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Abstract

In this paper, we analyze the price movements of the Indian domestic airline industry. In the first part, we conduct a detailed econometric analysis of five selected domestic routes. In the second part, we study the weekend effect on the average airfare. Our research suggests that competition steps up airfares as the departure date comes closer and weekend airfares are higher than weekday airfares. The application of Revenue Management and Dynamic Pricing is the common practice in the Indian domestic airlines industry.

Key words: Airline Industry, airfare movement, dynamic price dispersion, competition, Revenue Management.

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1. Introduction

The market for homogeneous (or close substitute) goods and services is often characterized by price differential (between products), price dispersion (over time) and price discrimination (among customers). The airline industry, being one of the most suited examples of all these features, has been the main focus of such studies over the years.

The application of Revenue Management and Dynamic Pricing (RMDP) (Talluri and Van Ryzin, 2004) system is an integral part of the IT system in the airline industry. It helps to update airfares dynamically based on the actual booking (till that time) and the expected demand forecast, and sets corresponding booking limits for the updated airfares for each flight. In a competitive environment, every airline operator offers airfares based on their own competitive pricing approaches (Bilotkach, V. et al. 2007). There are two types of passenger airlines carriers – Full Service Carriers (FSC) and Low Cost Carriers (LCC). These carriers operate in the same competitive airline market. When the booking window for a particular departure day's flight opens (say, 60 days earlier), we observe that the airfare is relatively low and LCCs set their fares lower compared to conventional FSC (Pels et al. 2004). Then the airfare dynamically increases as the departure date gets closer. However, FSCs and LCCs may follow different strategies to do so.

The Indian domestic airline industry is operated by both FSCs and LCCs. Domestic air traffic grew at 18.5 per cent per annum during 2004-05 to 2010-11 (Report June 2012, Ministry of Civil Aviation, Government of India). In this study, we analyze the airfare movements from the airfare histories of competing airlines for selected air routes. However, there is practically no literature that discusses the airfare movement in the Indian domestic market. This paper is probably one of the early attempts that discuss the airfare movement in the context of the Indian domestic airline market.

In this paper we plan to address the following questions:

1. Do all airlines demonstrate an increasing trend when we move across the booking profile (say from sixty days prior to departure to day of departure)?
2. Can this increasing trend across all airlines be captured by a multiple regression analysis? To what extent is the interaction effect present in the regression analysis?
3. To what extent can the effect of the day of the week be explained by this regression analysis?

4. If the time along the booking profile can be grouped into different time windows, is there a significant group effect that can be explained by the regression model?
5. To what extent can the variation across the airfares across the booking profile be explained by negatively sloped linear function of time (expressed as the number of days to departure)? To what extent can average airfare across all sectors be expressed by this function of time?

This paper is organized as follows. In Section 1, we provide an introduction about the Indian airline industry with its market characteristics. In section 2, we review literature on the dynamic pricing mechanism. Section 3 provides the data sources. Section 4 explains the price movement analysis on selected five origin destination cities. In this section, we introduce four different models to capture price movements. In the first model, we develop a pooled ordinary least square analysis. In the second model, regression analysis with a dummy variable (the day effect) is developed. In the third model, the same analysis with an interaction dummy for slope effects is discussed. In the fourth model, the same analysis is done for time effect. The selected results of the four models are provided in section 5. The weekend effect in the airline pricing model is discussed in section 6. In section 7, we explain the results and data analysis of the weekend effect. In section 10, we indicate the usefulness of the study to customers (passengers), service providers (Airline Companies), and regulators. In the last section, we draw some conclusions about the nature of Indian domestic airlines industry.

2. Literature Review

Borenstein and Rose (1994), Stavins (2001), and Gerardi and Shapiro (2009) discussed, the relationship between market competition and price dispersion with cross sectional data. McAfee and Velde (2007) demonstrated that dynamic price discrimination is driven by customer dynamics rather than price discrimination over an existing set of customers. Dana (1998) examined a model in which firms offer advance purchase discounts in a market with individual and aggregate demand uncertainty. Pels and Rietveld (2004) studied the pricing behavior of the London-Paris market where both LCCs and FSCs operate. Bilotkach et al. (2010) examined the pricing strategies of non-stop flights for the New York to London air route.

Talluri and Van Ryzin (2004) analyzed equilibrium in a competitive market with uncertain aggregate demand where firms pre-commit to a capacity. Often, irregular pricing strategies help firms to avoid price wars with their competitors, while price dispersion is often an outcome of uncertainty in demand and capacity costs are high in an oligopolistic market (Dana, 1998). Brueckner et al. (1992) discussed linking airfares on airline hub-and-spoke networks under different network characteristics.

Gerardi and Shapiro (2007) studied empirically, the price dispersion in the airline industry under a competitive market structure. They found that there is a negative relationship between market competition and price dispersion. Gallego and van Ryzin (1994) discuss inter-temporal price discrimination in a revenue management aspect. Su (2007) studied intra-firm price discrimination and classified consumers based on their waiting cost, and set prices dynamically based on various rationing rules. Hernandez and Wiggins (2008) studied the non-linear pricing strategy of the US airline industry. They found that there is a negative correlation between market concentration and price dispersion. Hazledine (2006) studied price discrimination for homogenous products where the firm had charged according to the consumers' willingness to pay and in this market structure, average prices were independent of price discrimination strategies.

Escobari and Gan (2007) studied price dispersion where capacity costs are higher with uncertain demand. They used United States (US) airline data and observed that the second degree price discrimination is applicable when offering advanced discounts on purchase. Piga and Bachis (2007) examine the daily change in airfares for full-service carriers (FSCs) as well as low-cost carriers (LCCs). They conclude that each airline's distribution of prices tends to rise as the departure date comes closer. Mantin and Koo (2010) extended their airfare dispersion studies by introducing the time effect and the weekend effect. A similar airfare dispersion study was done by Obermeyer et al. (2013) in European airline markets. In their study, they established that efficient airlines were better able to differentiate airfares compared to their inefficient counterparts.

3. Data Source

Our airfare data collection process is divided into two parts. In the first part, we have collected the minimum airfare data (for the economy class), airline wise, on five origin destination cities, and in the second part, we collect the minimum airfare data from 69 domestic airline routes across India (for the economy class). We divide our analysis into three sections. In the first section, we analyze the price movement analysis model on the selected five origin-destination cities across different competing airlines. In the second section, we study the weekend effect on the average prices on the selected 69 domestic air routes across India.

The data of daily economy class airfares of 31 departure dates (December 1 to December 31, 2012) has been collected for selected city pairs from a popular travel website (www.yatra.com). We collect the one way minimum airfare for all the airlines operating on that particular route from 60 days prior to each departure date. There are six main airlines operating in the Indian domestic air-routes -- Airline 1, Airline 2 and so on. Airline 1, 2, 3, and 6 are private LCCs that operate in almost all the routes in our sample study. Airline 4 is a government regulated FSC airline which has the maximum coverage all over the country. Airline 3 and 5 are under the same private company, but Airline 5 is a FSC airline while Airline 3 faces intense competition from the low cost airlines.

4. Price Movement Analysis Model on selected five origin destination cities

A priori, we expect fares of flights departing in the same time window to compete with each other. Thus, we see how the fare of one flight changes as the fares of the other competing airlines change. We do a panel data analysis on the selected five origin destination cities with 31 cross sections, that is, departure days (December 1 to 31, 2012) and 60 observations, that is, the airfare 60 days prior to departure. We develop four different models for each route separately to check for cross sectional and time effects. The model formation and the corresponding explanations of four different models are provided below.

Indices:

$i = i^{th}$ date of departure

$j = j^{th}$ airlines operates in the country

$t = t^{th}$ days prior to departure

m = day of the week for the departure

n = time break

$r = r^{th}$ selected origin-destination air route

Sets:

I = Set of departure date, indexed over i, i= 1,2,………..,31

J = Set of airlines, j= 1,2,………..,J

T= Set of days prior to departure, t= 1,2,………..,60

M = Set of day of the week, m= Sunday, Monday, Wednesday,…….., Friday.

N = Set of time break, n = 1, 2, 3, 4, 5

R = Set of selected origin-destination air routes, r = 1, 2, 3, 4, 5

Parameters:

β_{jr} : Coefficient of airfare (price) of j^{th} airlines for route r. for all j ε J, r ε R.

$\delta_{m\,r}$: Coefficient of dummy variable m^{th} day of the week for the departure for route r. for all j ε J, r ε R.

α_{jmr} : Coefficient of interaction dummy variable, product of dummy variable m^{th} day of the week for the departure and airfare (price) of j^{th} airlines for route r. for all j ε J, m ε M, r ε R.

γ_{nr} : Coefficient of dummy variable n^{th} time effect for route r. for all n ε N, r ε R.

Variable:

P_{ijtr} : Airfare (Price) of j^{th} airlines on i^{th} departure day, t days prior to departure for route r. for all j ε J, i ε I, t ε T, r ε R.

$D_{m,r}$: Dummy variable of m^{th} day of the week for the departure for route r. for all m ε M, r ε R.

$(P_{ijtr} * D_{mr})$: Interaction dummy variable of P_{ijtr} and D_{mr}. for all i ε I, j ε J, t ε T, m ε M, r ε R.

$Dd_{n,r}$: Dummy variable of n^{th} time effect for route r. for all n ε N, r ε R.

Model 1 - Pooled ordinary least squares analysis:

$$P_{ijtr} = \beta_0 + \sum_{j=1}^{j-1} \beta_j * P_{ijtr} + \varepsilon_{it} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

For all i ε I, j ε J, t ε T, r ε R

Model 2- Dummy Variable for the day effects:

A particular cross section might have a higher intercept. In this case this would imply that the average fare for a particular flight is high on a particular departure day. *A priori*, we expect this to be true on a weekday. So we have taken Saturdays to be the reference category.

$$P_{ijtr} = \beta_0 + \sum_{j=1}^{j-1} \beta_j * P_{ijtr} + \sum_{m=Sun}^{Fri} \delta_m * D_{mr} + \varepsilon_{it} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

For all i ε I, j ε J, t ε T, m ε M, r ε R

Where, D_{mr} : Dummy variable of departure day m for route r,

m= Sunday, Monday, Wednesday,…….., Friday.

And r = 1, 2, 3, 4, 5

e.g., $D_{sun,1}$ =1 for departure day Sunday for the route 1 and 0 otherwise.

A positive and significant δ_m would indicate that on mth departure day, average fare is higher than that of Saturday (benchmark category).

Model 3 - Dummy for slope effects:

From the given data set consisting of flight fares and dummy variables, we create interactive variables. An interactive term is the product of a dummy day of departure and a flight fare. We create a new variable which is the product of P_{ijtr} and D_{mr}.

$$P_{ijtr} = \beta_0 + \sum_{j=1}^{j-1} \beta_j * P_{ijtr} + \sum_{m=Sun}^{Fri} \delta_m * D_{mr} + \alpha_{1m} * P_{i1tr} \sum_{m=Sun}^{Fri} D_{mr} + \cdots \ldots + \alpha_{(j-1)m} * P_{i(j-1)tr} \sum_{m=Sun}^{Fri} D_{mr} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

For all i ε I, j ε J, t ε T, m ε M, r ε R

We test for the individual significance of the coefficients of the interaction terms. Say α_{1m} is positive and significant. This would imply that a change in the airline fare P_{ijtr} for a unit increase in airfare P_1 is significantly higher for Sunday compared to Saturday (benchmark category). The assumption of dummy variables remains the same as discussed in Model 2.

Model 4 - Time effects:

We expect airfares to rise as the day of departure comes closer. To check this, we plot the data (days prior to departure against flight fares for all the flights for each route) and note the critical points where fares jump. We then divide the time horizon into five parts according to the airfare changes, assign a time dummy for each part, and regress each flight fare on other flight fares and time dummies for each route.

$$P_{ijtr} = \beta_0 + \sum_{j=1}^{j-1} \beta_j * P_{ijtr} + \sum_{n=1}^{4} \gamma_n * Dd_{n,r} + \varepsilon_{it} \qquad \text{.....................(4)}$$

For all i ε I, j ε J, t ε T, n ε N, r ε R

Where, $Dd_{n,r}$: Dummy variable of time effect n for the route r.

n= set of time break 1,2,3,4 ; and time break 1 defined departure days 1-7, time break 2 defined departure days 8-15, time break 3 defined departure days 16-30, time break 4 defined departure days 31-45, and time break 5 defined departure days 46-60.

r = 1, 2, 3, 4, 5

For example, $Dd_{1,1}$ =1 for departure days 1-7 for the route 1 and 0 otherwise.

Here we consider time break Dd_{5t} as a benchmark category. A positive and statistically significant dummy will indicate an increase in fares corresponding to that time period.

In the following section, as we move from model 1 to model 3, we analyze price movements in greater depth. In model 4, we discuss the price movement along with the day of departure (time) effect.

5. Results and Data Analysis on five selected origin destination cities

In this section, we plan to explain the first four questions outlined in section1. As described in Section 4, four sets of estimation have been done for each route. The characteristics of the routes and fare statistics are summarized in the following table:

Table 1: Route Characteristics and Fare Statistics

Route r	**Distance (km)**	**No. of Airlines**	**Nature of Cities**		**Avg. Price**	**Std Dev.**	**Min Price**	**Max. Price**
			Origin	**Destination**				
Route 1	293	4	Bangalore	Chennai	3834	2699	2920	21828
Route 2	1754	5	Delhi	Chennai	6573	1817	5110	28598
Route 3	450	5	Mumbai	Ahmedabad	3326	669	2833	12090
Route 4	1165	6	Mumbai	Delhi	5872	1360	3650	12988
Route 5	1666	4	Delhi	Kolkata	6414	1843	3620	21966

Thus, Route 1 is the shortest and this route is operated by three LCC service providers, namely Airline 1, Airline 2, Airline 3,and one government operated FSC namely Airline 4. Route 2 is the longest route. Route 4 is the busiest route. Route 3 is a short distance busy route while Route 5 is a long distance busy route. In our study, we take only non-stop flights from origin to destination cities. These five routes are operated by both LCCs and FSCs. These carriers are operated by both private airlines and government airlines. The details about the Airlines' operations are shown in the following table.

Table 2: Route wise Airlines Operation

Name of Airline	Type of Airline	Operated By				
		Route 1	Route 2	Route 3	Route 4	Route 5
Airline 1	LCC, Private	Yes	Yes	Yes	Yes	Yes
Airline 2	LCC, Private	Yes	Yes	Yes	Yes	Yes
Airline 3	LCC, Private	Yes	Yes	Yes	Yes	Yes
Airline 4	FSC, Government	Yes	Yes	Yes	Yes	Yes
Airline 5	FSC, Private	No	Yes	No	Yes	No
Airline 6	LCC, Private	No	No	Yes	Yes	No

We apply the four models mentioned in section 4 to the selected five routes mentioned in table 2. Here we provide one result for each model and analyze the results according to the competing airlines' pricing behavior by introducing different categorical variables.

In the following, we define P_{a1}, P_{a2}, P_{a3}, P_{a4}, P_{a5} and P_{a6} as an airfare of Airline 1, Airline 2, Airline 3, Airline 4, Airline 5, and Airline 6 respectively.

Model 1 - Pooled ordinary least squares analysis:

In this model, we answer the first question described in section 1 and provide the results of Route 4. Here, we have taken the airfare of Airline 1 (LCC and private airline) as an explained variable, and the airfares of Airline 2, Airline 3, Airline 4, Airline 5, and Airline 6 are the explanatory variables. The regression result of model is given in the following table.

Table 3 : Results of Model 1

$$P_{a1} = \underset{(9.9754)^{**}}{-58.2356} + \underset{(0.0186)^{**}}{0.3419} * P_{a2} + \underset{(0.0038)^{**}}{0.0153} * P_{a3} + \underset{(0.0195)^{**}}{0.8142} * P_{a4} + \underset{(0.0059)^{*}}{0.0129} * P_{a5} - \underset{(0.0079)^{**}}{0.199} * P_{a6}$$

N = 1860 $R^2 = 0.9949$ $R^2_{adj} = 0.9949$ F= 72982.2**

** Significant at 1% level, *significant at 5% level

Standard error values are in parentheses

The independent variables of this model are significant, and the overall model is also significant. The airfare of Airline 4 (FSC, Government) has a positive impact on the airfare of Airline 1 but the airfare of Airline 6 (LCC, Private) has a negative impact on Airline 1's airfare. Hence, we can conclude that the changes in the fare of Airline 2, Airline 3, Airline 4, Airline 5, and Airline 6 have a significant impact on the airfare of Airlines 1 and the corresponding fare changes indicate a high degree of competition. Based on the analysis, we find that there is a strong competition on the price movement across the booking profiles. This can also be explained by the fact when one airline reduces the price, all other follow suit.

Model 2- Dummy Variable for day of the week effects:

In this model, we answer the second question that is discussed in section 1 of this paper, by providing the results of route 2. Here, we assume the airfare of Airline 4 (FSC and Government) as an explained variable and the airfare of Airline 1, Airline 2, Airline 3, Airline 5, and dummy variables day of departure (Sunday, Monday, Tuesday, Wednesday, Thursday, and Friday) as the explanatory variables. The regression results of model 2 are given in the following table.

Table 4: Results of Model 2

$$P_{a4} = \underset{(105.0858)}{161.8628} + \underset{(0.0689)^{**}}{0.247} * P_{a1} + \underset{(0.0739)^{**}}{0.4895} * P_{a2} + \underset{(0.018)^{**}}{0.2033} * P_{a3} + \underset{(0.0357)^{**}}{0.1615} * P_{a5} - \underset{(72.2975)^{**}}{446.732} * D_{sun}$$

$$- \underset{(71.9516)^{**}}{632.7396} * D_{Mon} - \underset{(76.2405)^{**}}{630.0096} * D_{Tue} - \underset{(76.2631)^{**}}{672.8101} * D_{Wed} - \underset{(76.3495)^{**}}{698.9348} * D_{Thurs} - \underset{(76.6898)^{**}}{716.981} * D_{Fri}$$

$N = 1860$ $R^2 = 0.8032$ $R^2_{adj} = 0.8021$ $F = 754.50^{**}$

** Significant at 1% level, *significant at 5% level

Saturday is the benchmark category

Standard error values are in parentheses

In this model, we examine competitive pricing behavior with days (day of departure) effect. We consider Saturday as a benchmark category. In the above model, all the variables are significant and the overall model is also significant. In the above table (table 4), we observe that the coefficients of day (days of departure) variables have a negative impact on the airfare of Airline 4 (FSC, Government) with respect to day of departure, Saturday (benchmark category). In the above table, we also observe that the day of departure variables, Saturday and Sunday (weekend), have a significant impact on Airlines 4's airfare compared to other days of departure. So, the weekend airfares are higher than the airfare of weekdays.

This strengthens our conclusion (Model 1) that the price movements across airlines are strongly associated and also shows that the day of departure has an impact on the airfare. However, the degree of impact is different on different days on different airlines.

Model 3 - Dummy for slope effects:

$P_{a3} = 50.1259 + 0.0175^* P_{a1} + 0.7856^* P_{a2} + 0.1876^* P_{a4} + 52.626^* D_{sun} + 70.015^* D_{Mon} + 77.8638^* D_{Tue}$

(18.1515)** (0.0078)* (0.0185)** (0.017)** (25.3136)* (25.3802)** (26.4259)**

$+ 22.8763^* D_{Wed} + 21.8021^* D_{Thurs} + 100.8692^* D_{Fri} + 0.9827^* (D_{Sun}^* P_{a1}) + 0.9817^* (D_{Mon}^* P_{a1})$

(26.2467) (26.2017) (26.6565)** (0.0343)** (0.0332)**

$+ 0.9477^* (D_{Tue}^* P_{a1}) + 0.5828^* (D_{Wed}^* P_{a1}) + 0.9688^* (D_{Thurs}^* P_{a1}) + 0.0041^* (D_{Fri}^* P_{a1})$

(0.0159)** (0.9692) (0.0354)** (0.021)

$- 0.8054^* (D_{Sun}^* P_{a2}) - 0.8131^* (D_{Mon}^* P_{a2}) - 0.7765^* (D_{Tue}^* P_{a2}) - 0.3969 (D_{Wed}^* P_{a2})$

(0.0306)** (0.0288)** (0.0219)** (0.9628)

$- 0.784^* (D_{Thurs}^* P_{a2}) + 0.1122^* (D_{Fri}^* P_{a2}) - 0.1845^* (D_{Sun}^* P_{a4}) - 0.1814^* (D_{Mon}^* P_{a4})$

(0.0207)** (0.0377)** (0.0289)** (0.0287)**

$- 0.1874^* (D_{Tue}^* P_{a4}) - 0.1833^* (D_{Wed}^* P_{a4}) - 0.182^* (D_{Thurs}^* P_{a4}) - 0.1418^* (D_{Fri}^* P_{a4})$

(0.017)** (0.0359)** (0.0356)** (0.0325)**

N = 1860 $R^2 = 0.9924$ $R^2_{adj} = 0.9923$ F= 8835.80**

** Significant at 1% level, *significant at 5% level

Saturday is the benchmark category

Standard error values are in parentheses

Model 4 - Time effects:

In this sub section, we answer the fourth question raised in section 1 of this paper. We discuss the results of route 2 by applying model 4 (of section 4). Here, we consider the airfare of Airline 1 as a dependent variable. The regression results of model 4 are provided in the following table.

Table 6: Results of Model 4

$$P_{a1} = \underset{(79.4614)^{**}}{1056.7276} + \underset{(0.0192)^{*}}{0.7099} * P_{a2} + \underset{(0.0065)^{**}}{0.0311} * P_{a3} + \underset{(0.0073)^{**}}{0.0305} * P_{a4} + \underset{(0.0122)^{\#}}{0.0224} * P_{a5} + \underset{(66.4414)^{**}}{746.3104} * D\_1$$

$$+ \underset{(48.3033)^{**}}{544.6914} * D\_2 + \underset{(28.355)^{**}}{237.3501} * D\_3 - \underset{(18.7292)^{**}}{51.3111} * D\_4$$

N = 1860 $\quad R^2 = 0.9637 \quad R^2_{adj} = 0.9635 \quad F = 6135.15^{**}$

** Significant at 1% level, #significant at 10% level

D_5 is the benchmark category

Standard error values are in parentheses

The above results partially capture the dynamic increasing behavior of airfare movements when the day of departure becomes closer and closer.

From this section, we conclude the following:

1. Irrespective of whether an airline is an FSC or an LCC, airfares along the same route become competitive, and are sensitive to days of departure.
2. The Time effect model explains that close to the day of departure, the airfare gradually increases and becomes more competitive.

In the following section, we extend our study with the introduction of time effect and day (days of departure) effect. This study has been done on the selected 69 domestic airline routes across India.

6. Weekend effect in airfare pricing on the Indian Domestic Airlines Market

In this section, we answer the fifth question that is stated in section 1 of this paper. Here we plan to study the time effect and day effect on the average airfare of Indian domestic airlines. The dependent variable, average price, represents average prices of selected routes across the Indian domestic airline market, collated 60 days prior to departure. In our analysis, we took Saturday and Sunday (collectively) as a weekend variable. The different day variables are treated as a dummy variable and the time variable represents days before departure. Here, we introduce one more time variable in the square of time form. In our model, we assume day of departure, Friday, as a benchmark category. Therefore, our detailed projected model is shown below.

Model 5

$$\textbf{Average\_Price} = \beta_0 + \beta_1\,\textbf{Time} + \beta_2\,\textbf{Time}^2 + \beta_3 D_{Mon} + \beta_4 D_{Tues} + \beta_5\, D_{wed} + \beta_6\, D_{Thurs} + \beta_7 D_{Weekend} + \varepsilon_{ij} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

Where,

Average_Price: Average price of all selected origin destination city pairs on different days prior to departure.

Time: the number of days prior to departure

$Time^2$: Square form of Time

D_{Mon}= 1 when departure day is Monday

0 otherwise

Other Days dummy variables are defined accordingly.

Friday is the benchmark category and dummy variable Weekend developed by combining departure day -Saturday and Sunday.

7. Results and Data analysis of weekend effect

The following analysis has been done based on the 69 routes' domestic airfares across India. In this model, we have adjusted Friday as a benchmark category. The estimated result of *model 5* has been shown in the following table.

Table 7: Estimated Regression result of weekend effect Model 5

$$\text{Average\_Price} = \underset{(32.2235)^{**}}{6723.5576} - \underset{(1.8688)^{**}}{129.0688} * \text{Time} + \underset{(0.0297)^{**}}{1.3886} * \text{Time}^2 - \underset{(29.7395)^{**}}{63.6294} * D_{Mon} - \underset{(31.3482)^{**}}{125.0301} * D_{Tue}$$

$$- \underset{(31.3482)^{**}}{122.5524} * D_{wed} - \underset{(31.3482)^{**}}{93.7513} * D_{Thurs} + \underset{(26.2278)^{**}}{117.5451} * D_{Weekend}$$

N = 1860 $R^2 = 0.8629$ $R^2_{adj} = 0.8623$ $F = 1664.73^{**}$

** Significant at 1% level

Friday is the benchmark category

Standard error values are in parentheses

Based on the analysis, we find that Average Prices are negatively influenced by time and day of the week and positively influenced by square of the variable. All independent variables are statistically significant. From the above result, we find that the Average prices of Monday, Tuesday, Wednesday and Thursday are lower than the average prices of Friday. And, the Average prices of Weekend (Saturday and Sunday) are higher than the average prices of Friday. This again strengthens our conclusion that the weekend's airfares are higher compared to weekday fares. Thus, when the days before departure are relatively higher, then average prices (airfare) would be low and vice-versa.

The above model captures a significant weekend effect on average airfare and the inverse relation between time and average price. Now, to identify the strength of the weekend effect, weekday effect, and time effect more accurately and broadly, we build up the following model.

Model 6

$$\textbf{Average\_Price} = \beta_0 + \beta_1\, \text{Time} + \beta_2\, \text{Time}^2 + \beta_3 D_{Weekday} + \beta_4 D_{Weekend} + \varepsilon_{ij} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(6)}$$

Where,

Average_Price: Average price of all selected origin destination city pairs on different days prior to departure.

Time: the number of days prior to departure

$Time^2$: Square form of Time

$D_{Weekday}$= 1 when departure day is Monday, Tuesday, Wednesday, Thursday

0 otherwise

$D_{Weekend}$= 1 when departure day is Saturday and Sunday

0 otherwise

Friday is the benchmark category.

Results:

In Model 6, we examine the impact of average price with respect to Time, $Time^2$, Weekday, Friday, and Weekend. In this model, we develop the variable Weekday by combining the departure day of Monday, Tuesday, Wednesday, and Thursday, and the variable Weekend has been developed by combining the departure days, Saturday and Sunday. The estimated result of model 6 has been shown in the following table.

Table 8: Estimated Regression result of weekend effect Model 6

$$\text{Avg\_Price} = \underset{(32.2474)^{**}}{6723.5576} - \underset{(1.8702)^{**}}{129.0688} * \text{Time} + \underset{(0.0297)^{**}}{1.3886} * \text{Time}^2 - \underset{(24.6549)^{**}}{99.0284} * D_{Weekday} + \underset{(26.2472)^{**}}{117.5451} * D_{Weekend}$$

N = 1860 R^2 = 0.8624 R^2_{adj} = 0.8621 F= 2907.54**

** Significant at 1% level

Friday is the benchmark category

Standard error values are in parentheses

The independent variables are significant and the overall model also significant. The weekend airfares are higher than the benchmark category, Friday's (departure days) airfare, and the weekday's airfare is less than Friday's airfare. The explanatory variable Time has a significant negative impact on the explained variable Average price.

In the above analysis, our findings are somewhat different from the work done by Mantin and Koo (2010). The relationship between Average Price (airfare) and Time variables remains the same and is significant. Weekend airfares are higher than weekday airfares and have a significant relationship with Average airfare.

From this analysis, we can draw the following important conclusions:

a) Weekend (Saturday, Sunday) airfares are higher than weekday airfares.
b) The 'Time (days prior to departure)' variable has a significant negative impact on the average airfare, that is, it captures the dynamic increasing nature of airfare movements as the departure days get closer and closer.

Based on the weekend effect results on average prices, we can say that leisure passengers purchase their air ticket early and also prefer to buy air tickets on a weekday than on a weekend. It has been established that there is an increasing dynamic price movement as the departure day gets closer. So, most of the Indian domestic airlines service providers apply revenue management dynamic pricing (RMDP) strategies. These operators are either FSC or LCC and their conventional pricing strategies are different (Pels, Rietveld, 2004). As a result, there exists price dispersion among the competing service providers.

10. Relevance for this Research to Stakeholders

This analysis can be useful to all the stakeholders (passengers, new entrants, etc.) that are crucial to airlines. First, the existing competitive airlines operators can identify the degree of competition and set their airfare according to the market demand and segment the airfare market based on the weekdays and weekends with respect to days prior to departure. The airfares become very high one or two days before the Diwali festival in November. In India, the DGCA (Director General of Civil Aviation) is the nodal agency as a regulator. The DGCA can use this study as a reference to control unusual increases in airfares.

Second, this will help both the existing and new airline companies to understand their competitor's price behavior. Third, it may be useful for price sensitive passengers when they are taking their decision to buy their air ticket. If this rule is strictly regulated by the DGCA, the airline can increase and decrease prices according to the demand, but only up to a certain limit.

11. Conclusion

All the results compiled together indicate that competition is evident in the Indian domestic airline market. Generally as the days prior to departure come closer, fares increased evenly and fares jumped on a regular interval, which indicates a block pricing strategy. Weekend (Saturday, Sunday) airfares are higher compared to weekday airfares. Each route is characterized by its own significant route characteristic behavior and the competing airline operators set their prices according to these route characteristics. The overall average airfare movements are affected by the days (day of departure) and time (days prior to departure). These features prove that the application of revenue management and dynamic pricing is a common practice in the Indian domestic airlines industry.

From our study, we draw the following conclusions:

1. The pricing (airfare) movement depends on the degree of airfare competition (strategies) between LCCs and FSCs and every competing airlines apply revenue management and dynamic pricing strategies.
2. Price sensitive passengers prefer to travel on weekdays and would purchase air-tickets decision earlier.

This study can be extended through developing the exact booking data, and then the demand as a function of price and competitors' price can be developed.

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