputs of the aviation industry. According to Cooper, *et al*. (2007) [14], a number of units should be greater than or equal to the product of number of inputs and number of outputs.

$$\Rightarrow \quad n \geq (p \times q)$$

Where, n = number of Decision-Making Units (DMUs); p = number of inputs, q = number of outputs

As (p×q) for the current study is 4, and number of DMUs for the current study is 6 fulfilling the condition, two input-two output combinations may be considered here. The data on the input and output variables for all 6 airline companies (DMUs) during the period 2004-05 to 2018[21]-19 are collected from Handbook of India Air Transport Statistics 2018[21]-19 published by the Director General of Civil Aviation (DGCA) (DGCA, 2019) [20]. With a view to assess the efficiency of competing Indian airline companies each year, Data Envelopment Analysis (DEA) is applied (Berger & Humphrey 1997) [7].

3. Selection of Environmental Variables

The environmental variables governing efficiency of the Indian airline companies are selected based on a detailed review of the existing literature. The review helps in finalising the list of contextual variables that may influence the efficiency of airline companies. Most of the research works reviewed for the purpose of selection of environmental variables has paid attention to the mainstream processes in an aviation company that eventually led to its revenue generation. Major environmental variables considered in these studies are: fleet size, passenger load factor (Zhu, 2011) [46], available ton kilometres, revenue passenger kilometre (Schefczyk, 1993) [39], operating cost, non-passenger revenue (Jain & Natarajan, 2015) [25], fuel cost, personnel cost, aircraft cost, number of flight (Chiou & Chen, 2006), destination, (Xu & Cui, 2017) [12, 44], abatement expense (Cui & Li, 2016) [18] number of employees, fuel consumption, total number of seats, maintenance expenses, cost of equipment (Lu *et al*., 2012), total assets, staff salary, seat kilometre, total revenue, network size, and selling cost (Dayi *et al*., 2020) [30]. A few researches have also identified some undesirable variables that may also impact the efficiency of a company, such as flight delays (Chen *et al*., 2017), emission level (Cui & Li, 2016) [18], accident frequency, carbon footprint (Fardnia et al., 2020), etc. A few environmental variables also comprise financial (e.g. profitability and liquidity ratios) (Assaf & Josiassen, 2011) and non-financial variables (e.g. occupancy ratio) (Safiuddin, 2019) [36] that are used to analyse the financial health of airline companies. With a view of analysing the impact of select environmental variables on the Overall Technical Efficiency (OTE) of the aviation companies, in the initial model, 13 Independent Variables (IVs) have been considered based on existing literature. The model assumes that a linear relationship exists between dependent and independent variables that best approximates all the parameter coefficients as under:

Dependent Variable (DV): Overall Technical Efficiency (OTE).

Independent Variables (IVs):

- Operating and Administrative Expenses (OAE).
- Employee Expense (EE).
- Total expenditure (TE).
- Average weight load factor (%) (AWLF).
- Passenger KM performed (million) (PKP).
- Ton KM performed (TKP).
- No. of Employees (NE).
- NP Margin (NPM).
- D/E (DER).
- PBIDT (PBIDT).
- ROE (ROE).
- Quick Ratio (QR).
- Reserve (RES).

4. Data Collection

The yearly data of aforesaid input and output variables of the selected airline companies operating during the study period (2004-05 to 2018[21]-19) are collected from Capitaline database (Capitaline, 2019) [8] and Handbook on Indian Aviation Statistics published by the DGCA (DGCA, 2019) [20].

5. Regression Diagnostics

Selection of Regression Diagnostics is as under:

Years Dropped:

- Detection of Outlier.
- Detection of Influence.
- Detection of Leverage.

Variables Dropped:

- Test of Multicollinearity.

6. Detection of Outlier

Outlier is an extremely high or extremely low data point relative to the nearest data point and the rest of the neighbouring co-existing values in a dataset (National Institute of Standards and Technology: Engineering Statistics Handbook, 2024) [33]. Thus, detection of outlier is extremely important. Outlier detection is usually done in the preprocessing phase of data analytic. If the standardized residual for a particular observation is more than 2, it is considered to be an outlier in the model. Outlier Observations are as under:

▪ Jet Airways:	2019
▪ SpiceJet:	2005
▪ Indigo:	2019
▪ GoAir:	2017

The year/years of different airline companies for which the value of standardized residual is more than 2 are summarised in the above table. It is observed that in 2019[36], Jet Airways, in 2005, SpiceJet, in 2019[20], Indigo, and in 2017, GoAir have extreme values. Hence, these are considered as the outlier years for these companies and are ignored while constructing the final model.

7. Detection of Influence

If an observation substantially changes the estimation of the regression coefficient, it is considered to be influential in the model. Thus, it is important to detect the influence affecting the model. Influence is measured with the help of Cook's D (Cook, 1977) [13]. If the value of Cook's D is more than 4/n where n is the number of observations, the corresponding observation is considered to be influential in the model. Here 4/n = 0.0487 (where n = 82) (Peña, 2006) [3].

Table 1: Identification of Influence

Year	Company	Cook's D
2009	Air India	0.33209
2018	Jet Airways	0.0537
2005	Spice Jet	8.43625
2013	Kingfisher Airlines	1.5226
2016	Indigo	0.13795
2017	Go Air	0.10468

Source: Compilation of secondary data using MS Excel, 2019

The aforementioned years for different companies have a substantial influence on regression coefficients. Specific year(s) under each model that is influential in the estimation of regression coefficients should be ignored while developing the final model.

8. Detection of Leverage

Leverage denotes those observations that have an unusually large effect on the estimation of regression coefficients. If the leverage value for an observation is more than (2K+2)/n, the observation is considered to have high leverage on the estimation of regression coefficients. The number of observations (n) = 82. As K is 13, the detection criteria are calculated as follows: (2×13+2) ÷82 = 0.3415. If the calculated value of leverage for a particular year in a model is more than its critical value, it will be considered to have high leverage on the estimation of the regression coefficient of that model (Courthoud, 2023) [15].

Table 2: Identification of Leverage

Year	Company	Leverage
2006	Air India	0.3781
2007	Air India	0.35257
2009	Air India	0.73747
2019	Air India	0.36492
2019	Jet Airways	0.42269
2005	Spice Jet	0.87921
2016	Indigo	0.37188
2019	Indigo	0.4738
2017	Go Air	0.75938

Source: Compilation of secondary data using MS Excel, 2019

The years that have leverage values higher than the critical value for the model are identified in the above table. The identified years have an unusually large effect on the estimation of the regression coefficient. Hence, the years with high leverage in each model can be ignored while developing the final model. In this way the effect of leverage can be nullified.

9. Test of Multicollinearity

If predictor variables in a linear regression model have a perfect or near-perfect linear relationship among them, it is called the problem of Multicollinearity. In the presence of Multicollinearity in the model, the regression coefficients cannot be uniquely computed. They become highly unstable and standard errors get widely inflated. One of the important measures of detecting Multicollinearity is the Tolerance level and Variance Inflation Factor (VIF). Tolerance is calculated as 1- R^2_j, where R^2_j is the percentage of variance of the dependent variable explained by the j^{th} predictor variable. The value of tolerance lies between 0 and 1. If the tolerance value is close to 1, no Multicollinearity exists among predictor variables. On the other hand, if the tolerance value is closer to 0 or less than 0.1, it can be concluded that the corresponding variable has severe Multicollinearity with other variables. VIF is just the reciprocal of tolerance. If the VIF value for a particular variable is more than 10, we infer that this variable has high Multicollinearity with other variables (Zach, 2020) [45].

Table 3: Collinearity Statistics

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Operating and Administrative Expenses	0.327	3.058
	Employee Expense	*0.072*	*13.865*
	Total expenditure	*0.041*	*24.330*
	Average weight load factor (%)	0.561	1.782
	Passenger KM performed (million)	0.11	9.097
	Ton KM performed	*0.039*	*25.835*
	No. of Employees	0.178	5.622
	NP Margin	0.847	1.181
	D/E	0.908	1.102
	PBIDT	0.473	2.114
	ROE	0.851	1.175
	Quick Ratio	0.821	1.219
	Reserve	0.498	2.006

Source: Compilation of secondary data using MS Excel, 2019

From the result of regression analysis, the tolerance and VIF values of each variable are presented in the above table. The model suffers from the problem of Multicollinearity, since Employee Expense, Total Expenditure and Ton KM Performed have VIF>10. Thus, the model may be reconsidered after ignoring Ton KM performed, Total Expenditure, Employee Expense since they have high VIF.

10. Multiple Linear Regression Model

Based on the above discussion and after applying the regression diagnostics two observations are noted:

Observation 1

The following observations have been ignored for being outliers or having leverage or influence effect:

a. Air India (2006, 2007, 2009, 2019) [20] = 4 obs.
b. Jet Airways (2018, 2019) [20, 21] = 2 obs.
c. SpiceJet (2005) = 1 ob.
d. Kingfisher Airlines (2013) = 1 ob.
e. Indigo (2016, 2019) = 2 obs.
f. GoAir (2017) = 1 obs.

Initially, there were 82 observations. After ignoring the above, the study will now be conducted with [82-(4+2+1+1+2+1)] = 71 observations.

Observation 2

Employee Expense, Total Expenditure, and Ton KM Performed have been ignored completely since they had a collinearity effect.

Selection of Variables

After application of regression diagnostics on the initial model, it is possible to select the final variables required to develop the regression model as under:

Dependent Variable (DV): Overall Technical Efficiency (OTE)

Independent Variables (IVs):

- Operating and Administrative Expenses (OAE)
- Average weight load factor (%) (AWLF)
- Passenger KM performed (million) (PKP)
- No. of Employees (NE)
- NP Margin (NPM)
- D/E (DER)
- PBIDT (PBIDT)
- ROE (ROE)
- Quick Ratio (QR)
- Reserve (RES)

Formulation of Regression Equation

⇨ $OTE = \alpha_i + \beta_1\, OAE_{i,t} + \beta_2\, AWLF_{i,t} + \beta_3\, PKP_{i,t} + \beta_4\, NE_{i,t} + \beta_5\, NPM_{i,t} + \beta_6\, DER_{i,t} + \beta_7\, PBIDT_{i,t} + \beta_8\, ROE_{i,t} + \beta_9\, QR_{i,t} + \beta_{10}\, RES_{i,t} + E_{i,t}$

In the above equation, α = OTE in the absence of IVs; β_1, $\beta 2 \ldots \beta_{13}$ are regression coefficients of IVs. Estimated values of β represent the nature and direction of the relationship between OTE and corresponding IV. E is an error term i.e. OTE not explained by any of the IVs; 't' is the time period.

11. Statistical Tool and Package used

To identify the significant determinants governing the efficiency of the companies in the Indian Aviation Sector, multiple liner regression model was used. DEA Solver, an MS Excel, 2019[20] based analytical package and SPSS 20.0 are used here.

Results and Discussions

1. Addressing to Objective 1: Estimating Efficiency of Indian Aviation Companies

OTE is a measure of divergence of actual production of a DMU from the standard production on the feasibility set. There are two approaches for calculation of OTE – input orientation (i.e. radial reduction in inputs to produce a standard outputs) and output orientation (i.e. radial expansion of outputs at a standard level of inputs). In this study, input-oriented OTE of select airline companies for each year during the study period has been computed. It measures the inefficiencies of the airline companies due to faulty input/output configuration and as well as inappropriate scale of operations. Average efficiency of the individual companies for all the years in the study period and average efficiency of the group of select companies in each year during the study period has been calculated based on mean OTE scores. Subsequently, volatility in the efficiency across companies as well as across years has been computed using SD of the OTE scores (**Table 10**).

a. Calculation of and analysis OTE scores for each company and each year

Using DEA methodology, the overall technical efficiency (OTE) score of 6 airlines on a scale of 0 to 1 is calculated. Table 4 illustrates the OTE score of selected aviation companies from 2005 to 2019[20]. The OTE score of Air India is 1 for all years during the period of study except 4 years, 2012, 2013, 2014, and 2015[25, 31]. Moreover, the OTE of Air India is 1 for the maximum number of years as compared to other companies. The OTE score of Jet Airways is 1 for 7 years during the period of study i.e. 2005, 2006, 2007, 2012, 2013, 2015, and 2019[3, 31, 36]. However, in the remaining years, the OTE score is below 1. The OTE score of Spice Jet is 1 for only 6 years during the period of study i.e. 2009, 2010, 2012[31], 2013, 2014, and 2016. In the dataset, Kingfisher Airline acts as an outlier since the airline was only operational till 2013. The OTE score of Kingfisher Airline is 1 for only 1 year during the period of study i.e. 2009. The OTE score of Indigo is 1 for 7 years during the period of study i.e., 2008 to 2014. It must be noted that Indigo Airlines was not operational throughout the period of study since the company started its operation in 2007[11]. The OTE score of Go Airways is 1 for 6 years during the period of study i.e., 2005, 2006[3], 2007, 2010, 2011, and 2015.

Table 4: Average Efficiency of Companies and their Volatility over the Period of Study

Year	Air India	Jet Airways	SpiceJet	Kingfisher Airlines	Indigo	GoAir	Mean	SD
2005	1.000	1.000	0.744	0.454	-	1.000	0.840	0.217
2006	1.000	1.000	0.508	0.661	-	1.000	0.834	0.209
2007	1.000	1.000	0.914	0.808	0.636	1.000	0.893	0.134
2008	1.000	0.906	0.992	0.503	1.000	0.696	0.849	0.188
2009	1.000	0.978	1.000	1.000	1.000	0.368	0.891	0.234
2010	1.000	0.963	1.000	0.700	1.000	1.000	0.944	0.110
2011	1.000	0.652	0.923	0.791	1.000	1.000	0.895	0.131
2012	0.600	1.000	1.000	0.600	1.000	0.783	0.831	0.180
2013	0.654	1.000	1.000	0.078	1.000	0.852	0.764	0.331
2014	0.725	0.992	1.000	-	1.000	0.975	0.938	0.107
2015	0.793	1.000	0.920	-	0.960	1.000	0.934	0.077
2016	1.000	0.947	1.000	-	0.832	0.726	0.901	0.107
2017	1.000	0.769	0.490	-	0.694	0.652	0.721	0.167
2018	1.000	0.699	0.479	-	0.605	0.651	0.687	0.173
2019	1.000	1.000	0.437	-	0.474	0.674	0.717	0.245
Mean	0.918	0.927	0.827	0.622	0.862	0.825	0.830	
SD	0.141	0.115	0.220	0.248	0.184	0.187	0.101	

Source: Compilation of secondary data using MS Excel, 2019

The mean OTE of Air India is 0.918, i.e. 92% (approx.) which implies input can be reduced by another 8% to produce the same amount of output to be efficient. The mean OTE of Air India is 92% which is more than the average OTE of all companies taken together. The mean OTE of Jet Airways is 0.927, i.e., 93% (approx.) which implies input can be reduced by another 7% to produce the same amount of output to be efficient. The mean OTE of Jet Airways is 93% which is more than the average OTE of all companies taken together. Moreover, the average OTE of Jet Airways is the highest as compared to other companies during the period of study. The mean OTE of Spice Jet is 0.827, i.e. 83% (approx.) which implies input can be reduced by another 17% to produce the same amount of output to be efficient. The mean OTE of Spice Jet is 83% which is equal to the average OTE of all companies taken together. The mean OTE of Kingfisher Airline is 0.622, i.e., 62% (approx.) which implies input can be reduced by another 38% to produce the same amount of output to be efficient. The mean OTE of Kingfisher Airlines is 62% which is much less than the average OTE of all companies taken together. The reason for such a low mean OTE is mainly that the company was not operational throughout the study period. Kingfisher Airline records the lowest OTE of 0.078 in the year 2013 after which the company shut down its operation. The mean OTE of Indigo is 0.862, i.e. 86% (approx.) which implies input can be reduced by another 14% to produce the same amount of output to be efficient. The mean OTE of Indigo is 86% which is more than the average OTE of all companies taken together. The mean OTE of Go Air is 0.825, i.e. 82% (approx.) which implies input can be reduced by another 18% to produce the same amount of output to be efficient. The mean OTE of Go Air is 82% which is marginally less than the average OTE of all companies taken together.

The volatility of OTE scores of selected airline companies which fluctuates widely over the period of study. It shows that the OTE score of Kingfisher Airlines is the most volatile (24.8%), while the OTE score of Jet Airways is the least volatile (11.5%) during the period of study. The average overall efficiency of selected aviation companies from 2005 to 2019[20] is 83% and the average volatility of the OTE score is 10.1%. This is an indicator of the underperformance of aviation companies and the waste of resources during the period of study. This is mainly due to certain challenging financial and non-financial factors faced by the Indian airline business like the volatility of jet fuel prices, increase in labor cost, and highly competitive business environment (Safiuddin, 2019) [36].

The highest average OTE of 94% (approx.) was found in 2010, when Air India, Spice Jet, Indigo, and GO Air's OTE score was 1. The lowest average OTE of 69% (approx.) was found in 2018[21] when the OTE scores of all companies except Air India were below 1. OTE scores of individual companies over the study period are shown in Figure 1. Similarly, Figure 5 shows the volatility of OTE scores of selected airline companies which fluctuates widely over the period of study. The highest volatility of OTE score was observed in the year 2013 (33.1%), when out of 6 selected airlines only 3 airlines performed efficiently and the remaining 3 airlines performed below the efficiency level. The lowest volatility of the OTE score of 7% (approx.) was observed in the year 2015 when out of 6 selected airlines most of the airline companies performed efficiently.

As shown in Table 4, three airlines have been consistently efficient relative to their peers throughout the sample period of 2005 to 2019[36]. Air India, Jet Airways, and Indigo have been 100% efficient for the maximum number of years compared to their peers Spice Jet, Kingfisher Airlines, and Go Air. Air India operates at 92% (approx.) efficiency, Jet Airways operates at 93% (approx.) efficiency, Spice Jet operates at 83% (approx.) efficiency, Kingfisher Airlines at 62% (approx.) efficiency, Indigo at 86% (approx.) efficiency and Go Air at 82% (approx.) efficiency compared to their peers. Jet Airways has the highest efficiency of 92.7% compared to the peer airline companies. The volatility of OTE scores of selected airline companies also fluctuates widely over the period of study. The OTE score of Kingfisher Airlines is the most volatile while the OTE score of Jet Airways is the least volatile during the period of study. The OTE score of all selected companies was most volatile in 2013 and it was least volatile in the year 2015.

2. Addressing to Objective 2: Analysing the Impact of Select Environmental Variables on Efficiency

After selection of the dependent and independent variables, the final regression model is developed based on six assumptions of Multiple Linear Regression Analysis

(MLRA). Now, we need to find out whether the final model fulfils all the assumptions of MLRA.

a. Assumption for the Multiple Linear Regression Analysis (MLRA)

1. Assumption−1: Two or more independent variables in regression

In the current study, ten independent variables, Operating and Administrative Expenses (OAE), Average Weight Load Factor (%) (AWLF), Passenger Kilometre (KM) performed (million) (PKP), Number of Employees (NE), NP Margin (NPM), D/E (DER), PBIDT (PBIDT), ROE (ROE), Quick Ratio (QR), Reserve (RES) are present. Hence, first assumption of MLRA is satisfied.

2. Assumption−2: Normality of residuals

In order to detect whether residuals are normally distributed, one-sample Kolmogorov-Smirnov test is conducted which is applicable when number of observations is greater than 50. The hypothesis for this test is as follows:

- **H_0:** Population distribution of residuals is normal
- **H_1:** Population distribution of residuals is not normal

At 5% level of significance and n degrees of freedom, if the probability associated with the test statistic is less than 0.05, H_0 cannot be accepted based on this current sample and vice versa.

P−Value (0.261) is less than 0.05 at 5% significant level. Hence, the residuals are normally distributed.

3. Assumption−3: Independence of residuals

In the section, independence of observations is analysed by the Durbin-Watson (DW) test. At 5% level of significance, the critical values of DW test are obtained from the critical value table designed by Savin & White. Here, for a particular level of observation and number of predictor variables the upper (d_U) and lower (d_L) values of d statistics are specified.

In our study, there are 71 observations and 10 predictors. At 5% level of significance, the critical values of d_L and d_U and DW statistic are estimated. Result of Durbin – Watson Test is 1.449. The value of the DW statistic ranges from 0 to 4 with a midpoint 2 (CFI Team, 2023) [9]. If the DW statistic is approximately a value close to 0, it indicates strong positive serial correlation, while a value close to 4 indicates strong negative serial correlation. The DW statistic of 2 or nearly 2 indicates no autocorrelation problem in the series. The critical values of d_L and d_U are 1.162 and 1.792 respectively. Hence, 4- d_U is 2.208. Here, the DW statistic is 1.449. Since, the value of DW statistic lies between d_L and 4-Du, the observations are independent.

4. Assumption-4: Linearity between dependent variable and independent variables

In the current section, the relationship is checked between the DV and IVs. The methodology adopted is as under:

Hypothesis:	**H_0:** There is no linear relationship between the OTE and IVs. **H_1:** There is linear relationship between the OTE and IVs
Test Statistic:	F –Test
Significant Level:	5%
Decision Rule:	If P−Value less than 0.05, H_0 is rejected.

It is observed that P−Value (0.019) is less than 0.05 at 5% significant level. Hence, H_0 is rejected and there is linear significant relationship between the DV and IVs. So, the model is useful.

5. Assumption−5: Homoscedasticity in residuals

Homoscedasticity is an error term or noise in the relationship between DV and IVs. Homoscedasticity means the homogeneous variance. Homoscedasticity is tested by the Breusch−Pagan (BP) test (University of Wisconsin-Madison, 2021) [42].

Under this method, unstandardized residuals (Res_1) and unstandardized predicted values (Pre_1) are saved from linear regression model and following result under the BP test is calculated with the help of SPSS 20.0. The methodology of BP test is as follow:

Hypothesis:	**H_0:** The error variances are homoscedastic. **H_1:** The error variances are not homoscedastic.
Test Statistic:	Breusch-Pagan (BP) Test
Significant Level:	5%
Decision Rule:	If P−Value less than 0.05, H0 is rejected.

The aforementioned hypothesis is tested using Bruech Pegan Godfrey (BPG) test.

The P-Value (0.8024) is greater than 0.05 at 5% significant level; there is no evidence to reject the Null Hypothesis. The residuals are homogeneous. Since H_0 is accepted, error variances are homoscedastic and the problem of heteroscedasticity is not present.

6. Assumption−6: No collinearity or no Multicollinearity

Multicollinearity increases the standard errors. It makes some variables insignificant although they are significant. One of the important measures of detecting Multicollinearity is Tolerance level and Variance Inflation Factor (VIF). Tolerance is calculated as 1- R^2_j, where R^2_j is the percentage of variance of dependent variable explained by j^{th} predictor variable. The value of tolerance lies between 0 and 1. If the tolerance value is close to 1, no Multicollinearity exists among predictor variables. On the other hand, if the tolerance value is closer to 0 or less than 0.1, we can conclude that the corresponding variable has severe Multicollinearity with other variables. VIF is just the reciprocal of tolerance. If VIF value for a particular variable is more than 10, it is inferred that this variable has high

Multicollinearity with other variables (Allison, 2022) [1]. The result of collinearity statistic is given here:

Table 5: Result of Collinearity Statistic

Parameters	Tolerance	VIF (Variance Inflation Factor)
Operating and Administrative Expense	0.312	3.205
Average weight load factor (%)	0.432	2.317
Passenger KM performed (million)	0.216	4.634
No. of Employees	0.202	4.948
NP Margin	0.520	1.923
D/E	0.769	1.301
PBIDT	0.545	1.835
ROE	0.947	1.055
Quick Ratio	0.782	1.278
Reserve	0.600	1.667

Source: Compilation of secondary data using SPSS 20.

Table 16 shows that value of Tolerance is greater than 0.1 and value of VIF are less than 10 for all parameters. So, the models are acceptable and there is no occurrence of Multicollinearity.

b. Model formulation

After analysing above assumptions, the MLRA is conducted in the current study.

Formulation of Regression Equation

⇨ $OTE = \alpha_i + \beta_1\ OAE_{\ i,t} + \beta_2\ AWLF_{\ i,t} + \beta_3\ PKP_{\ i,t} + \beta_4\ NE_{\ i,t} + \beta_5\ NPM_{\ i,t} + \beta_6\ DER_{\ i,t} + \beta_7\ PBIDT_{\ i,t} + \beta_8\ ROE_{i,t} + \beta_9\ QR_{\ i,t} + \beta_{10}\ RES_{\ i,t} + E_{\ i,t}$

c. Model estimation

The MLRA is conducted to get the estimated model coefficients. The estimated unstandardized coefficients of the MLRA are mentioned here:

▪ (Constant)	1.49
▪ Operating and Administrative Expense	1.21E-05
▪ Average weight load factor (%)	-0.009
▪ Passenger KM performed (million)	6.74E-07
▪ No. of Employees	-1.63E-05
▪ NP Margin	0.002
▪ D/E	0.002
▪ PBIDT	7.92E-06
▪ ROE	0.022
▪ Quick Ratio	0.028
▪ Reserve	-4.47E-06

Hence, the estimated regression equation is shown as under:

⇒ $OTE = 1.49 + 1.21E\text{-}05\ OAE_{\ i,t} - 0.009 AWLF_{\ i,t} + 6.74E\text{-}07\ PKP_{\ i,t} - 1.63E\text{-}05 NE_{\ i,t} + 0.002\ NPM_{\ i,t} + 0.002\ DER_{\ i,t} + 7.92E\text{-}06\ PBIDT_{\ i,t} + 0.022\ ROE_{i,t} + 0.028\ QR_{\ i,t} - 4.47E\text{-}06 RES_{\ i,t}$

From the above model, it is evident that Average Weight Load Factor, Number of Employees, and Reserve negatively affect Overall Technical Efficiency of the companies in aviation sector, while all other variables positively influence it during the period of study.

d. Significance of the parameter estimate

Under this section, significance of the variables for prediction of OTE is tested based on the following hypothesis:

- **H_0:** There is no significant relationship between OTE and each individual IV;
- **H_1:** There is significant relationship between OTE and each individual IV.

In order to test the above hypothesis, t-test is conducted. The result of the test is as follows:

Table 6: Test of Significance

Parameters	t-Stat	P−Value	Decision Rule	**Decision on H_0** (H_0: No significant relationship exists between individual IVs and OTE)
Operating and Administrative Expense	1.73	0.089	p-value>0.05	H_0 accepted
Average weight load factor (%)	-2.165	0.034	p-value<0.05	H_0 rejected
Passenger KM performed (million)	0.219	0.827	p-value>0.05	H_0 accepted
No. of Employees	-2.28	0.026	p-value<0.05	H_0 rejected
NP Margin	1.488	0.142	p-value>0.05	H_0 accepted
D/E	0.576	0.567	p-value>0.05	H_0 accepted
PBIDT	0.333	0.74	p-value>0.05	H_0 accepted
ROE	2.378	0.021	p-value<0.05	H_0 rejected
Quick Ratio	2.444	0.018	p-value<0.05	H_0 rejected
Reserve	-1.666	0.101	p-value>0.05	H_0 accepted

Source: Compilation of secondary data using SPSS 20.0

Table 6 reveals that Average Weight Load Factor, Number of Employees, ROE and Quick Ratio are significant in predicting OTE. But Operating and Administrative Expense, Passenger KM performed (million), NP Margin, D/E, PBIDT, and Reserve do not significantly influence OTE during the period of study.

e. Strength of association

The strength of the model is measured by the result of R (0.532), R Square (0.283) and Adjusted R Square (0.164). R’s value reports strength of association, which is 53.2%. The percentage of variance of DV predicted by other IVs is evaluated by R square, which is 28.3%. Adjusted R Square measures the goodness of fit, which is only 16.4%.

f. Model fitness

The overall fitness of the model is justified by the F-test based on the following hypothesis:

- **H_0:** All the slope coefficients are 0 simultaneously;
- **H_1:** All the slope coefficients are not 0 simultaneously.

P−Value (0.019) is less than 0.05 and Null Hypothesis is rejected. This model is good fit to explain OTE. It shows that the ten independent variables together significantly predict OTE during pre-reforms period.

Conclusion

Indian aviation industry is destined to grow in the forthcoming future. The study contributes to the body of literature by estimating in details the operational efficiency of major airline companies of India. The empirical estimates shows that airlines are operating with an operational efficiency between 62.2 per cent and 92.7 per cent. The analysis suggests that Jet Airways out performed all competing airline companies. It may be concluded that strategy followed by Jet Airways to maintain operating efficiency can be proved beneficial for Indian aviation industry. The regression model chosen for the analysis shows that the ten independent variables chosen for the study significantly predicts the OTE score of the select airline companies during the pre-reform period. According to the current study average load factor, number of employees, ROE and quick ratio are significant in predicting OTE whereas operating & administrative expenses, passenger KM performed, net profit margin, P/E ratio, PBIT ratio and reserve are not significant in predicting OTE. However, a small number of airlines selected is a limitation of the current study. A more detailed and rigorous estimation of the relationship between the operating efficiency and other environmental factors would yield better understanding about the growth and efficiency of Indian airline industry.

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