Why does the price of the same airline seat change so dramatically—and what does it reveal about competition and market power?

Dynamic Skies offers a compelling, data-driven exploration of pricing dynamics and fare dispersion in India's domestic airline industry.Grounded in extensive time-series evidence, this Research Monograph examines how airlines strategically adjust prices across different market structures, from monopoly and triopoly routes to moderately competitive markets. Using robust econometric tools, it demonstrates that price dispersion is not accidental or irrational, but a persistent outcome of dynamic pricing shaped by demand growth, market concentration, and regulatory context.

The analysis moves beyond theory to offer insights with real implications for competition policy, consumer welfare, and airline strategy. Derived from rigorously evaluated doctoral research and presented as a standalone scholarly contribution, Dynamic Skies fills a critical gap in the literature on emerging aviation markets. This book explains not just how airline prices change—but why they do.

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Dynamic Skies:
Price Dynamics in the Indian Airline Industry

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Price Dynamics in the Indian Airline Industry

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Preface

This research monograph, *Dynamic Skies: Pricing Dynamics and Price Dispersion in the Indian Airline Industry*, represents a focused and independent scholarly work derived from one part of my doctoral research. The original PhD thesis, of which this book constitutes a distinct component, has been formally evaluated and subsequently published in internationally recognized academic repositories, including ProQuest.

The present monograph has been conceived with the objective of offering a coherent, self-contained, and analytically rigorous examination of pricing dynamics and price dispersion within the Indian airline industry. While grounded in the broader doctoral inquiry, this volume has been carefully restructured and refined to function as a standalone research contribution, suitable for scholars, researchers, policymakers, and practitioners interested in airline economics, pricing behaviour, and market structure in emerging economies.

The empirical analyses, interpretations, and conclusions presented in this book are based entirely on original research conducted by the author. No artificial intelligence tools were used at any stage of the conception, analysis, writing, or revision of the original doctoral work or this derived monograph. The manuscript adheres strictly to established norms of academic integrity, and similarity checks conducted using standard plagiarism detection software reported zero percent similarity, affirming the originality of the content.

This volume emphasizes empirical evidence and analytical clarity over descriptive narration. While necessary institutional and industry context has been provided to situate the analysis, the primary focus remains on understanding how pricing strategies evolve across different market structures within the Indian airline industry, and how these strategies manifest in observable price dispersion. The findings are intended not

only to extend the academic literature but also to inform regulatory discourse and strategic decision-making in the aviation sector.

As this monograph represents only one part of a larger doctoral study, it is hoped that it will stimulate further inquiry and comparative research, both within and beyond the Indian context. Any limitations that remain are solely the responsibility of the author and are acknowledged as opportunities for future research rather than deficiencies in intent.

We are indebted to the academic community whose prior work provided the theoretical foundations for this study, and to the institutional repositories that ensure the accessibility and preservation of original scholarly research. We also acknowledge the broader scholarly ecosystem that values rigor, transparency, and originality—principles that have guided this work throughout.

The authors wish to acknowledge the limited and responsible use of artificial intelligence tools at the post-research stage, solely for structuring, editing, and reorganising the originally submitted doctoral thesis into standalone research monographs for publication purposes. The author wishes to acknowledge the limited and responsible use of artificial intelligence tools at the post-research stage, solely for structuring, editing, and reorganising the originally submitted doctoral thesis into standalone research monographs for publication purposes.

Abstract

This research monograph examines the nature and evolution of pricing dynamics and price dispersion in the Indian airline industry, with particular emphasis on how market structure influences fare variability over time. Situated within the broader literature on dynamic pricing and industrial organization, the study investigates airline pricing behaviour in an emerging market characterized by rapid demand growth, regulatory transitions, and varying degrees of market concentration.

Using time-series data on domestic airfares and industry indicators, the analysis employs quantitative techniques including measures of market concentration, dispersion indices, correlation analysis, and cointegration tests to examine the relationship between pricing strategies, passenger demand, and macroeconomic variables. The study differentiates between highly concentrated and moderately concentrated market phases, allowing for a comparative assessment of pricing behaviour across distinct competitive environments.

The findings reveal that airline prices in India exhibit significant temporal variability and persistent price dispersion, reflecting the strategic use of dynamic pricing mechanisms. Evidence suggests that changes in market concentration and traffic growth are closely associated with pricing patterns, indicating that competitive intensity plays a critical role in shaping fare dispersion. The results further highlight the presence of long-run relationships between air traffic growth and pricing variables, underscoring the structural nature of pricing dynamics in the industry.

By providing an empirically grounded analysis of airline pricing in India, this monograph contributes to the limited body of research on pricing behaviour in emerging aviation markets. The study offers insights of relevance to academic researchers, policymakers, and industry practitioners concerned with competition, consumer welfare, and pricing strategies in the airline sector.

Chapter 1

Introduction & Research Questions

1.1 Introduction

Charging different prices for the same product and service from different customers has been used by merchants for revenue maximisation. The common man has always questioned this on ethical grounds unless it is socially justifiable.

Discount/concession given to the priority sectors like students, senior citizens, soldiers, physically challenged, etc., has been considered a commendable practice by all societies. It shows that discrimination for the sake of the well-being of a priority sector of society is acceptable. At the same time, any kind of discrimination, including price, based on gender, race, colour, caste, religion, etc., has been illegal in many countries, including India, unless it aims to advance that weaker section. Article 15 in the Indian Constitution prohibits discrimination on the grounds of religion, race, caste, sex or place of birth unless it is a provision for the advancement of any socially and educationally backward classes of citizens (The Constitution of India, 2020). The governments take maximum retail price, price ceiling, floor pricing, and various other regulatory measures to eliminate price discrimination in India.

The travel sector is generally considered an area where the government controls the fares. However, this government control does not seem to be there in the area of all interstate bus transport. During festival season, prices increase tremendously, often inviting public grievances and media attention. Civil aviation is the travel segment where these ups and downs in the fare are very common worldwide, including in India. For example, for a one-hour flight from Kochi to Bangalore in economy class, one may get a ticket from ₹899/- (Airasia, 2017a) to ₹10,804/-(Airasia, 2017b) in the same airline without any change in the service quality. Sometimes, the rate has increased to ₹15,600/- (Spice Jet, 2016) for the same route and economy class. This discrimination was purely based on the time of purchase of the ticket.

Airline companies try to maximise revenue by applying this discriminative pricing based on purchase time (Aguirre, 2012). Airline pricing is generally based on anticipated demand (Borenstein, 1985). Booking much in advance may not ensure a lower price, though it is more economical than last minute purchase. This results in the ups and downs of ticket prices, which in turn causes price dynamics. This practice is expected not only on international routes but also on domestic routes. This kind of discrimination should naturally invite public protest on an ethical basis. But there are no such reports in the media about domestic civil aviation, with few exceptions during the Corona pandemic. Moreover, it has become a common practice in the civil aviation sector. Even the Indian Railway has started practising dynamic pricing on selected trains (IRCTC, 2022).

1.2 Significance of the Study

Civil aviation is one of the nation's key industries, connecting the country quickly. It had been considered a luxury mode of travel for a long time. But, the emergence of the Low-Cost Carriers (LCC) business model has widened the scope of air travel. It has widened the scope of the civil aviation, resulting in higher growth than any other industry. Total domestic passenger traffic increased by 24%, 30% and 42% in 2005, 2006 and 2007, respectively (DGCA, 2011). The LCC's market share increased from 5% in 2004 to 63% in 2009 (NTDPC, 2013). Moreover, India has seen the fastest air connectivity growth of 89% from 2014 to 2019 among the world's top 20 most connected countries (IATA, 2019). A change in the global aviation industry influences the Indian aviation sector since the market is interconnected through the same operators. Millions of passengers choose air travel every year, which tends to increase.

LCC segment of the aviation market introduced a new pricing strategy of advance purchase with discounted fares and promotional offers, as seen in the global aviation market. This pricing strategy was introduced to the US aviation market when Southwest Airlines started the LCC concept following the deregulation of airline pricing in 1978 by the US (Media, 2015). The LCC model and its pricing became a trend when Ryanair Airlines introduced it in Europe in 1990 (Malighetti et al., 2009). Gradually, this non-linear pricing has become the face of the LCC, which created dynamic pricing with the introduction of internet penetration techniques (Hernandez et al., 2017). For example, Air India has offered economy seats in India since 1984, but Air Deccan introduced LCC in 2003 (Chakravarty, 2011). In the same year, the private sector captured more than 50% of the domestic traffic, which crossed 80% within five years (DGCA, 2011). The rapid growth of LCC under the liberalisation of economic regulation (Gialloreto, 1995) and its internet-based pricing strategy has accelerated the growth of civil aviation across the world. LCC business model was introduced in the Indian market in 2002 (O'Connell & G Williams, 2006) and got established in 2004 (NTDPC, 2012).

Dynamic pricing, the result of an internet-based pricing strategy (Gillen & Hazledine, 2006), is an approach to controlling capacity and optimising revenue by influencing purchase decisions of the customers (Burger & Fuchs, 2005). The terms price dynamics and revenue management are used separately by many researchers (Dutta & Santra, 2017) (Gillen & Mantin, 2009) (Xia et al., 2004). In short, dynamic pricing results from the set of pricing strategies, including frequent modifications of prices (Ayadi et al., 2017), introduced for the revenue management in the LCC model assuming the random arrival of customers (Karthik & Mitra, 2016). Under this pricing method, the price changes in response to the demand and supply forces. Since the capacity/supply is fixed well in advance, the seller adjusts the price over time as per the demand. Since demand increases during festival seasons and weekends, the price also increases (Beria & Laurino, 2016). The market also fluctuates with the price elasticity of travellers since there are other modes of travel, including train service, especially on the domestic route. Airline seats are time-dated product which expires at a point of time. Hence, it is a price discovery mechanism (Feldmann, 2008). Thus, the limited number of seats or limited supply, close substitutes of travel or dynamic demand and the perishable nature of the product make air travel and its pricing more complex.

The literature review revealed that the research world had ignored the Indian civil aviation segment. In Europe, Australia, the United States of America and a few Asian countries like China, Korea, and Japan, several studies have been conducted by researchers. These researches contribute to the literature, benefiting the industry and travellers. However, comparatively few research articles in India have been published in this area, irrespective of their importance. The present study intends to explore some of the essential areas ignored by the researchers on the price dynamics of India's domestic civil aviation market.

1.3 Statement of the Problem

Indian civil aviation industry has been showing steady growth since its beginning on 18th February 1911 (Chakravarty, 2011). Nationalisation of civil aviation in 1953, or liberalisation policies of the 1990s, had negligible impact on this growth trend till 2003. This growth tendency dramatically increased after 2003 with the introduction of Low-Cost Carriers. Indian civil aviation industry carried 183.90 million passengers in 2018, of which more than 67% was handled by the domestic market (DGCA, 2019). Hence, the airline price dynamics affect a large number of passengers. Dynamic pricing has been accepted as a pricing model in the Indian domestic and global civil aviation markets. Yet, there were allegations of excessive pricing by airlines in India in 2010, particularly during festive/holiday seasons and during periods of strike by airline employees. In 2011, there were allegations of below-cost pricing against a full-service carrier (NTDPC, 2012). Quoting these incidents, the National Transport Development Policy Committee suggested the government to regulate air travel service pricing in India to offer non-predatory, non-discriminatory, and reasonable prices for air travellers and transparency in pricing (NTDPC, 2013).

Selling the same product to different persons at different prices (first-degree price discrimination) invites criticism from the public. This tendency of revenue maximisation by the merchants was always controlled and penalised by the governments. At the same time, second-degree price discrimination in the form of quantity discounts and quality differences, along with third-degree price discrimination by differentiating consumers into different groups, has been accepted by Indian society without raising much criticism.

The domestic airline routes of India differ in passenger density (DGCA, 2019) and market concentration in terms of the number of airline companies operating on a route. Tier-I cities with a population of more than four million (18 airports) occupy nearly 93% of the total seat deployment by scheduled airline operators (Deloitte, 2013). Except for those routes under the Regional Connectivity Scheme of the Government (Kumar, 2017), all routes are characterised by dynamic pricing. In short, dynamic pricing based on first-degree price discrimination prevails in the Indian civil aviation market without much criticism and government intervention. While considering the ethical aspects of discrimination, an essential factor to be considered is the growth of the civil aviation industry on the shoulders of LCC. Statistics prove the accelerated growth of air passengers carried by LCCs, which has flourished under the dynamic pricing system. This growth has facilitated the development of other sectors of the economy. Fu et al. argue that numerous research papers confirm the significant worldwide welfare gains and economic growth brought by the liberalisation of civil aviation (Fu et al., 2010). This situation invokes curiosity and raises the following questions:

1. Does Indian civil aviation industry show a different growth pattern after introducing price dynamics?
2. What is the extent of price dispersion due to price dynamics?
3. Does the dispersion vary with market concentration?
4. What are the determinants of price dynamics?
5. Do all airlines show an increasing price with closeness to departure?

These questions of interest need systematic processing and analysis to unearth the underlying facts. Therefore, the following research objectives have been formulated to discover the underlying truth of the above research questions.

1.4 Objectives of the Study

The major objective of the study is to conduct an in depth investigation on the various aspects of price dynamics in the Indian civil aviation segment. Multiple elements of price dynamics, its major determinants under different market situations, the attitudes of passengers towards price dynamics, and antecedents of attitudes towards price dynamics are covered in this study. The following are the specific objectives under which the study was conducted:

1. To analyse whether the Indian civil aviation industry shows a different growth pattern after dynamic pricing became ubiquitous.
2. To analyse the price dispersion based on market concentration in the domestic civil aviation of India.
3. To analyse the determinants of price dispersion caused by dynamic pricing in the domestic civil aviation of India.

1.5 Hypotheses

The following hypotheses are formulated based on the literature review and the research objectives.

$H_{0\,1} - H_{0\,6}$ Air Passenger Traffic growth is not co-integrated with the per capita GDP of the nation before and after dynamic pricing became ubiquitous.

$H_{0\,7} - H_{0\,9}$ Price movements of neighbouring days of departure of the same airline are not significantly correlated under different market situations, viz, monopoly, partial monopoly, and triopoly.

$H_{0\,10} - H_{0\,11}$ Price movements of competing airlines on the same day are not significantly correlated under different market concentrations, viz partial monopoly and triopoly.

$H_{0\,12} - H_{0\,14}$ Booking prices are not significantly correlated to the time gap to the departure date under different market situation, viz, monopoly, partial monopoly, and triopoly.

$H_{0\,15} - H_{0\,17}$ Neighbouring day prices does not significantly influence the festival day prices under different market situation, viz, monopoly, partial monopoly, and triopoly.

$H_{0\,18} - H_{0\,19}$ The prices of different time segments are not significantly correlated.

$H_{0\,20} - H_{0\,26}$ The prices of other flights on the route or the time of booking does not significantly influence the prices of a flight.

1.6 Scope of the Study

The study is basically limited to India's domestic civil aviation market with scheduled flights. The total air passenger traffic of India was compared with that of a few other selected nations to address the question of the growth pattern. Cargo handled by the scheduled flights and its impact, if any, on the fare is not covered under this study. Moreover, the 'domestic civil aviation' in this research does not cover chartered flights and scheduled and non-scheduled helicopter services. The theoretical aspects covered in the study are dynamic pricing, price dispersion caused by dynamic pricing, major determinants of price dynamics, and the attitudes of passengers towards dynamic pricing.

1.7 Methodology of the Study

The study deals with the analysis of price dispersion. For this purpose, the study handles both primary data and secondary data. The entire methodology of the research is discussed below.

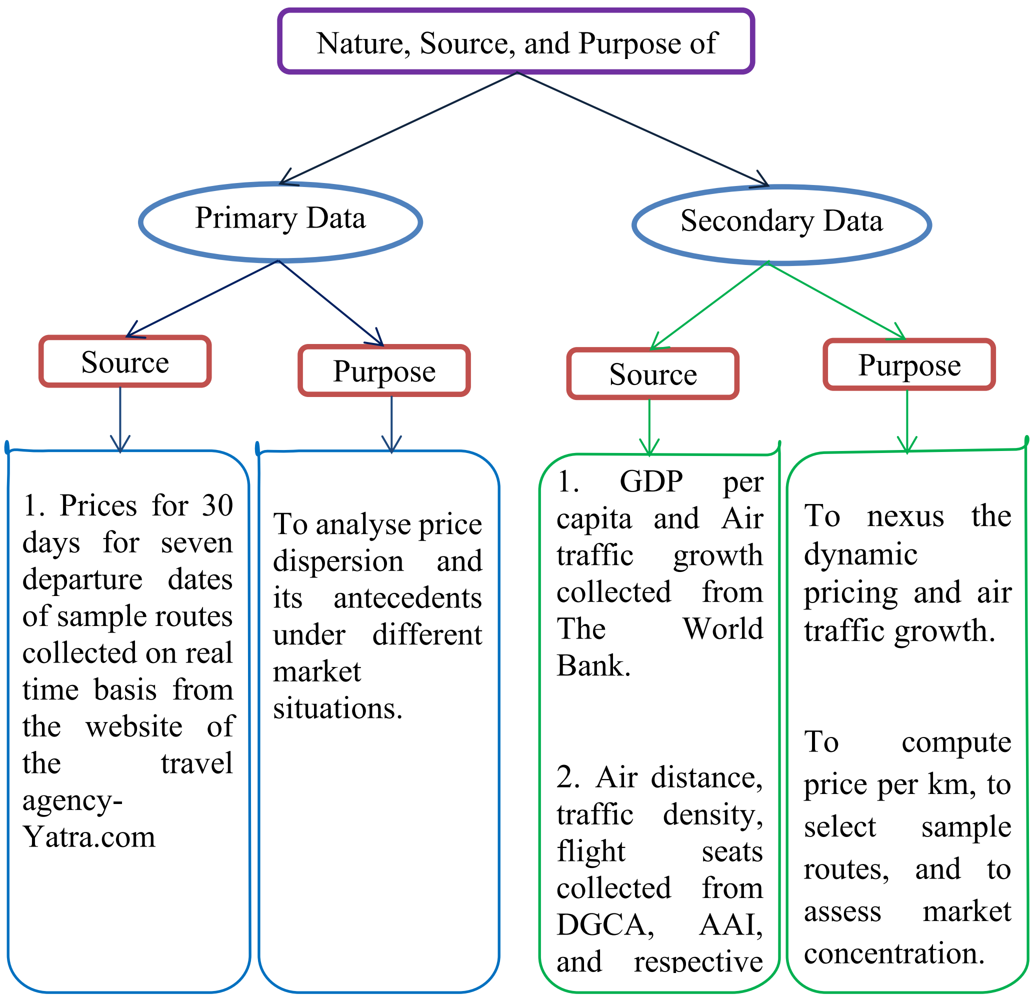
1.7.1 Nature and Source of Data

The time series data collected from both primary and secondary sources. The secondary data relating to GDP per capita and air traffic growth were used to establish the relationship between dynamic pricing and air traffic growth. These data were collected from the published records of The World Bank. Other secondary data such as, air distance, route traffic density, flight seat availability, etc. were collected from the published records of Director General of Civil Aviation (DGCA), Airport Authority of India (AAI), and the concerned airline websites. The primary data were collected by the researcher from the website of a reputed travel agency – Yatra.com. This includes the ticket prices quoted by various airlines over selected routes on selected departure dates.

Figure 1.1 shows the details and purpose of data used in this research.

Figure 1.1

Nature, Source, and Purpose of Data



Source: Compiled by the Researcher

1.7.2 Population of the Study

There are 129 licenced airports in India, including civil enclaves of defence airfields with scheduled airlines (AAI, 2018). There are 914 routes connecting these airports with scheduled flights as on 31st March 2018 through 15 airline companies (DGCA, 2018b). Table 1.1 shows the details of the population of this study. The study population comprises 123 million passengers travelling through these domestic routes (DGCA, 2019).

Table 1.1

Population of the Study

Population Elements for 'Price Collection'	No.
Total Number of Airports	129
Total Number of Airports with Scheduled Flights	87
Total Number of Scheduled Operators (Airline Companies)	16
Total Number of Fleets	584
Total Number of Routes	914
Total Number of Domestic Civil Aviation Passengers in the year 2018	123 million

Source: Compiled by the researcher from various reports of DGCA and AAI

1.7.3 Sample Selection for Collection of Price

Representation of routes with different travel densities, routes of all available types of market concentration and inclusion of leading airline companies was the main focus of sample selection. For this, multi-stage stratified random sampling was followed, which is explained below.

1.7.3.1 Selection of Routes

There are 914 routes connecting 87 airports in India. Out of this, only 574 routes had daily/direct flights. The remaining 340 routes did not have daily flights. Hence, they were eliminated from the study. The routes having daily scheduled flights were arranged in the order of monthly domestic city pair traffic. Then, these 574 routes are divided into two strata. The first stratum of 287 routes (574/2) consists of city pair routes, having a monthly traffic density of 8,000 passengers or more. The second stratum of 287 routes consists of city pair routes with a monthly traffic density below 8,000.

The first stratum was again divided into two based on traffic density. The first 54 routes carry 47.5% of the total domestic passengers. These routes were also characterised by a minimum passenger density of more than fifty thousand in a month. The second part of the first stratum, which consists of 233 routes, carried 43.8% of the total domestic passenger. Two routes were taken randomly from each part. Two of the 13 routes connecting island airports were selected randomly. A total of five routes were chosen from the first stratum. The lottery method was followed for random sampling.

The second stratum of 287 routes carried only 8% of the total domestic passenger. Five routes were selected randomly from this stratum. The presence of a single fleet and single airline company mainly characterises these routes. The excluded portion of 340 routes carried 0.7% of the total traffic. These excluded portions of the routes did not have daily direct flights. The sample routes selected and their monthly traffic as of 31st March 2018 is shown in Table 1.2.

Table 1.2

Scheme of Selection of Sample

Classification	No. of Routes		
Total no. of Routes			**914**
Routes with Direct Daily Flights		574	
High Traffic Routes	54		
Medium Traffic Routes	233		

Low Traffic Routes	287	
Routes without Daily Flights		340
Routes Selected as Samples		
	Passenger Traffic per month	
High Traffic Routes		
Mumbai - Bangalore	1,57,007	3,01,307
Delhi - Kolkota	1,44,300	
Medium Traffic Routes		
Delhi - Kochi	43,591	
Port Blair - Kolkata	30,646	1,15,921
Chennai - Port Blair	28,320	
Mumbai - Thiruvananthapuram	13,364	
Low Traffic Routes		
Pune - Kochi	9,601	
Ahmedabad - Lucknow	4,903	
New Delhi - Dibrugarh	4,455	22,594
Varanasi - Khajuraho	2,115	
Hyderabad - Nanded	1,520	

Source: DGCA

Three public sector airline companies and 13 private sector airline companies offered scheduled airline flight services in the domestic sector of India in the year 2018 (MCA, 2019). Blue Dart and Heritage Aviation did not carry scheduled passenger services among the private sector companies. Zoom Air, Air Odisha, and Air Deccan closed their scheduled passenger service by October 2018. Only eight private-sector airline companies continued their scheduled service for the whole year (DGCA, 2018a). The selection scheme has ensured the representation of one major public sector airline and seven private sector airlines, as given in Table 1.3.

Table 1.3

Sample Airline Companies

Sl.No.	Airline Companies	Passengers Carried*
	Public Sector	
1	Air India Ltd.	1,54,97,575
	Private Sector	
2	Jet Airways (India) Ltd.	1,90,29,065
3	SpiceJet Ltd.	1,71,04,236
4	Go Airlines (India) Pvt. Ltd.	1,24,63,932
5	Inter Globe Aviation Ltd. (Indigo)	5,77,68,264
6	Air Asia Pvt. Ltd.	68,23,534

7	Tata SIA Airlines Ltd. (Vistara)	52,61,205
8	Turbo Megha Airways Pvt. Ltd. (True Jet)	5,86,390

*Source: DGCA (Total number of passengers carried by the airline company in the year 2018)

1.7.3.2 Selection of Departure Dates

For each selected route, prices were collected for seven consecutive departure dates. Prices had also been collected for major festival days of the destination routes. Festival holidays are supposed to attract more traffic from passengers. Hence the collected data include prices of weekdays, weekends and festival days. Diwali, Onam and Christmas were the festival holidays on which data were collected.

1.7.3.3 Collection of Price Points

Airline Companies show their price quotes for various routes on their booking websites. Collecting these data from the websites of all airline companies every day was impossible due to practical constraints. Online travel agencies display the quotes of the price of all these airlines on their websites for the customers. The researcher conducted a pilot study to compare the price quotes of online travel agencies and airline companies. In most cases, both websites offered the same rate. Few airline companies have quoted comparatively more prices than the travel agency quotes. There were no differences in price quotes for air tickets between the travel agencies. Only service charges of airline travel agencies varied, which are not included in the quotes displayed. But there was a difference in the number of flights displayed on selected routes on the websites of travel agencies. The website of Yatra.com was selected for the collection of data since it displayed a maximum number of flights. Datta and Santra also used this website to collect data for their study on airline price dynamics

(Dutta & Santra, 2016). The researcher depended on this website for the collection of prices.

1.7.3.4 Sample Size of Ticket Prices

The prices quoted by the airlines would last till the next update of price by the airline company. Neither the airline company nor the online travel agency stores and displays the historical data of price quotes.

Researchers have adopted various sampling methods for their studies on airline price dispersion. Stavins analysed data on 5,804 tickets offered for flights on twelve routes on the same day to see the effect of market concentration in the US market (Stavins, 2001). Stanisław and Nowacki selected three major airlines and four routes to analyse Poland's price dispersion (Stanisław & Nowacki, 2014). Dutta and Santra selected five routes and six airlines to study the day-of-the-week effect of airline companies in the Indian domestic market (Dutta & Santra, 2016). Chakrabarty and Kutlu collected data for seven airlines on 22 routes to study the competition and price dispersion in the US market (Chakrabarty & Kutlu, 2014). This research gathered and analysed the total samples of 31,800 price points from 1,060 flights of eight airline companies.

1.7.4 Sample Selection of Pattern of Growth

The World Bank categorises countries as low-income, lower-middle-income, upper-middle-income, and high-income nations (The World Bank, 2022). India is in the group of lower-middle-income. There is some missing information in the published data of a few countries. Such countries are eliminated. For the rest lottery method is followed to select the sample nations. The researcher selected two countries from each category, apart from India.

1.7.5 Period of Study

Primary data on airline ticket prices were collected from July 2018 to January 2019. Primary data from airline passengers were collected in July and August 2020. Secondary data covers the period from 1970 to 2022.

1.7.6 Tools of Data Analysis

The researcher used the Gini coefficient and Lorenz Curve to measure the dispersion caused by the price dynamics. To calculate the extent of market competition/concentration, the researcher used Herfindahl-Hirschman Index (HHI). Time series plots and Kendall's rank correlation tau analysis are used to infer price movements. For evaluating the long-run relationship of GDP per capita and air passenger traffic growth, the researcher use Augmented Dickey-Fuller (ADF) unit root and Engle-Granger cointegration (EGC) test.

The researcher used the Ordinary Least Square model, Panel Data Models of Pooled Ordinary Least Square, Fixed Effects, Random Effects, and The Weighted Least Square to get the influence of competing flights of prices. For selecting best-fit models, the researcher used the Panel Specification Test (F-Test), the Hausman test, the Akaike Information Criterion, Schwarz Information Criterion, and Hannan-Quinn Information Criterion. For testing the normality of residuals, the researcher used the Chi-square test. To be conscious of spurious regression results, the researcher compared R-squared / LSDV R-squared with Durbin-Watson.

Descriptive statistics, Mann- Whitney U Test, and Kruskal- Wallis Test were used to analyse data collected through questionnaire. Using Partial Least Squares (PLS), the researcher created Measurement and Structural model, which was tested for reliability and validity.

1.8 Operational Definitions

Specific terms used in this research are defined to ensure smooth reading. The terminologies particular to this industry are also explained below.

1. **Price Discrimination:** When the tickets of the same flight are sold at different prices to different consumers, without any change in the services provided, it is called price discrimination.
2. **Dynamic Pricing:** Dynamic pricing is a strategy where the seller changes prices based on seat availability, expected demand, supply, and competition. This strategy creates price dispersion and leads to price discrimination. Price dynamics is used as a synonym of dynamic pricing in this research.
3. **Price Dispersion:** Since the airline price may vary from time to time due to dynamic pricing, there will be variations in ticket prices paid by different passengers on a flight. This variation in ticket prices on a day or various days of various flights on the route is termed price dispersion.
4. **Price Point:** Price point in this research means the bid/auction price offered for an airline ticket at a particular time. At this price, a customer can purchase an airline ticket at that time. However, airline companies start auctions before departure, even before six months. Therefore, the price will fluctuate, depending on market conditions, i.e. booking realised and vacant seats.
5. **Price Quote:** The airline ticket price for a particular class of travel on a specific route offered by an airline company at a particular time. Price points and price quotes are used as synonyms.
6. **LCC:** Low-Cost Carriers are airline business model which offers tickets at the lowest price by minimising operation costs. The products offered by LCCs are economy class and Premium economy class.
7. **FSC**: Full Service Carriers are those airlines offering only business class service to their customers. They are a traditional airline business model.
8. **Fleet**: Each flight of an airline company on a route is termed the fleet.

9. **Leisure Travellers:** Passengers who plan their travel well in advance to choose a low-fare air ticket are termed 'Leisure travellers'. They are a price-sensitive traveller who books in advance or changes their travel plan to ensure a low-priced ticket

10. **Business Travellers:** Passengers who plan their travel quickly are termed 'business travellers'. They are ready to pay more for their tickets because of an emergency.

11. **Domestic Civil Aviation:** The segment of civil aviation in India consisting of:

    a. **Domestic Airports**: Various airports (including international airports and civil enclaves of the defence airports) in India serving scheduled domestic flights are termed domestic airport.

    b. **Scheduled Domestic Flight**: A commercial flight operating with a pre-fixed schedule, where the departure and arrival occur in the same country, is termed a scheduled domestic flight.

    c. **Airline Passengers**: Passengers travelling by a scheduled flight.

12. **Monthly Traffic Density:** The number of passengers carried by all the airlines on a particular route (one side only) for the whole month.

13. **Hub and Spoke**: Hub is a major airport that serves as a central point for coordinating flights from minor airports termed spokes.

14. **Passenger Load Factor:** PLF is a measure of capacity utilisation of airlines, the percentage of available seating capacity filled by passengers (DGCA, 2016).

15. **Civil Aviation:** Civil aviation industry and airline industry are used as synonyms in this research.

16. **Monopoly**: A monopoly route, in this research, refers to a route where only an airline company operates, even if it does not exhibit other characteristics of monopoly.

17. **Partial Monopoly**: A partial monopoly route, in this research, refers to a route where a single airline company operates most of the days of the week. In one or two days, two airline companies operate.
18. **Triopoly**: A triopoly route, in this research, means a route where three airline companies operate on all days of the week.
19. **Concentrated Market**: Airline routes dominated by a maximum of three airline companies are termed a concentrated market in this study.
20. **Moderately Concentrated Market:** Airline routes dominated by four or more airline companies are termed a moderately concentrated market in this study.

1.9 Limitations of the Study

1. Airline companies do not publish the number of seats sold at a particular price quoted. The actual number of passengers with tickets of the same price will influence the Gini coefficient. The company may change the prices if the seats are not sold for a few days. Moreover, the load capacity of flights also differs. But the researcher considers only 30 price points for a day of departure. Hence the dispersion reflected through the Gini coefficient is not the actual dispersion of prices.
2. Companies may change their price quotes more than once a day. The researcher collected data only once a day. Any fluctuations within the time intervals are not taken for the study.
3. There are a number of connected flights on many routes. The limited resources did not allow such data collection within the time limit. Therefore, their influence on prices, if any, is not considered in this study.

4. To have uniformity in the data for all routes, only the ticket prices of direct flights on a route have been considered for analysis. The effects of flights with stops and connected flights on direct flight tickets are not studied in this research.
5. The major tool for analysis of dispersion used is the Gini coefficient. Researchers have used this most common tool to analyse airline price dispersion. However, some critics often treat Gini as a measure of only income disparity. Therefore, the limitations of this tool might have affected the analysis.
6. The market share of airline companies was calculated from their total seat availability on a particular route. Passenger load factor on the specific route was not available and not considered in the calculation of the Herfindahl-Hirschman Index.

1.10 Scheme of Presentation

The study is presented in nine chapters. The scheme and contents of each of the chapters are briefly described here.

Chapter 1: Introduction & Research Questions

This chapter gives a brief introduction to the study, including the significance of the study, research objectives, research hypotheses, methodology of the study, operational definitions and limitations of the study.

Chapter 2: Pricing Theory and Literature

Previous studies conducted by researchers on airline price dynamics of various continents are discussed in this chapter to form a theoretical background to this concept. The chapter also provides insight into the research gap identified.

Chapter 3: The Indian Airline Industry: Context for Pricing Analysis

Price dynamics is the globally accepted pricing method of the civil aviation industry. This chapter intends to provide an in-depth understanding of the industry where price dynamics are practised. A brief description of the civil aviation industry, including its history, and an analysis of civil aviation growth before and after introducing price dynamics are there in the chapter. The chapter also discusses the role of dynamic pricing in the growth of the airline industry through cointegration analysis.

Chapter 4: Price Dynamics in Concentrated Markets

The extent of price dispersion and its antecedents in the concentrated segment of India's domestic civil aviation market is analysed in this chapter. The chapter analyses the price dynamics under monopoly, partial monopoly, and triopoly situations.

Chapter 5: Price Dynamics in Moderately Concentrated Markets

The extent of price dispersion and its antecedents in the moderately concentrated segment of India's domestic civil aviation market is analysed in this chapter. The chapter analyses the price dynamics under an oligopoly situation.

Chapter 6: Findings, Implications, and Future Research

The study findings based on the objectives are given in this chapter. The chapter also concludes the research and point out areas for further investigation.

Chapter 2

Pricing Theory and Literature

2.1 Introduction

The airline business is considered highly complex, with perishable nature of elastic demand. The pricing mechanism of civil aviation is also complex, with its complexities of demand penetration and revenue maximization techniques. Time-based pricing is the globally accepted pricing technique in the civil aviation segment. Under this technique, the passengers are classified into leisure and business travellers based on the ticket purchase time (Vulcano et al., 2002). Passengers who plan and book the lowest fare ticket well in advance are considered more price-sensitive leisure travellers. On the other hand, those who book flexible tickets of higher fare buckets and in proximity to the departure date are considered business travellers who are less price sensitive. This pricing method creates dynamics in pricing. Price dynamics, in turn, create dispersion in passenger prices. This chapter deals with the existing literature on the price dynamics of airline markets to formulate theoretical background for the research.

The researcher has reviewed 477 literatures related to the civil aviation industry available from 1905 to 2023 for an in-depth understanding. It includes research articles, theses, various reports of civil aviation regulatory agencies, related Acts, articles from the websites of major players in the industry, newspaper articles, etc. This chapter covers 263 of this literature. The rest are included in other chapters.

The chapter covers studies on the airline industry from all five continents with scheduled flight service and intercontinental air transportation. It includes 26 PhD theses submitted by various scholars, mainly to the universities of the US, collected by the researcher from the database of ProQuest LLC. Most of the research articles are collected from Elsevier Science Ltd. Major literature in this area from 1905 to 2023 has been covered in this review. Even though western researchers in American and European countries have contributed a lot to the literature, Indian civil aviation is still an area almost untouched in several areas.

This chapter reviews the global literature on airline price dynamics, mainly the sources that influence airline price dispersion caused by price dynamics, the extent and pattern of airline price dispersion, and the factors leading to passenger attitudes towards airline price dynamics.

2.2 Price Dispersion in Airline Industry

> "There is an incentive to engage in price discrimination whenever a good is sold at a price in excess of its marginal cost" (Varian, 1989).

The willingness of people to pay for a particular good and service differs. This gives an opportunity for the seller to make price discrimination. Varian observed that if there is excess price over marginal cost, someone is willing to pay more for a unit of a good. Therefore, the monopoly and oligopoly price discrimination theory arises naturally (Varian, 1989).

The leading cause of price dispersion is the discrimination adopted by airline companies. Ian Gale observed that the business traveller pays more than twice for an unrestricted ticket than an advance-purchase one. The difference in fares is greater than the cost of serving the various passengers. Price discrimination explains these patterns (Gale, 1993).

Price dispersion exists in the US airline industry on an unmatched scale (Ross L B, 1994). Borenstein and Rose also observed considerable dispersion in the airline prices of the US market. With the measure of price dispersion (Gini coefficient), they observed a 36% variation in prices from the mean price. Price dispersion is likely to decline as traffic density due to competition increases. Discriminatory pricing and variations in the costs of serving different passengers are the basis of the dispersion in airline prices (Borenstein & Rose, 1994).

Extreme price discrimination, highly fluctuating demand, fixed capacity, extremely perishable nature of the product and complex fleet planning are the major characteristics of the global civil aviation industry. The global airline industry is subject to wide price discrimination. Lyle observes that air transport demand fluctuates highly and the product is extremely perishable, with a low marginal cost per seat, in times of 'excess' capacity (Lyle, 1995).

Through his predictive model, James D Dana proves that yield management based on price dispersion would also benefit business travellers. For airline companies, uniform pricing is inefficient where the demand is uncertain, and equilibrium price dispersion helps them to shift demand (Dana, 1999).

Verlinda found that monopoly markets favour a wider fare distribution, whereas duopoly and competitive markets exhibit a tighter fare distribution. He argues that the dispersion of airline fares results from airlines' efforts to practice second-degree price discrimination (Verlinda, 2005).

Gillen observed extensive price discrimination in the Canadian airline market. This discrimination was based on the date of booking and other factors. The number and size of the airline significantly influence the average prices paid on a route. Compared to Low-Cost Carriers (LCC), 'Legacy' carriers could charge a substantial price premium (Gillen & Hazledine, 2006). The term Legacy is used as a synonym for Full Service Carriers (FSC).

McAfee and Velde consider price dispersion as static randomization by firms in pricing, where each customer pays an identical price. Marginal cost and the time of purchase influenced dynamic price discrimination in the US Market (McAfee & Te Velde, 2007).

Demand characteristics and competitive pressure from the presence of LCCs significantly influence dynamic price dispersion. Variables like population, income and the share of business passengers influence demand. But the market is not affected by the competition intensity. The impact of these variables intensified as the departure date approached (Mantin & Koo, 2009).

Roose studied the dramatic variation in airfares offered in the Australian airline market. Dramatic variation was found across fare classes for a given booking day and between booking days. The week before travel witnessed a steep rise in the lowest available fares on a flight. Price variation by booking day was evident for economy fares only (Roos et al., 2010).

Consumers' heterogeneity, inventories, capacity constraints and the perishability of airline seats are the reasons for asymmetric pricing in the airline industry. As a result, prices absorb higher demand states, preventing the seller from selling out soon. Conversely, lower capacity utilization rates absorb lower demand states rather than lower prices (Escobari, 2012). In other words, there are chances of high prices due to high demand but a rare chance for low prices due to lower demand. Therefore, instead of further reduction, seats will be left vacant.

LCCs and network carriers use this pricing strategy more because the airlines primarily compete on their base ticket fares, and passengers generally compare these fares when deciding which flight to purchase (Wit & Zuidberg, 2012).

Kang observed passenger heterogeneity as the dominant factor that drives airline price dynamics. The other elements are capacity, time remaining until departure and competition. In his counterfactual model assuming homogeneous consumers, the price dispersion in the equilibrium decreased by 72% (Kang Jian, 2012).

Peak-load pricing helps to increase revenue since there would be a shift of traffic to off-peak because of price elasticity. This pricing method would benefit society and the passengers. Passengers would be happier to travel in a less crowded atmosphere, especially at a lesser cost. Employees would be relieved from their burden. This shift could also reduce the cost of traffic congestion to the environment. Though at a premium, these benefits are also transferred to peak-load passengers (Friedman & Gerstein, 2014).

Studies of Taiwan-China showed that the time of the day, hot season and vacations positively affect prices and advance booking. Morning flights in the hot season are booked in advance. Fare and seat inventory control are varied for different flights (Chiou & Liu, 2016).

Studies in India show a significant difference in mean fares offered by airlines and no significant difference in mean fares when passenger book tickets one week in advance (Thirunavukkarasu & Nedunchezian, 2016). However, Mathur observed that morning flights, weekend flights and festival flights are more expensive than other flights in India (Mathur, 2020).

2.2.1 The Pattern of Airline Price Dispersion

Patterns of fares offered vary from time to time over the routes. While some routes showed an increasing price pattern to departure date, others showed fairly uniform prices for legacy and LCCs. The fare structures of an airline company seldom show any indication of price leadership in the European market (Button et al., 2007).

Different airline companies have different pricing policies. For example, EasyJet, Europe's most successful low-cost short-haul airline, had a simple fare structure. There was only one class, and the price was the single variable to control the demand (Koenigsberg et al., 2008).

Studies in the African airline market revealed no monotonic relationship between airfare and time. The researchers could not observe monotonic growth or decrease in price with the closeness to the time of departure (Petrovic et al., 2011). A monotonic relationship means a continuous increase or decrease in the price without any opposite action.

Chakrabarty and Kutlu studied the effect of price dispersion on inter-firm, inter-flight and frequency competitions. They observed that when the number of flights became large, passengers considered a convenience, and the impact of convenience dominated than competition effect. Furthermore, as the number of flights increases, first dispersion increases showing a positive relationship, then it becomes constant, and when the total number exceeds 300, price dispersion increases considerably. In essence, when the competition effect is controlled, an S-shaped relationship exists between market concentration and price dispersion (Chakrabarty & Kutlu, 2014).

Based on the studies in the US market, Cohas opined that air travel patterns vary substantially between business and leisure travellers (Cohas et al., 1995).

2.3 Sources of Airline Price Dispersion

The literature review reveals that airline revenue maximisation techniques are the primary reason for price dispersion in the airline market. Business models, product differentiation within the models, along with cost differences are the basic reasons for price dispersion in any market. The specific features of the airline market, such as unpredictable demand and limited but perishable supply, force airline companies to focus on revenue maximisation techniques rather than on cost-based pricing. Passenger heterogeneity is one of the specific features of the airline market, which smoothens airline companies' chances of price discrimination. Price discrimination techniques are designed to focus on this consumer heterogeneity. Technology smoothens the task of price discrimination, which in turn results in the price dynamics in the airline market.

2.3.1 Business Models

The low pricing strategy of LCCs will naturally attract less wealthy passengers who typically travel by bus or train. They are less attentive to the service quality of the airline. Business models help quality-sensitive travellers to identify the nature of carriers. Thus the business models are vehicles for delivering the value proposition to the customer (Lawton & Solomko, 2005).

The aviation industry has mainly three business models: FSCs, LCCs and Chartered flights. A new model called Ultra Low-Cost Carriers (ULCC) is also mentioned in the literature. Customers view these segments differently, and so make the demand for them. Studies show that the intention to use FSC is the service perception of passengers. But service perception has less effect on the intentions to use LCC. Moreover, LCCs weakened the price discrimination ability of the FSCs (Chiou & Chen, 2010). Legacy carriers have complex products, while LCCs have simple products and pricing strategies (Gillen & Gados, 2009).

The introduction of the $10 'night fare' in 1971 between Houston and Dallas by the Texas-based Southwest Airlines Company (S Airlines, 2020) was a landmark that turned the airline industry's profile. This new strategy has been a major inspiration to most other companies in the sector. This could attract more passengers to the sector to widen the market. US DoT report (Bennett & Craun, 1993) and Richards (K. Richards, 1996) point out that Southwest Airlines' low-cost attempts have rapidly increased traffic volume and a simultaneous fall in fares.

The introduction of LCC has attracted a significant portion of business travellers to Europe. Short-haul business travellers were more price sensitive than others in this movement (Mason, 2000). The entrance of a leading low-cost carrier has increased traffic and reduced the average airfare in the US market (Vowles, 2001). FSCs offer comfortable seats, free food, special services like transfer of baggage, loyalty programs, etc. No-frills services such as no baggage transfer, no seat assignment, limited seat comfort, catering against payment, secondary airports, no special services, only direct distribution, no loyalty programs, etc., were the features of LCCs (Graf, 2005). Based on the survey conducted at Jammu airport, Nagar argues that service quality is the main focus of FSCs, whereas low price is the main focus of LCCs (Nagar, 2013).

The coexistence of FSCs and LCCs exhibited price stability and lower price dispersion in the European market (Gillen & Morrison, 2003). British airline market showed three main airline business models (traditional, low cost and chartered), which contribute significantly to airport aeronautical and non-aeronautical revenue (Papatheodorou & Lei, 2006). Mason and Morrison argued that LCC means just differences in the airline business models, and these models contribute to the relative profitability of the airline companies (Mason & Morrison, 2008).

From two weeks before departure, price volatility increases significantly. Before these two weeks, price volatility is reasonably stable. But the type of business model greatly impacts the volatility measures (Gillen & Mantin, 2009). Entry of Low-Cost Carriers introduced in India, multiple slab tariffs such as apex fares, internet auctions, special discounts and last-day fares (Dasgupta et al., 2009).

In the oligopoly routes of the European market, the presence of LCCs reduced the fares significantly (Fageda & Ferna, 2009). Likewise, entry and substantial growth of LCCs at US airports significantly lowered average fares and stimulated passenger volumes (Abda et al., 2012).

Based on the study conducted in the European market, Mason proved that the mergers of similar business models would increase the firms' profitability (Lenartowicz et al., 2013). Daft and Albers opined that the survival of an airline company is based on its ability to differentiate the high-priced and low-priced airline services. An LCC should focus on its low-cost, low-price branding. FSCs should focus on their extended services. Deviations from this core principle may affect the airline's existence (Daft & Albers, 2013).

The worldwide LCC penetration rate grew by 16.3% in 2013. LCCs account for 57.7% of seats in South East Asia and 58.4% in South Asia (Pearson et al., 2015). Price dispersion increases when FSCs and LCCs operate in the same market (Dutta & Santra, 2017).

Corbo observed the presence of a new model ULCC that charges for all aspects of travel beyond the ticket in Europe and the US (Corbo, 2016). Bachwich and Wittman also observed the same business model in the US airline industry, considerably affecting airline price reduction (Bachwich & Wittman, 2017). However, this model has not yet taken the wide attention of scholars.

2.3.2 Product Differentiation by Airlines

Product differentiation and value-added services have been taken as a medium for customer differentiation. Extra leg space, window seats, front row seats, side seats, etc., have been sold at extra charges by the airlines, resulting in price dispersion. Eric has identified that product differentiation was a source of price dispersion in the US airline market. He said that online travel agents made this differentiation, and the same travel request would offer tickets with 28% price dispersion by different online travel agents (Eric et al., 2002).

According to Gillen & William, horizontal product differentiation and vertical bundled integration are the major aspects of air travel products. Horizontal product differentiation takes place between airline travel products. Between airlines and airports, vertical integration takes place. FSCs and LCCs differed in offering services like online booking, check-in facilities, priority boarding, airport lounges, seat assignment, in-flight service, etc. The simplicity of product and delivery process design was the basic strategy of LCCs (Gillen & Morrison, 2003).

Lazarev considers product differentiation as a method of differentiating business and leisure travellers. For example, airline companies in the US market offered high-priced tickets with no cancellation fee. Business travellers are less price sensitive but always avoid cancellation charges (Lazarev, 2013).

2.3.3 Cost of Operation

Input costs (including labour, fuel, materials and flight, maintenance and lease), airport charges, taxes and levies, agency costs, and cost of services are the major components of the cost of operation of airline companies. Danish A Hashim studied the cost structure in Indian Airlines and found a high degree of ‘scale economies’. He opined that the scale economies would limit the scope of competition. High maintenance costs will increase the cost of operation (Hashim, 2004). In his later research, he observed that the high operating cost was transferred to the consumers in the form of proportionately higher charges. High fuel costs, high airport charges, serving uneconomic routes, expenses on ticketing, sales promotion and passenger services increase the cost of air travel in India (Hashim, 2014).

Tulsi observed that per passenger-kilometre economy fares vary considerably with distance. This was 80% lesser for long-haul flights than for short-haul flights. This is possible because long-haul flights have a lesser cost of operation. However, the economy fare differs with route and region. For example, the average fare per passenger-kilometre on short distant routes was three times more in Europe than in Asia-Pacific. But, the differences were insignificant for long distant routes (Kesharwani, 2001).

In India, there existed unfair discrimination between traditional turboprop aircraft and Jet aircraft in the sales taxes for fuel. Other higher input costs such as maintenance charges, aircraft lease rentals and manpower costs were also higher in India. The fuel cost accounted for around 35 % of the total costs for FSCs and 44 % for LCCs (Bansal & Khan, 2008). In addition, some airports differentiate charges during peak days and off-peak days (Socorro et al., 2010), which may be transferred to customers to increase price dispersion.

Karwowski analysed eight globally leading airline companies from seven countries and observed that the carrying value of aircraft accounts for more than 50% of the company's total assets. Airlines from Sweden and Germany were exceptions, where the aircraft cost accounted for only 26% and 40% of their total assets. In most cases, the aircraft's expected life was 20 years (Karwowski, 2016).

Bitzan and Peoples observed that the contributing cost-saving sources differ for FSC, LCC, and 'other' carriers. Changes in load factor and average distance flew benefit FSC's productivity gains. Unexplained technical change increased the cost of LCCs. Productivity gains due to changes in load factor, stage length and unexplained technical change helped the 'other carriers' to reduce their costs (Bitzan & Peoples, 2016).

In India, when the ATF (Aviation Turbine Fuel) prices had roughly doubled in a year and tripled in four years, the government gave subsidies to support the industry from running sick (Krishnan, 2008). The approximate cost structure of aviation in India, published by DGCA, also shows that fuel cost is the major cost of operation. Operating cost per available seat kilometre differs from airline to airline (DGCA, 2018). Seat km means the seating capacity of the carrier. The operational expense of airlines is significantly influenced by its operating characteristics like seats, stage length, payload, ownership and fuel price (J. Singh et al., 2019). Table 2.1 show the cost structure of airlines in India.

Table 2.1

Cost Structure of Airlines in India

SI. No.	Item of Expenditure	Percentage
1	Fuel Cost	31.2
2	Rental of Flight Equipment	14.2
3	Administrative Cost	11.7
4	Flight Maintenance	9.8
5	Airport and User Charges	9.7
6	Sales and Promotion	6.2
7	Other Expenses	5.5

8	Depreciation	4.6
9	Flight Crew Salary and Expenses	3.8
10	Pax Services (Cost of Serving a Passenger)	3.3
	Total	100.0

Source: Report of DGCA

2.3.4 Demand and Supply

The airline industry is characterised by unpredictable demand. Season, departure date, departure time, holidays and weekends influence the demand. Features of destination airports, such as hubs, spokes and size of the airport, also have an influence on the demand for airline tickets. Moreover, demand is also subject to the traditional demand and price theory.

Goetz compared the demand for the airline with the per capita income of the 50 largest US metropolitan areas. He found that the demand for airlines and the per capita income of the metropolitan area were correlated in the US market (Goetz, 1992).

John A MacDonald points out that dispersion can be societally beneficial irrespective of the level of uncertainty. It may fall as uncertainty increases. His studies also show that overall market dispersion falls with increasing concentration of flights provided by LCCs (A. M. John, 2007).

Studies of IATA showed that demand elasticity faced by an individual airline was higher than that faced by the whole market (Mark & Pearce, 2008). There was evidence of stochastic peak-load pricing in the US airline industry. It means the airlines set higher prices when they expect a high demand likely to exceed the capacity (Urday, 2008).

In the European market, firms adopted the strategy of offering discounted prices through 'last minute offers' to cope with the uncertainty about the arrival of the business segment (Koenigsberg et al., 2008). Fares tend to decrease as the seats offered at the departure increase (Malighetti et al., 2009).

Capacity and time influenced airline prices in the European market. Fares increased as the remaining seats were fewer. Each extra sold seat induces a 3.11% increase in a flight's fare on an average (Alderighi et al., 2015). Studies of prices of EasyJets' at Amsterdam Schiphol airport showed that quantity discounts are greater for flights with a larger fraction of available seats at the time of booking (Cattaneo et al., 2016).

Some airlines react to their rivals' price and load factors. This is because, due to the increased booking of rival carriers' seats, the total available seats in the market were reduced. It was observed in the US airline market that airlines increased their prices as their rivals' available seats disappeared. This was irrespective of the number of days remaining before the departure date and the number of seats remaining (Clark & Vincent, 2012).

Demand for airline tickets increased due to the low-cost tickets offered by LCCs. An increase in traffic to Malta was shown as an example by Graham and Dennis in their studies (Graham & Dennis, 2010).

The airfares of nearby airports influence the demand for a ticket. This impact was observed by Qian and Kim in the US market, where the decrease in the airfares at the local airport resulted in higher passenger volumes (Q. Fu & Kim, 2016).

Srinidhi opined that dynamic pricing might not lead to profit all time. A price increase may result in a decrease in demand. The volatility of currency exchange may also influence the demand for an airline in India (Srinidhi, 2010). She also observes that the country's macroeconomic environment plays a major role in demand origination. Variables like investments, GDP, etc., contribute much to international airline demand (Srinidhi & Manrai, 2014).

2.3.4.1 Seasonal and Cyclical Effects

Leisure travellers are regarded as price-sensitive and time-rich passengers. They exhibit a strong seasonal pattern evident in their behaviour. During holidays and festivals, this sensitivity is more evident. LCCs offered discounted prices to attract these passengers, including those who travel to visit friends and relatives (Papatheodorou & Lei, 2006).

Traditional carriers have dual price policies, which become more notable during the low season. Prices of charter flights in London reacted to the prices of other airlines in the low season periods but not in the high season (Garrigos et al., 2010).

The economic recession of 2001 and the subsequent crisis proved the cyclical nature of the airline business. Based on that, Hatty argued that air traffic growth rates show a high degree of cyclicity. This cyclicity showed a correlation with economic growth cycles measured by the GDP (Hatty & Hollmeier, 2003).

Due to initial panic and fear of flying, the terrorist attacks of September 11, 2001, caused a negative transitory shock of over 30% and an ongoing demand shock of about 7.4%. The exceptional fuel prices in the first three quarters of 2008, coupled with a deteriorating global economic recession, severely affected the airline industry, causing operating losses of $5.8 billion for the year and leading to multiple bankruptcies (Ito & Lee, 2005). Based on the analysis of the global scenario after the 2001 and 2008 crises, Franke and John opine that long-term trends should be distinguished from cyclical trends. Price dynamics in the airline industry are influenced by both cyclical and non-cyclical trends. Cyclical effects last for a limited period of time. Long-term trends account for an on-going basis (Franke & John, 2011). Panel data analysis covering two business cycles in the US airline industry showed that price dispersion was highly pro-cyclical in nature (Cornia et al., 2012).

Seasonality was exhibited in the price strategies of airline companies. Peak hours and high and low season periods brought monthly and hourly seasonality to the London civil aviation market. This seasonality affected the pricing policy of airlines in this market (Narangajavana et al., 2014).

The findings of Tesfay also agree that the airline industry is seasonal. The price fluctuates as a result of the 'passenger load factor' stabilisation efforts of airline companies (Tesfay, 2016). Fares tend to increase during peak tourism months and deflate during the off-season (Wei & Grubesic, 2016).

Studies in the European market showed the highest price level during the holiday period to the lowest-ranked tourist destinations and that the price dispersion was highest during the holiday period to the top-ranked tourist destinations (Martinez et al., 2017).

Dutta and Santra observed the common practice of dynamic pricing and revenue management in India. They found that weekend (Saturday, Sunday) airfares were higher compared to weekday airfares. The competition increases airfare as the departure date approaches (Santra & Dutta, 2015). They also found a strong positive correlation between the prices of different airlines on the same route and time window (Dutta & Santra, 2016). Based on the covid-19 impact, Agrawal suggests loss minimisation through variable cost recovery strategies to cope with the cyclical decline in demand (Agrawal, 2020).

2.3.4.2 Destination Airport

The uneven spatial pattern of airline pricing was observed for the top 114 air passenger cities in the US market. Researchers explained this regional inversion in fares by varying levels of competition and concentration at airports throughout the country (Goetz & Sutton, 1997).

Studies in European countries revealed that the tickets offered by the airlines of the destination country exhibit very low price dispersion compared to foreign carriers. Carriers originating from the destination country showed less dispersion than others on the same route (Szopiński & Nowacki, 2014). Moreover, the destination country exerts the price level based on the distance. Price dispersion was more dependent on the date of travel and destination type (Martinez et al., 2017). Prices are high when the destination's gross domestic product per capita is greater. Quantity discounts were lower for longer routes, larger destination airports, and routes for which the airline's market share was higher (Cattaneo et al., 2016).

Business (weekday) and leisure (weekend) prices had fallen with competition in the US aviation market. Price for the leisure segment had fallen even faster, and therefore increased dispersion could be observed with increased competition (Hernandez et al., 2017).

A comparative study of US and China airline markets revealed lower price dispersion in the US. The researchers argue that the maturation of the internet market leads to less price dispersion (Bock et al., 2007). A comparative study of Indian and Chinese airline markets showed that the Indian market exhibits high price elasticity than the Chinese market. High LCC penetration rates in India are assumed as a reason for this phenomenon (Wang et al., 2018).

In India, domestic passenger traffic is highly responsive to economic growth reflected in the GDP. A 10% increase in GDP resulted in a 16.4% increase in domestic passenger traffic. The GDP elasticity of international passenger traffic was also highly responsive to economic growth (Singh et al., 2016).

2.3.4.3 Airport Domination and Hubs

The dominance of major airports by one or two carriers results in hub formation in the US market, which leads to higher fares for consumers, was cited by Vijver in his thesis (Vijver, 2014). Every large airport that is dominated by a single carrier also serves as a hub in the respective carrier's network (Bilotkach & Pai, 2014). An airline's share of passengers on a route significantly influences its ability to mark up the price above cost. They tend to charge higher prices than other major airlines with smaller operations there (Borenstein, 1989). Brueckne and Spiller point out that hubs are able to funnel passengers, which in turn increases traffic densities. He argued that since hubs would take away the passengers of other city pair markets, the prices of those routes may increase (Brueckne & Spiller, 1991). Alfred E Kahn's findings also match the findings of Brueckne (Kahn, 1993) Hub dominance, market share, and type of destination served to influence the pricing (Vowles, 2000). Harris observed that the presence of a hub in a city-pair market increases local and pass-through demand resulting in an increased fare (Harris & Emrich, 2007).

Generally, customers prefer to buy a direct flight to reduce waiting at the connection point. Direct flights are cost-effective for the airline company also, compared to a flight with a stop. Hence flights with stops would charge a higher price for the ticket. But since direct flights are considered superior quality, airlines may charge more for such tickets. Sometimes, a connected flight can be price effective for a customer due to competition. Some customers may take advantage of this, which will, in turn, reduce the demand for direct flights. This hidden city ticketing may also influence the pricing of airlines (Aslani et al., 2014).

Emine Yetiskul argued that the reason for the lower cost of an airline is the simplicity of its operations. This includes offering frequent direct services in a Point to Point network. However, since time cost influences consumer preference, it increases demand. Hence there will be more frequency of flight (Emine et al., 2005).

2.3.4.4 Aviation Liberalisation Policies

Liberalisation of the European Union airline industry has resulted in no intensified competition in the internal market, neither in fares nor in frequencies for the first year (Wit, 1995). But Bowen observed that liberalization has opened up routes to new airlines and incumbent carriers in newly industrialised countries. In addition, deregulation gave carriers greater flexibility in responding to market opportunities and shedding unprofitable operations (John T. Bowen & Leinbach, 1995). Button, the former head of aviation policy in Paris, argued that the implementation of US deregulation had increased passenger traffic by 55 percent with a 60 percent increase in scheduled revenue passenger miles (Button, 1998).

Goetz opined that deregulation in the US had lowered fares and increased passenger enplanements and service frequency. After the deregulation, he identified a core-periphery structure of the airline industry in the US, which has created an oligopolistic situation. Cores are geographical areas with higher levels of development, political power, highly skilled workers, high per capita capital investment, etc. There were 22 cores in the US airline industry dominated by one or two airline companies in 1997. He further argued that the core had benefited more than the periphery (Goetz & Sutton, 1997). Later, he found that the industry was characterized by entry barriers and large economies of scale. He also observed that these inexorable economic forces were producing increased levels of monopoly and oligopoly control over city-pair markets resulting in higher fares (Goetz, 2002). His further studies also proved that deregulation in the US airline industry has resulted in higher passenger volumes, more service to the most popular destinations, and lower fares on average (Goetz & Vowles, 2009).

Endo observed an increase in the volume of imports in passenger air transport services the US and Japan. The bilateral aviation policies of both countries have increased the number of citizens flying foreign carriers (Endo, 2007). Liberalisation of the European airline industry has expanded their regular air services both in seats and routes. But there was a decrease in charter business (Dobruszkes & Mondou, 2013). Bush observed that liberalisation has resulted in the increased choice of routes and service levels as well as lower fares in Europe (Bush & Starkie, 2014). Tavana observed that in an unrestricted fare environment, demand would spiral down over time (Tavana & Weatherford, 2017).

Africa implemented regulatory frame work for airlines in 1993 and provided subsidies to airline companies (Prins & Lombard, 1996). But the study reveals that the Aviation policy of gradual liberalisation has increased the air passenger traffic flows in South Africa (Surovitskikh & Lubbe, 2015).

2.3.5 Demand Uncertainty

Uncertain demand is the main feature of the segment of LCC. This is because; both business and leisure travellers constitute their customer base. Airline companies adopt various strategies for identifying these market segments to adopt strategies for price discrimination. These strategies result in price dispersion in the airline market.

Uncertainty about the demand at its peak creates an asymmetry in the equilibrium prices. Adopting price dispersion helps the firm cope with this situation when the costs of some consumers of changing departures are high (Dana, 1999) (Escobari, 2012). An increase in price dispersion represents an optimal response to demand uncertainty with price rigidities (Stole, 2000).

Advance selling of air tickets was one of the strategies used by the airlines to cope with uncertain demand. It increased the total sales and the profit of the service providers in the European market (Xie & Shugan, 2001). Companies show no fixed fare strategy for airlines in the US market. Price dispersion differed with routes, and the dispersion was extreme in certain routes (Brennan, 2005).

Market structure influences the effect of route demand uncertainty on carrier price dispersion. Route demand uncertainty has no effect on carrier price dispersion in the monopoly market. An increase in route demand uncertainty is associated with a decrease in carrier price dispersion in duopoly and competitive markets. As the market becomes more competitive, a negative relationship is magnified (S. Li, 2007).

Last-minute selling strategy and opaque selling strategy of ‘willing to pay’ bids are used by airline companies to face demand uncertainty. Customers’ expectation of these strategies influences the demand and price dispersion (Jerath et al., 2010).

Uncertainty in demand makes the pricing complex for airlines (S. Lee, 2010). Dost and Geiger suggested a 'consumer indecisiveness map' based on consumers' willingness to pay to face consumer uncertainty (Dost & Geiger, 2017).

2.3.6 Density of Flight

Studies in the US aviation market proved that price dispersion declines as the density of flight increases. A carrier with a large share of the flights on a route would have less price dispersion (Borenstein & Rose, 1994).

Shapiro observed that price dispersion was more on big-city routes than on the leisure route of the US market. Monopoly routes are characterized by more price dispersion than competitive routes. Routes with a large proportion of leisure travellers are characterized by much less price dispersion than routes with larger proportions of business travellers (Shapiro, 2008). Many small airports in rural and remote communities of the US continue to exhibit high fares and low variability or high fares and high variability (Wei & Grubesic, 2016).

2.3.7 Empty Core

Minimum Efficient Scale (MES) is the lowest cost point at which a company can compete effectively in the industry. The problem of an 'empty core' arises when the demand at a price is less than the MES. Button suspected this issue in the European market (Button, 1996). Antoniou identified this problem in the European market and suggested the horizontal merger of European airlines to solve the issue (Antoniou, 1998). In his later study, Button observed that the inherently unstable nature of air transport markets (an empty core) leads to undersupply of services in the US market. These, along with a structural shift in the composition caused by the growth of LCCs, were pushing down the fares (Button, 2002).

2.3.8 Competition / Market Concentration

Competition is one of the important factors the reasons for price dispersion. Based on the studies in the US market, Stavins opined that Price discrimination decreases with market concentration. The discount on tickets was found to be lower on routes with higher market concentration (Stavins, 2001). Morrison and Winston observed that competition influenced the pricing dynamics. Fares increased with the market concentration and fell with increased competition (Steven A Morrison & Winston, 1990). Borenstein also found increasing dispersion on routes with more competition. In other words, market concentration has a negative impact on price dispersion (Borenstein & Rose, 1994).

Qihong observed a non-monotonic and positive relationship between market concentration and price dispersion (Q. Liu, 2003). Vowles argued that while distance has a statistically significant positive relationship with fares, competition reduces the prices (Vowles, 2006).

The key factor affecting price dispersion in the airline industry is the cross-price elasticity of demand for air travel, reflecting competitive-type discrimination. Price discrimination was practised in the US airline industry to compete with rival carriers, not to compete with rival modes of transportation (Kim, 2006).

The findings of Junwook suggest that many of the variables associated with market power and market competition characteristics have mixed impacts on price dispersion (Chi, 2014). A higher market share was likely to increase price discrimination against business travellers in the US market. A higher market share enables the carrier to have high pricing power. This may decrease the number of discounted fares to vacation travellers, which results in less price dispersion for lower airfares (Chi, 2008).

Pricing and product differentiation helped the US airlines to become more competitive than most of the European competitors (Pitfield, 2008). Price competition is a way that the carriers compete and manage demand and yield (Pitfield, 2009). Charging premium fares in days closer to take-off becomes impossible due to competition, and hence LCCs avoid competition with other LCCs in the US market (Button & Ison, 2009). Orcholski argued that code sharing of airlines reduces the number of empty seats, which in turn decreases the price dispersion (Orcholski, 2011). Price dispersion was not significantly affected by the low and high extremes of market concentration (Chakrabarty & Kutlu, 2014).

Discounts on advance fares rise with an increase in competition. The average fare, route distance, frequency of flights, and passenger load factor had a positive correlation in the European market. Fares tend to decrease as the seats offered at the departure increase. The correlation of dynamic pricing to route length and the frequency of flights was negative (Malighetti et al., 2009).

In the US, competition has a positive effect on price discrimination if the competition is between major airlines. Here competition reduces lower-end prices than upper-end prices. But an entry by low-cost carriers results in a significant negative relationship between competition and price discrimination (S. Lee, 2010). But in Australia, less variation was evident on flights with competition between major airlines than on monopoly routes (Roos et al., 2010).

Thomas-zadeh found a strong relationship between the previous price of a rival and the current price of each airline in the Turkish duopoly market (Thomas-zadeh, 2014).

A study in the European airline industry found pricing dynamics varied with the competition. 'The rate at which prices increase over time' decreased with the competition. Competition controls to price-discriminate the late-arriving passengers. This limitation to discrimination increases with customer heterogeneity in the market. The study also observes that price discrimination is relevant when there is initial scope for discrimination (Siegert & Ulbricht, 2015). In a later study, they clarified that the rate at which prices increase towards the scheduled departure date is significantly reduced in more competitive markets (Siegert & Ulbricht, 2020).

High-speed railway has adversely affected the demand structure of the airline industry in China. Domestic airports have suffered capacity shortages, air space congestion, and difficulties in enhancing their on-time performance to compete with high-speed railways (Fu et al., 2012). It acts as a close substitute for short-haul routes (Ma et al., 2020).

2.3.9 Influence of Technology

Studies show that price discrimination is made easy by technology. Increased use of the internet and mobile applications by passengers made it easy for airline companies to collect and analyse the data to take flexible and quick decisions on price.

Price dispersion is a persistent phenomenon in the US market. It varies systematically with market structure. The internet has widened the scope of price dispersion (Scholten, 2003). Eugene studied the impact of internet usage on airline prices. He observed that the changes in internet penetration reduce the average price and price dispersion at an inter-firm level. Price dispersion within the firm increases with internet adoption by airline companies (Orlov, 2005). Sengupta observed that online prices were about 13 percent less than offline prices. He argued that there exists a non-monotonic relationship between increased internet usage and dispersion. The dispersion initially increased, followed by a monotonic decline as the fraction of people with access to the internet rose (Sengupta, 2007).

Computer reservation systems increased the scope of extensive price discrimination (Gillen & Gados, 2009). The propensity for search and ticket purchases increases with an increase in the mean price and dispersion. It means that an increase in the price dispersion discourages not only the chance of purchase but also the search propensities (M. Lee, 2009).

David John, in his research on ‘online retail market price dispersion’, argues that online market places may display lower dispersion than shop-bots. Seller reputation (brand) was the key factor contributing to the variation of prices in the online market (D J DiRusso, 2010).

Sengupta and Wiggins opine that online purchasers pay about 11 percent less than offline purchasers. They observed an inverse relationship between price dispersion and the share of internet usage (Sengupta & Wiggins, 2014).

Saranga and Nagpal found the negative impact of structural and regulatory factors on the performance of airlines. The LCCs in India achieved significant operational efficiencies. Various factors influence their cost efficiency. Technical efficiency will determine the pricing power of the Indian airline industry in future. It is required to cut down costs and to gain market power through efficient management. In India, airlines that had higher technical efficiencies enabled the airlines to offer highly valued service to customers and were able to charge price premiums (Saranga & Nagpal, 2016).

Deployment of the technological tools for dynamic pricing is easy in the internet environment. Price adjustment speed, fast access to price information, the possibility for instantaneous price comparison, and amplification of consumer reactions were the contributions of technology that has contributed to the intensity of dynamic pricing (Ayadi et al., 2017).

Various kinds of computational techniques are used by airlines to increase their revenue. Demand prediction and price discrimination are their major focus. Historical ticket price data, ticket purchase date, and departure date are the major focus of these predictions (Ahmed et al., 2019).

2.3.10 Passenger Heterogeneity

Passenger heterogeneity, due to varying travel needs, is one of the remarkable features of the civil aviation market, especially for the LCC segment (Vulcano et al., 2002) (Chen, 2005). This is mainly due to the coexistence of business and leisure travellers in the segment (Mason, 2000) (Papatheodorou & Lei, 2006) (Martínez-garcia et al., 2012) (Siegert & Ulbricht, 2015). Differences in the strength of brand preferences also bring heterogeneity in the airline market (Borenstein, 1985). Heterogeneity can be considered the basis of dynamic pricing (Clemons et al., 2002) (S. Lee, 2010) (W. Li et al., 2018). Tsai points out that heterogeneity does exist in the fences of booking time, ticket validity, changing fee, and fare (Tsai, 2016).

Literature shows that price dispersion increases as the market becomes heterogeneous. Siegert observed that the price difference is almost zero with homogenous passengers. But there was a price increase of 0.65 percentage per day more than the prices on markets with six competitors in the monopoly routes in the European airline markets with a highly heterogeneous customer base (Siegert & Ulbricht, 2015).

Studies in the European airline market also show that yield management intervention are less effective for leisure travellers, and price dispersion will be lesser if the share of leisure travellers are more on a route (Bilotkach et al., 2015).

According to Graham & Metz, infrequent flyers make up a heterogeneous consumer group. Their non-flying is influenced by personal circumstances than aviation factors (Graham & Metz, 2017).

Based on the passenger survey conducted in Mumbai, Connell and Williams identified two distinct segments of FSC and LCC in the Indian market. Some passengers are sensitive to changes in fare, and some are sensitive to offers and flight products. Leisure passengers in FSCs regard flight products, such as schedule and reliability, up to a 30% hike in price. A major portion of leisure travellers prefers LCCs (O'Connell & G Williams, 2006).

The strength of the brand preference of consumers was an important factor in passenger discrimination in the US markets (Borenstein, 1985). Their brand preferences are likely to be changed (Chen, 2005). Airline companies provide schemes like ‘frequent flier programs’ to keep the customer with them and to avoid switching costs (Daraban & Fournier, 2009).

2.4 Strategies Adopted for Price Discrimination

Various price discrimination strategies are adopted by airlines to adjust with passenger heterogeneity and fluctuating demand. First-degree price discrimination, advance price requirements, high price on refundable tickets, low price on non-refundable tickets, peak-load pricing etc. (Shapiro, 2008) are used by airline companies, which creates dynamics in pricing.

2.4.1 Market Segmentation

Airline companies implement price discrimination techniques mainly by segmenting heterogeneous groups of consumers. Advance purchase requirements, non-refundable tickets, and Saturday-night, etc. are a few examples (Cornia et al., 2012). Demand among business travellers differs from that of leisure tourists. For example, business traveller stays for shorter periods due to time constraints. Price do not affect their decisions regarding flight time and day or ticket type (Martínez et al., 2012).

Chang and Sun observed a significant difference in the choice behaviours of business travellers and non-business travellers in Taiwan-China. Non-business travellers had a greater willingness to pay more for luggage service, daytime arrivals, and to use a secondary airport (Chang & Sun, 2012).

Keith Mason says that air business travel is like a hybrid market. It has the elements of both industrial and consumer markets. He has identified three segments of business class: schedule-driven consumers, corporate segment, and informed budgeter segment. Price elasticity and Product features differ with these segments (Mason & Gray, 1995).

Business travellers like to book their ticket as the departure date is close and are ready to pay more for this since they do expect a change in the date of travel. This brought high price discrimination in the Canadian airline market (Gillen & Hazledine, 2006). Turkmen suggested a segmentation based on price elasticity in his revenue management model focusing on the airline companies in Canada (Turkmen, 2008). Last-minute deals offered by EasyJet in the European market helped to partially price discriminate within the tourist segment (Koenigsberg et al., 2008). Button observes that the airline can maximize its revenues by charging higher fares to those who book closer to take-off time (Button & Ison, 2009).

Leisure travellers are less time-sensitive than business passengers. Therefore they may have a higher willingness to take flights from secondary airports (Fageda et al., 2015). They are less conscious of the services provided. They choose the lowest-priced carrier. On the other hand, business travellers tend to be less price elastic (Lee & Luengo, 2004).

Price elasticity and brand preference of these two segments are generally different (Borenstein, 1985) (Granados et al., 2012)(Stacey, 2015)(Morlotti et al., 2017). An extra sold seat induces a 2.56 percent increase in the flight fare in the European market (Alderighi et al., 2012).

Consumers are segmented on the basis of their willingness to pay for the product (Balaiyan et al., 2019), which is described as inter-temporal price discrimination. Lazarev found that inter-temporal price discrimination leads to higher prices for business travellers. It also results in lowering the ticket quality for leisure travellers. But it benefited leisure travellers with lower prices and higher supply (Lazarev, 2013).

An empirical study on the Indian airline market showed a separate segment called 'corporate booking' through direct agreements with a corporate entity or specialised corporate agents. This study found that for this sector, booking started about 12 months before the departure dates. Airlines offer special prices and terms for this category (Karthik & Mitra, 2016).

A study on 37,000 flights operated by EasyJet Airlines revealed that dynamic pricing takes place even if there is no change in the ticket prices offered. This happened since the companies changed the number of low-priced seats (Alderighi et al., 2017).

2.4.2 Ticket Restrictions

Ticket restrictions adopted by airline companies increase price dispersion. Round ticket discounts, separate prices for fully refundable/partially refundable/non-refundable tickets, separate prices for tickets on the basis of restrictions for cancellation/date changes, etc., are the common discrimination strategies adopted. Spicejet offers special prices for hand bag only tickets to attract more customers (Spicejet, 2018). Special charges for seat selection, food and beverages, etc., are also strategies used to increase revenue.

Joanna Stavins found a connection between lower airfare and ticket restrictions. He also observed that discounts decrease with an increase in market concentration. Price dispersion attributed to ticket restrictions increases with competition (Stavins, 2001).

Non-transferability of air tickets, restrictions for purchasing low-priced tickets, etc., had facilitated the possibility of price discrimination in the airline market. Individual price categories, individual price levels, and seat inventory allocation are available for sale to these price categories. This is a strategy adopted by airlines for price discrimination against FSCs. But the emergence of LCCs has reduced the scope of price discrimination by FSCs. Even though FSCs are separate market segments, their pricing policy and strategy are considerably affected by the LCCs (M. W. Tretheway, 2004).

Cancellation penalties of LCCs, like no refund, restrict the passengers from informing their cancellation to the airline company. Koppelman argued that the prediction of cancellation helps to reduce the number of empty seats (Garrow & Koppelman, 2004). Overbooking is widely applied in the service industry, including the airline industry, to hedge against cancellations which may result in service denial to the customers. Denied service will affect the reputation and thereby reduce the revenue of service providers. This also brings immeasurable losses to some denied customers (Guo et al., 2016).

2.4.3 Proximity to Departure Date

The business sector generally books tickets close to the departure date to avoid cancellation. Therefore, increased prices are charged by airline companies at the proximity of departure, on the expectation of less price elasticity from this segment. There are many studies which show that price increases drastically as the departure date is closer. This observation was made on the New York to London route (Bilotkach et al., 2010), in the US market (Gillen & Mantin, 2009), (Button & Ison, 2009), (Chellappa et al., 2011), (Alderighi et al., 2015), in the European airline market (Xie & Shugan, 2001), (Jay Graham et al., 2010), (Alderighi et al., 2012), (Domínguez-Menchero et al., 2014), (Siegert & Ulbricht, 2015), (Szopiński & Nowacki, 2015), (Alderighi et al., 2017), in the Russian international flights (Lantseva et al., 2015). But studies in the Russian market revealed that prices of domestic airline tickets decreased with a decrease in the time interval before departure (Lantseva et al., 2015).

2.4.4 Holidays and Weekends

Holidays and weekends are generally characterised by increased demand for seats. Airlines generally offer increased prices when they anticipate increased demand. Hence, these days show increased prices from the beginning of booking itself. Proximity to the departure date may again increase the prices as usual. Mega events also increase the demand for air travel to that location. Beria observed that the effect of mega-events was not limited to the event days but impacted the surrounding days. Holidays also create additional traffic but are influenced by the season (Beria & Laurino, 2016).

Some researchers are of the opinion that days before and after holidays exhibit higher prices than holidays (Escobari, 2012)(Y. Liu, 2013) (Ahmed Abdella et al., 2019)(Mathur, 2020). Koo observed significant seasonality in the market of Australia- Japan and Australia-China routes(Koo et al., 2013). There are many other scholars (Turkmen, 2008), (Garrigos-simon et al., 2010), (Lazarev, 2013), (Alderighi et al., 2015) who observed the effect of weekends and holidays on price dispersion. Pels gave a different opinion that offering holiday packages through tour operators resulted in low fares to holiday destinations, especially through charter airlines (Pels, 2009). A similar observation of lower fares on frequent shorter holidays made by Graham is cited by Castillo (Castillo & Lopez, 2014). Findings of Dobruszkes cited by Fageda, also suggest that holidays have been largely associated with low-cost travel (Fageda et al., 2015). The introduction of 'Emirates Holidays' helped Emirates Airlines to enhance service control and quality at a lower cost (Redpath et al., 2016). Hawkins opines that the impact of each festival and related holidays on the destination region differs on the basis of which market strategies are framed (Hawkins & Mothersbaugh, 2010).

2.4.5 Fare Buckets

Vinod identified three distinct fare products in the civil aviation market. The public fare is offered through online travel agencies' websites, the private fare is offered to wholesalers, tour operators, travel agents, etc., and the web fare is offered by airlines on their websites (Vinod, 2010).

Studies also show that dynamic pricing takes place even if customers cannot detect any change in the online offered fare (K. Button et al., 2007). In the preceding ten days of departure, a seat on sale will be moved to an upper bucket even if no sales have occurred (Alderighi et al., 2017). Various other scholars including, (Aslani et al., 2014), (Sengupta & Wiggins, 2014), (Bilotkach et al., 2015), (Thirunavukkarasu & Nedunchezian, 2016), (Tavana & Weatherford, 2017), (Madireddy et al., 2017) have also considered the effect of fare buckets in their studies of airline price dynamics.

2.5 The Measures of Price Dispersion

Various tools are used by researchers to study the extent of price dispersion. Stavins used standard deviation, the ratio of standard deviation to the mean and the ratio of the highest to the lowest price (Stavins, 1996). Chellappa used the price range and the coefficient of variation to analyse the price dispersion (Chellappa et al., 2011). Cornia measured price dispersion using three separate proxies: the interquartile range, the Gini coefficient, and the 90th and 10th price percentiles (Cornia et al., 2012).

2.5.1 Gini Coefficient

Measurement of inequality of income has been a matter of interest for a long back. The Gini coefficient is a common tool used for measuring the extent of price dispersion in the airline market. Dalton observed that Professor Corrado Gini's mean difference was an interesting measure of dispersion. It is the arithmetic average of the differences, taken positively, between all possible pairs of incomes (Dalton, 1920). Gini clarifies that the same methods are applicable not only to incomes and wealth but to all other quantitative characteristics like economic, demographic, anatomical or physiological (Gini, 1921). These tools were used for a rough estimate of degrees of inequality that can be obtained.

Borenstein and Rose used the Gini coefficient as a measure of the dispersion of prices in the airline industry. They said that a Gini coefficient of 0.10 implies an expected absolute price difference of 20 percent of the mean fare (Borenstein & Rose, 1994).

Qihong measured market concentration by Herfindahl-Hirschman Index (HHI) and price dispersion by the Gini coefficient. He observed that the relationship between the HHI and the standard deviation of prices was monotonic and positive (Q. Liu, 2003).

The Gini coefficient ranges from 0 to 1. A higher ratio shows higher discrimination. Gini coefficients close to zero imply very little difference between the fares that are paid by all passengers, and 0.25 implies an expected absolute price difference of 50 % of the mean fare on that route and carrier (Shapiro, 2008). The computations show that the alarming level of

Gini should be specified as at least equal to or larger than 0.5 rather than 0.4 (Tao et al., 2017).

Other researchers who used the Gini coefficient for the calculation of airline price dispersion include (Verlinda, 2005), (Kim, 2006), (A. M. John, 2007), (S. Li, 2007), (Chi, 2008), (S. Lee, 2010), (Cornia et al., 2012), (Gelhausen et al., 2013), and (Siegert & Ulbricht, 2015).

2.5.2 Lorenz Curve

Lorenz Curve was introduced in 1905 as a measure of the concentration of wealth. It is a graph where one axis shows the cumulated percentage of the population from poorest to richest. The percentages of wealth held by them are shown on the other axis. For an unequal distribution, the graph will show a bend in the middle. Concentration increases as the bow is bent (Lorenz, 1905). The Lorenz curve is also used as a graphical representation of the inequality of fare distribution (S. Li, 2007), (A. M. John, 2007), (Pacheco et al., 2015). It was also used to show the dispersion of air traffic in airports (Gelhausen et al., 2013), (Pacheco et al., 2015).

2.5.3 Herfindahl-Hirschman Index (HHI)

The US Department of Justice provided the level of competition and HHI in its guidelines for horizontal mergers in 2010. It classifies the market into three types: un-concentrated, moderately concentrated and highly concentrated. HHI<0.15 indicate 'un-concentrated markets', HHI between 0.15–0.25 indicates moderately concentrated markets, and HHI >0.25 indicates highly concentrated markets (Naldi & Flamini, 2014).

In airline pricing literature HHI has been widely used for analysing the extent of competition in the market. HHI is a commonly accepted tool for measuring market concentration (Laine, 1995). HHI is calculated as the sum of the squares of the market share of an operating carrier on a route, calculated based on the number of passenger seats available (Chakrabarty & Kutlu 2014). They divided the number of seats of each airline by the total number of seats of all the airlines by using the following formulae to calculate the market share.

$$\text{Market Share} = \frac{\text{Number of seats of each airline}}{\text{Total number of seats of all the airlines}}$$

Raymond Sin used HHI in three different ways, such as the number of passengers, number of flights, and number of carriers serving the route (Sin, 2005). Pitfield used HHI for analysing the competition on the impact of alliances on market concentration by route (Pitfield, 2007). Many other researchers also used HHI to calculate the market concentration (Stavins, 1996), (Peters, 2002), (Q. Liu, 2003), (Sengupta, 2007), (A. M. John, 2007), (S. Li, 2007), (Shapiro, 2008), (Mantin & Koo, 2009), (Hernandez et al., 2017), (Sengupta & Wiggins, 2014), (Pacheco et al., 2015). It should also be noted that few authors have questioned the explanatory power of HHI through their research (T. H. Hannan, 1997), (Chikoto et al., 2015).

2.6 Exploitation under Airline Price Dynamics

Steiner, in his article "A Liberal Theory of Exploitation", argues that an exploitative transfer, unlike theft, is bilateral (Steiner, 1984). According to the Stanford Encyclopedia of Philosophy, exploitation can also be mutually beneficial, where both parties walk away better off than they were ex-ante (Zalta, 2023). In other words, the exploitation concept in the context of the reserve price and selling price is conflicting on the grounds of concern for fairness and a concern for welfare, as Benjamin observes (Ferguson, 2016). Martin observed the same time production of positive and negative attitudes in the minds of airline customers due to dynamic pricing/revenue enhancement pricing practices (S B Martin, 2012). When customers perceive an unfair price, they are likely to perceive it as exploitation (Xia et al., 2004). A price fairness judgment is based on comparative transactions involving different parties, especially when they do not know the cost structure (Bolton et al., 2010). This can be confirmed by the work of

Jennifer, who observed extreme displeasure from loyal customers when Amazon attempted to introduce differential pricing (Lyn Cox, 2001).

When inexorable economic forces produced increased levels of monopoly and oligopoly control over city-pair markets, resulting in a larger share of travellers paying higher fares, the US Departments of Transportation and Justice were under pressure to take serious corrective actions (Goetz, 2002). In India the Parliamentary Standing Committee on Transport, Tourism and Culture observed airline dynamic pricing as exploitative when they observed ten times higher prices than the advance booking fare (PTI, 2018). They recommended the government to fix an upper limit for the airfare. The Ministry of Civil Aviation of India imposed minimum and maximum fare limits during the Covid-pandemic (DGCA, 2020). The ministry reminded through a press note in 2022 that airlines are free to fix prices depending on market forces, and it will interfere only when the pricing is found predatory (MCA, 2022). Reports show that Parliamentary panel members demand discussing the issue of airfares since they find it exploitative (ANI, 2023).

2.7 Deregulation and Dynamic Pricing

Dynamic pricing was gradually introduced in the airline industry after the deregulation measures initiated by US. Researchers argue that this deregulation helped to penetrate the aviation market and attracted more and more new passengers to the industry. Deregulation of the airline started in the US in 1978, and thereafter air passenger traffic increased tremendously (Goel, 2013). Moreover, it has reduced the average inflation-adjusted airline price per passenger by 49% (Brennan, 2005). Deregulation of South Africa’s domestic airline market in the 1990s increased passenger volume through affordable LCC proliferation (Surovitskikh & Lubbe, 2015). The deregulation of Australian aviation in the 1990s brought a tremendous increase in traffic through LCCs under two waves in 1990 and 2000 (Lawton & Solomko, 2005). However, researchers also spot negative aspects of the deregulation that it has made the industry fragile with overcapacity and price war (Jarach et al., 2009).

Liberalisation measures were initiated in Malaysia, Taiwan, Pakistan, Nepal, South Korea, the Philippines, etc., in the early-to-mid-1990s (Lawton & Solomko, 2005). In India, also deregulation began in 1994 through private participation in the airline industry (Naresh Chandra, 2003).

Literature review showed that deregulation and dynamic pricing have contributed to the high growth of the airline industry in some nations. The role of LCC is another element that has contributed to this boom in airline passenger traffic. The growth of an industry depends on several factors. The growth of the travel industry can be attributed to the development of other industrial sectors because each travel has a specific purpose. Dynamic pricing has nothing to do with this travel purpose. This argument needs to be supported by the general trend of industrial growth with the overall economic development of a nation.

2.7.1 GDP-Industry Cointegration

In Bangladesh, long-run co-integrated relationships were found between GDP and industry value; based on a bivariate cointegration test (Sultan, 2008). Croix and Liu found evidence for both for and against a monotonically increasing relationship between GDP and the predicted Pharmaceutical Intellectual Property Protection Index (Croix & Liu, 2009). Zortuk found unidirectional causality from tourism development to the GDP of Turkey between 1990 and 2008 based on Granger Causality Test (Zortuk, 2009). They used global GDP per capita, a time series plot from 1960 to 2005, and a random effect model to support their argument. A long-run relationship between tourism growth and GDP was found between tourism receipts, education investment, foreign direct investment, etc. and GDP of three Middle East countries from 1981 to 2008 based on a comprehensive panel data set (Saleh et al., 2015). The cointegration analysis of Uddin found that the agriculture sector of Bangladesh has a strong, positive and significant linear relationship with economic growth (Uddin, 2015).

Based on Granger causality, researchers found a strong relationship between the tourism industry and economic growth in Beijing, China (Songling et al., 2019). They observed data from 1994 to 2005. Industrial electricity and gas consumption have a positive and statistically significant impact on economic growth in Pakistan in the long run and the short run (Chandio et al., 2019). They also used Granger Causality Approach for their study. Causality between education and sustainable economic growth was observed in Guangdong, China, from 2000 to 2016 (Liao et al., 2019). This study was also based on Granger Causality Test. In India, a co-integrated relationship was observed between bank-related variables and economic growth based on a panel of data of 20 public sector banks from 2009 to 2019 (Alam et al., 2021).

Researchers found contradicting observations in the US economy. A study using cointegration and Granger causality tests also found no cointegration between economic growth and US tourism-related industries (airlines, casinos, hotels, and restaurants) from 1982 to 2004 (Tang & Shawn, 2009). Another study on the relationship between six tourism-related sub-industries and the GDP of the US found no long-run relationship between tourism sub-industries and economic growth, except for food and beverage sectors; other sub-industries being accommodation, air transportation, shopping, other transportation, recreation and entertainment (Aratuo & Etienne, 2019). They used data from 1998 to 2017 to run the Granger causality test.

2.7.2 GDP-Airline Industry Cointegration

Hakim and Merkert observed a long-run unidirectional Granger causal relationship between air transport activity and GDP for all countries of the South Asian region but found no bi-directional relationship (Hakim & Merkert, 2016). This observation was based on panel data from 1973 to 2014 from eight countries. Brida shows evidence of the positive and bidirectional long-run relationship between air transport demand and economic growth in Mexico from 1995 to 2013 (Brida, 2016). Our findings show that. Based on the data from 70 countries from 1990 to 2016, it was found that GDP has a certain degree of effect on air transport, which varies by the income level of countries (Kiracı & Bakır, 2019). There exists a statistically significant asymmetric impact of air transport on economic growth in the short and long run in the Australian context (Khanal et al., 2022). Based on quarterly panel data from 29 provinces in China, Yi Hu argues that there is evidence of a long-run equilibrium relationship between economic growth and domestic air passenger traffic (Hu et al., 2015). They used data from 2006 to 2012 to prove the strong short-run unidirectional relationship between GDP and Air traffic.

Marazzo et al. observed a relationship between air transport demand reflected by passenger-kilometre and GDP between 1966 and 2006 in Brazil (Marazzo et al., 2010). Based on a data set from the same period, a unidirectional Granger causal relationship was observed from economic growth to domestic air transport demand in Brazil, with a high elasticity in the short term (Fernandes & Pacheco, 2013).

Based on Cointegration and Granger causality approach, it was argued that a stable unidirectional relationship existed between air transportation to economic growth in the short run and the existence of bidirectional causality between air travel and tourism growth in Sri Lanka (Madurapperuma & Higgoda, 2020). This study used data from 1983 to 2019. The cointegration test of data from 1977 to 2009 revealed a long-run equilibrium relationship and causal unidirectional relations between air transport and the economic growth of Nigeria, leading to a positive influence of air transport on economic growth (Alexander et al., 2015). Analysis of the data from 1982 to 2005, Akinyemi also agree that the GDP of Nigeria is a crucial factor that influences the growth of its air travel (Akinyemi, 2018).

Brida et al. observed a causal relationship between air transport demand represented by aircraft movements and economic growth in Italy for the period 1971–2012 using Johansen cointegration analysis (Brida et al., 2016). They also found a long-run relationship between real GDP and the number of air passengers in Uruguay and Argentina (Brida et al., 2018).

2.8 Related Studies on Indian Civil Aviation Market

Srinivasan presented a descriptive analysis of the then scenario of the Indian aviation market (Srinivasan & Prasad, 2014). Mazumdar presented a mathematical model for seat allocation in the airline industry based on some assumptions (Mazumdar & Ramachandran, 2011). This chapter discussed 22 other research articles on the Indian airline industry collected from reputed research repositories. All these reviews proved that there are a few pieces of literature contributed by the researchers on the Indian civil aviation market, especially on the pricing of airline tickets. Table 2.2 shows the summary of research literature based on Indian civil aviation industry. The details including the data base, of the 24 research articles discussed in this chapter are also given. The table shows the need for attention to be given by Indian researchers to this area.

Table 2.2

Summary of Literature on Indian Civil Aviation

Data Base	Count	Area of Study
Elsevier Science Ltd	3	FSC, LCC Segments, Technical efficiency and cost efficiency, Operational Expenses
Springer Science	5	Price dispersion, Fare buckets, Demand forecasting, Cyclical influence on demand, Price fairness perception

Emerald Group of Publishing	2	Influence of macro environment on demand, Descriptive on Indian aviation.
IIMs	3	Cost of operation; Departure time, Festival and weekend effect on prices, Mathematical model for seat allocation
Jstor	3	Cost of operation
Proquest.com	1	FSC, LCC segments
Informs	2	Departure time effect on price; Factors influencing demand
Indian Citation Index	1	Fare Buckets
Publishingindia.com	1	Corporate segments
Research Gate	1	Service quality and customer satisfaction
The Indian Economist	1	Effect of capacity and departure time on price
Competition Commission of India	1	Cost of operation
Total	24	

Source: Compiled by the Researcher

2.9 Research Gap

As evident from Table 2.2, only a very few studies have been found in the global research literature reservoir on the price dynamics of Indian civil aviation. Empirical analysis of the price dispersion of the Indian airline market is very rare. The extent of price dispersion in the Indian market, based on market concentration, is also an ignored area. The role of dynamic pricing in the development of the civil aviation industry has also not yet been studied by researchers. Price dispersion based on market concentration is also an area yet to be explored. The influence of neighbouring day prices is also not yet studied by the researchers. The literature review reveals a research gap in the area of price dispersion caused by price dynamics in the Indian contest. This research titled "A Study on the Pricing Dynamics in the Indian Airline Market" is an attempt to bridge this knowledge gap.

Chapter 3

The Indian Airline Industry: Context for Pricing Analysis

3.1 Introduction

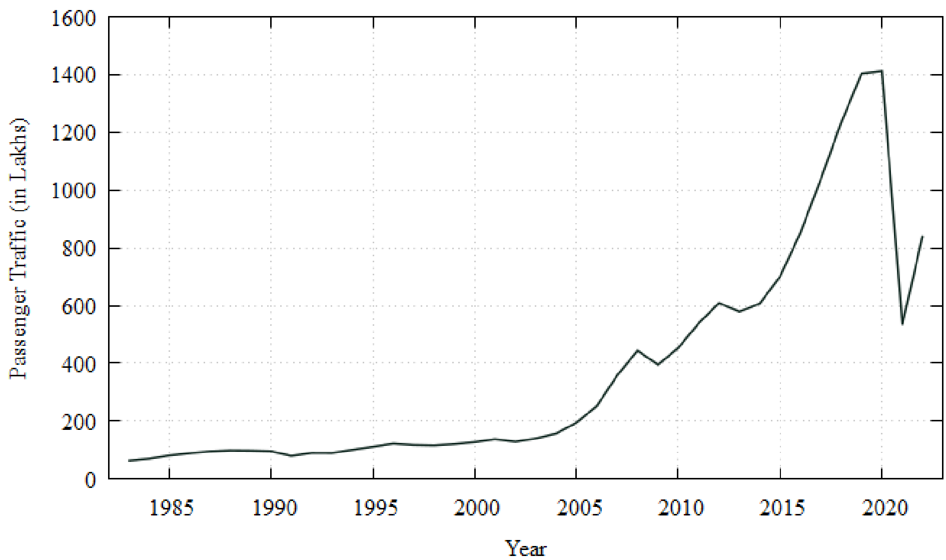
The airline industry is considered a prestigious industry by every nation. In India, the airline industry is functioning under the civil aviation ministry. Limited supply and highly fluctuating demand are the global characteristics of this industry. Cost-based pricing is regarded as an unsuitable pricing method for this industry. Dynamic pricing has been globally accepted as a suitable pricing method for revenue maximisation under fluctuating demand of the airline industry. This chapter intends to provide an idea about the Indian airline industry, its history and development pattern, major regulatory and other organisations in the field, and reasons for the common dropout of airline companies. This will provide a more understanding of the nature of the industry and some insight into the reasons for dynamic pricing.

3.2 Growth in Domestic Airline Traffic

The development of airports should not be limited to the number of airports alone. The number of fleets, seating capacity and the passenger and cargo handled also show the developmental status of the airports. The number of domestic passengers carried by the industry increased from one in 1932 to 441 in 1950. (Tata, 1961). Passenger traffic increased further from 117.41 lakhs in 1997 to 1,386.98 lakhs in 2018. That means the capacity has increased by 1,081% from 1997 to 2018. A 64% increase in the number of airports has resulted in a 1,081% increase in passenger carrying. Figure 3.1 shows the time series progression of domestic passengers carried by all the Indian carriers from 1982 to 2022.

Figure 3.1

Domestic Passengers Carried by Indian Carriers



Source: Compiled by the researcher from various reports of DGCA

The total passenger traffic shows an increasing trend from 1983 to 2022. The rapid growth in the total passenger traffic began in 2005, with a sudden increase of nearly 61% from the previous year. The trend continued with a rise of 42% in 2007 also. The year 2015 and 2016 continuously showed a more than 20% increase from the previous years. The following two years also showed a more than 17% increase in passenger traffic. Slight declines were there in the years 1989, 1990, 1991, 1993, 1997, 1998, 2002, 2009, and 2013. The total traffic declined by 62.23% in the year 2021 due to covid pandemic effect. The year 2022 showed an increase in the air passenger traffic by 57.85% from the previous year. Figure 3.2 shows the average Passenger Load Factor (PLF) from the year 1995 (data available from 1995 only) to 2022.

Figure 3.2

Average Passenger Load Factor (Domestic Airlines)

Source: Compiled by the Researcher from various reports of DGCA

As per Figure 3.2, the average PLF of all domestic airlines ranges from 55.5 to 86.8 per cent. Even in the year 2021, when passenger traffic was reduced due to covid pandemic, PLF was 73.4 per cent. In the year 2022, PLF increased to 81.5 per cent. This indicates that airline companies could adjust their supply with the demand.

3.3 Price Dynamics and Growth of the Airline Industry

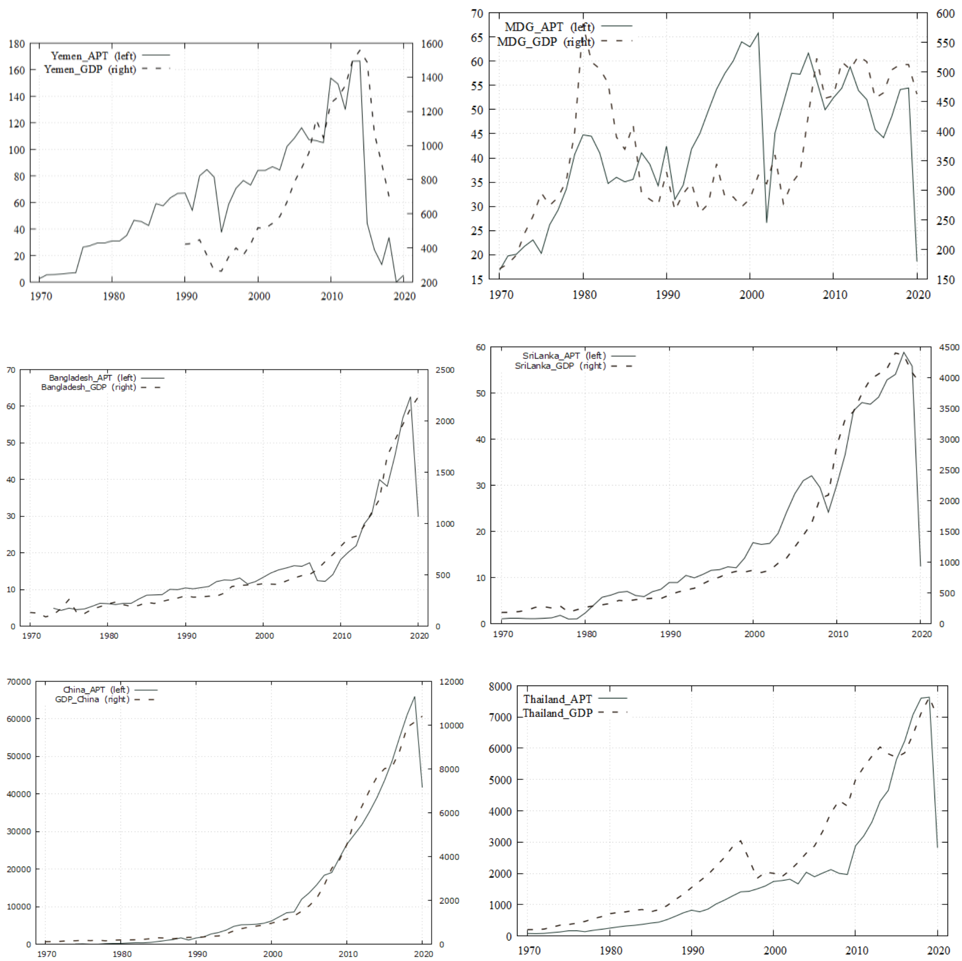
Dynamic pricing is the phase of the airline industry. There are many studies to support dynamic pricing because it contributes to the development of the airline industry sector. These arguments are based on the traffic growth that resulted from the deregulation of prices by governments. All these studies support the role of LCCs in making air transportation the transport of even the lower middle class of an economy. The lower fare buckets help to attract price-sensitive travellers. They also attract new customers for their first experience. The convenience, time-saving element, and comparatively low rate will help to retain such customers. The subsequent higher rates would help the airlines to compensate for the low bucket fares. Apart from this, justification of dynamic pricing strategy on the ground of its contribution to the development of the air travel industry can be spurious. Travellers choose air travel because of the convenience this sector offers, including speed and a comparatively low fare. But its influence on his travel purpose is relatively less. His travel purpose should be attached to the development of other industries. Hence the growth of the air travel industry should be compared with the growth of overall industrial development reflected through the GDP of the country. The literature review also supported this argument of the cointegration of individual segments with the GDP growth of that nation (Zhao et al., 2014)(Saleh et al., 2015)(Alam et al., 2021). Literature also provides ample evidence for the cointegration of the growth of the airline industry with the GDP of nations (Fernandes & Pacheco, 2013)(Alexander et al., 2015)(Madurapperuma & Higgoda, 2020). The development of industries would influence the income level of travellers, and a positive change in the income level may benefit a high-cost convenient mode of the travel segment.

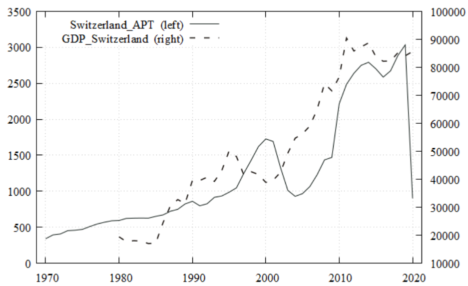
3.4 Cointegration of Airline Industry with GDP

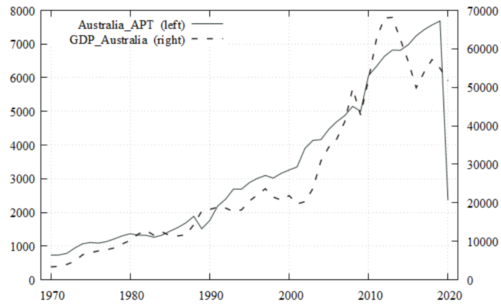
The development of the travel industry depends on the development of other industries, with no exception to air travel. Being high-cost travel, it has more dependence on the income level of the people. Based on this assumption, an analysis is conducted on the movement of the airline industry of selected nations with corresponding GDP per capita, considering the data before and after liberalisation. This analysis uses data published by World Bank. The World Bank categorises countries as low-income, lower-middle-income, upper-middle-income, and high-income nations (The World Bank, 2021). The researcher selected two countries from each category, apart from India. There is some missing information in the published data of a few countries. Such countries are eliminated, and for the rest lottery method is followed to select the sample nations. The selected countries include Yemen Republic and Madagascar from low-income nations, Bangladesh and Sri Lanka from the lower middle-income group, China and Thailand from the upper-middle-income group, and Switzerland and Australia from the high-income group. The time series plot of air passenger traffic and GDP per capita is shown in figure 3.3.

Figure 3.3

Air Passenger Traffic to GDP Per Capita of a Few Selected Countries







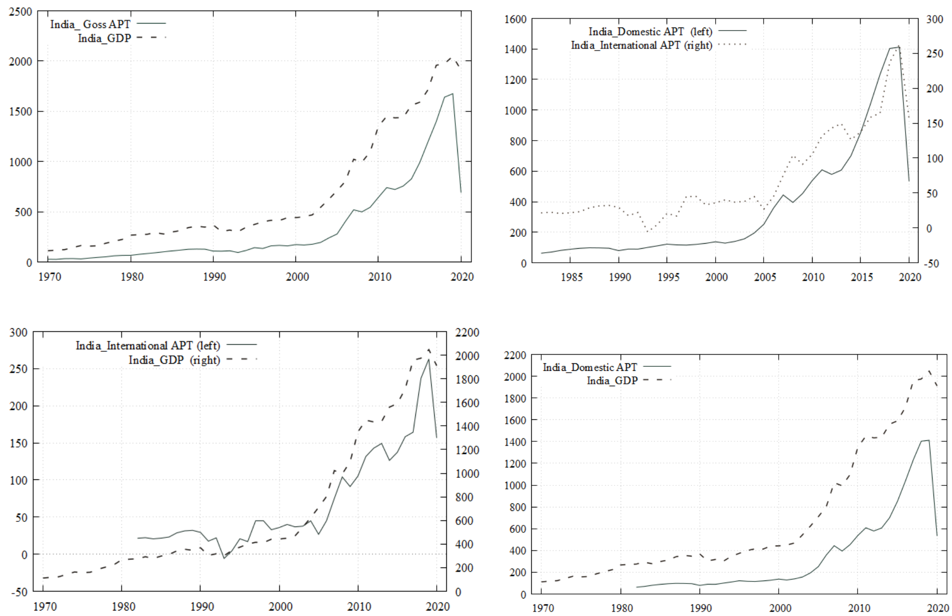
Source: Secondary Data

As per the figure, air passenger traffic moves in the same direction as the GDP per capita of all corresponding countries except for the low-income country Madagaskar. For Yemen and Switzerland, GDP per capita was unavailable for the whole period. An accelerated movement is visible from around the year 2000 for both airline passenger traffic and real GDP per capita. For high-income countries, accelerated movement is evident from 1990 onwards. The sharp decline in the travel sector due to covid pandemic is evident for all nations in 2020.

India also has the same pattern of correlated air passenger traffic growth and per capita GDP. This movement is evident even before the liberalisation of the 1990s, as in the case of other nations. Figure 3.4 shows the growth pattern of per capita GDP and air passenger traffic growth in India from 1970 to 2021. Overall development, domestic aviation growth, and international traffic are shown separately. Domestic passenger traffic data is collected from the published reports of DGCA.

Figure 3.4

Air Passenger Traffic to GDP Per Capita: India



Source: Secondary Data

Domestic air passenger traffic data is available from 1982 only on the published records of DGCA. Both domestic and international air transport traffic moves in the same direction as GDP per capita. As in many other countries, the sharp increase in GDP and air traffic is evident from 2000 onwards. This increase is apparent in both domestic and international traffic.

3.4.1 Cointegration Test – Before the Year 2000

The Engle-Granger cointegration (EGC) test determines the long-run relationship between two or more time series data. The EGC test assumes stationary data for all series (Engle & Granger, 1987). The test uses augmented Dickey-Fuller (ADF) unit root tests to check the data's stationarity (Dickey & Fuller, 1981). The researcher used the Akaike Information Criterion (AIC) for selecting the lag order. The data from 1990 to 2022 is divided into data up to 2000 and data from 2000. Deregulation started in the beginning and middle of the 1990s in many nations. But the effect of deregulation was in its full fledge by the year 2000 only, though it varies from country to country. Because of this, accelerated growth in air passenger traffic and GDP per capita was evident in most of the samples from the year 2000 only. The EGC test has three steps: (1) estimation of the cointegrating regression; (2) running a DF test to find out if each of the variables listed has a unit root; and (3) running a DF test on the residuals from the cointegrating regression. The researcher formulated the following research hypotheses for testing the cointegrating relationship:

$H_{0\,1}$ There is no significant relationship between air passenger traffic and the per capita GDP, before dynamic pricing became ubiquitous.

$H_{0\,2}$ Each of the variables in the data set, before dynamic pricing became ubiquitous, has a unit root.

$H_{0\,3}$ The residuals from the cointegrating regression in the data set, before dynamic pricing became ubiquitous, have a unit root.

Table 3.3 shows the results of cointegrating regressions using observations from 1970 to 2000. Airline passenger Traffic (APT) is the dependent variable for all the regressions.

Table 3.3

Cointegrating Regression Results: Before the Year 2000

Country	Period	Regressors	coefficient	t-ratio	p-value	Significance
Yemen	11	const	41.179	1.405	0.1780	
		Per Capita GDP	0.058	2.060	0.0550	*

Madagascar	31	const	25.414	3.245	0.0030	***
		Per Capita GDP	0.040	1.690	0.1018	
Bangladesh	28	const	0.513	0.637	0.5298	
		Per Capita GDP	0.032	10.630	0.0001	***
SriLanka	31	const	−2.399	−4.197	0.0002	***
		Per Capita GDP	0.020	17.240	0.0001	***
China	26	const	−1106.68	−6.221	0.0001	***
		Per Capita GDP	8.254	20.720	0.0001	***
Thailand	31	const	−54.079	−0.817	0.4205	
		Per Capita GDP	0.565	12.400	0.0001	***
Switzerland	21	const	269.617	1.520	0.1450	
		Per Capita GDP	0.019	3.803	0.0012	***
Australia	31	const	150.008	1.179	0.2479	
		Per Capita GDP	0.123	14.030	0.0001	***

India	31	const	−30.225	−5.801	0.0001	***
		Per Capita GDP	0.440	25.230	0.0001	***
		const	−23.851	−1.619	0.1250	
India Domestic	19	Per Capita GDP	0.394	8.078	0.0001	***

Source: Secondary Data, Gretl Output

$H_{0\ 1}$ is rejected for Bangladesh, SriLanka, China, Thailand, Switzerland, Australia, India, and India Domestic ($p<0.05$). $H_{0\ 1}$ is accepted for Yemen and Madagascar ($p>0.05$). In other words, there exists a significant relationship between air passenger traffic and the per capita GDP of all the nations at a one per cent significance level, except for Yemen, where the significance is only at 10%, and Madagaskar, where there is no significance at all. Both these nations are low-income countries. For India, a significant relationship exists between per capita GDP and domestic aviation traffic.

A cointegrating relationship is evident if:

(a) The unit-root hypothesis is not rejected for the individual variables, and

(b) the unit-root hypothesis is rejected for the residuals (uhat) from the cointegrating regression (Mackinnon & G, 1996).

Table 3.4 shows the result of the unit-root assumption of the EG cointegration test.

Table 3.4

Before the Year 2000: Augmented Dickey-Fuller Test Results

		APT		Per Capita GDP		uhat		
Country	Lag	test statistic: tau_c(1)	p-value	test statistic: tau_c(1)	p-value	test statistic: tau_c(2)	p-value	Decision
Yemen	4	-2.187	0.21	-1.506	0.53	-1.665	**0.69**	No CR
Madagascar	1	-0.465	0.90	-2.057	0.26	0.092	**0.99**	No CR
Bangladesh	1	-0.164	0.94	-1.054	0.74	-2.805	**0.16**	No CR
Sri Lanka	2	1.163	1.00	0.974	1.00	-2.268	**0.39**	No CR
China	1	1.517	1.00	1.644	1.00	-1.905	**0.58**	No CR
Thailand	5	2.455	1.00	0.776	0.83	-4.118	0.00	**CR**
Switzerland	8	1.409	1.00	-0.932	0.78	-3.123	0.08	**CR**
Australia	1	0.354	0.98	-1.000	0.76	-2.758	**0.18**	No CR
India	5	-0.945	0.77	-0.427	0.90	-4.583	0.00	**CR**
India-Domestic	5	1.251	1.00	1.109	1.00	-2.262	**0.61**	No CR

Source: Secondary Data, Gretl Output, CR= Cointegrating Relationship

As per the values given in Table 3.4, $H_{0\,2}$ is accepted for all the variables ($p>0.05$). $H_{0\,3}$ is rejected for Thailand, Switzerland, and India ($p<0.05$). Thus the results show that cointegrating relationship of GDP and Air Passenger

Traffic is evident only for Thailand, Switzerland, and India. The test results of these nations satisfied all the criteria of cointergrating relationship. A cointegrating relationship is not evident for domestic passenger traffic in India.

3.4.2 Cointegration Test: After the Year 2000

The second part of the analysis deals with data from the year 2000 to 2022 to reflect the effect of deregulation and accelerated growth of GDP and Air passenger traffic. The following hypotheses are formulated for the analysis of the cointegration of the growth of air passenger traffic with per capita GDP.

$H_{0\,4}$ There is no significant relationship between air passenger traffic and the per capita GDP, after dynamic pricing became ubiquitous.

$H_{0\,5}$ Each of the variables in the data set after the dynamic pricing became ubiquitous, has a unit root.

$H_{0\,6}$ The residuals from the cointegrating regression in the data set after the dynamic pricing became ubiquitous, have a unit root.

Table 3.5 shows the results of cointegrating regressions using observations from 2000 to 2022. Again, airline passenger Traffic (APT) is the dependent variable for all the regressions.

Table 3.5

Cointegrating Regression Results: After the Year 2000

Country	Period	Regressors	coefficient	t-ratio	p-value	Significance
Yemen	19	const	41.179	1.405	0.178	

		Per Capita GDP	0.058	2.060	0.055	*
Madagascar	21	const	53.066	4.265	0.000	***
		Per Capita GDP	−0.005	−0.167	0.869	
Bangladesh	18	const	1.007	0.571	0.575	
		Per Capita GDP	0.027	16.160	0.000	***
Sri Lanka	21	const	12.219	2.800	0.011	**
		Per Capita GDP	0.009	5.827	0.000	***
China	21	const	2460.650	1.183	0.251	
		Per Capita GDP	5.258	15.260	0.000	***
Thailand	21	const	−763.325	−1.025	0.318	
		Per Capita GDP	0.931	6.221	0.000	***
Switzerland	21	const	−176.785	−0.327	0.747	
		Per Capita GDP	0.030	4.010	0.001	***
Australia	21	const	1939.300	2.602	0.018	**

		Per Capita GDP	0.077	5.000	0.000	***
India	21	const	−258.370	−2.526	0.021	**
		Per Capita GDP	0.778	10.120	0.000	***
	21	const	−229.718	−2.429	0.025	**
India - Domestic		Per Capita GDP	0.664	9.345	0.000	***

Source: Secondary Data, Gretl Output

$H_0$4 is rejected for Bangladesh, SriLanka, China, Thailand, Switzerland, Australia, India, and India Domestic ($p<0.05$). H_0 4 is accepted for Yemen and Madagascar ($p>0.05$). In other words, there exists a significant relation between air passenger traffic and the per capita GDP of all the nations at a 99% significance level, except for Yemen, where the significance is only at 10% and Madagaskar, where there is no significance at all. Both these nations are low-income countries. For India, a significant relationship exists between per capita GDP and domestic aviation traffic.

A cointegrating relationship is evident if:

(a) The unit-root hypothesis is not rejected for the individual variables, and

(b) the unit-root hypothesis is rejected for the residuals (uhat) from the cointegrating regression (Mackinnon & G, 1996).

Table 3.6 shows the result of the unit-root assumption of the EG cointegration test.

Table 3.6

After the Year 2000: Augmented Dickey-Fuller Test Results

		APT		GDP		uhat		
Country	Lag	test statistic: tau_c(1)	p-value	test statistic: tau_c(1)	p-value	test statistic: tau_c(2)	p-value	Decision
Yemen	5	-1.294	0.63	-1.416	0.58	-0.975	**0.91**	No CR
Madagascar	1	-3.181	**0.02**	-1.514	0.53	-3.378	0.04	No CR
Bangladesh	1	2.810	1.00	1.896	1.00	-2.124	**0.46**	No CR
Sri Lanka	2	-1.557	0.50	-1.687	0.44	-1.920	**0.57**	No CR
China	2	-1.630	0.47	0.412	0.98	-3.643	0.02	**CR**
Thailand	3	-3.297	**0.02**	-1.099	0.72	-1.944	**0.56**	No CR
Switzerland	1	-1.498	0.54	-2.197	0.21	-2.081	**0.49**	No CR
Australia	1	-1.613	0.48	-1.974	0.30	-2.343	**0.35**	No CR

India	2	-1.536	0.52	-0.662	0.85	-3.703	0.02	**CR**
India - Domestic	8	0.083	0.96	-1.307	0.63	-3.752	0.02	**CR**

Source: Primary Data, Gretl Output, CR= Cointegrating Relationship

As per the values given in Table 3.6, H_{0} 5 is accepted for all the variables ($p>0.05$), except Madagascar and Thailand ($p<0.05$). H_{0}6 is rejected for China, India, and India-Domestic ($p<0.05$). Thus, the results show that cointegrating relationship of GDP and Air Passenger Traffic is evident only for China and India, including India-Domestic. The test results of both nations satisfied all the criteria of cointergrating relationship.

Industries contribute to the GDP of every nation. But it does not necessarily mean that a particular industry's growth and GDP go in the same direction, especially if that industry is not a major contributor to its GDP. As per the World Bank's published records, travel and tourism's direct contribution to a percentage share of total GDP was between 2.46 and 2.78 from 1995 to 2021 in Switzerland. In China, it was between 2.11 and 3.32. In Thailand, it was between 5.13 and 10. 70. Total contribution of travel and tourism to a percentage share of India's total GDP reduced from 14.27 in 2003 to 9.56 in 2020. The percentage share of government spending on total travel and tourism expenditure was between 0.90 and 1.02 in India during this period (The World Bank, 2022). All these points show that industry linkage is associated with the development of the GDP per capita of a nation, and it has no direct link with the dynamic pricing mechanism of the air travel sector. In India, the cointegrated movement of air passenger traffic with per capita GDP before and after the regulation of prices contributes to this argument.

3.5 Conclusion

There was steady and continuous growth in air passenger traffic, ever from 1932. India followed a fixed pricing method in the Indian airline industry till 1994 (MCA, 2022). The introduction of the LCC segment in 2003 can be associated with the accelerated growth of the Indian Airline Industry in 2004. Since customers have other options for transportation, price and income are essential elements in the development of air travel. In India, the growth of air transport traffic has a cointegrated movement with per capita GDP before and after liberalisation and deregulation. A significant relationship exists between air traffic and the per capita GDP of nations, though the cointegrated movement seems rare. The dynamic pricing method was introduced in 1994, but accelerated growth is evident from 2000 only, which is parity with GDP per capita growth. Hence, it is evident that the growth of the airline industry does not depend on the dynamic pricing strategy, though the price dynamics may help penetrate a market with close substitutes.

NB: Supplementary information on the institutional framework of Indian aviation, which supports the analysis in this chapter, is included in Appendix 3A.

Chapter 4

Price Dynamics in Concentrated Markets

4.1 Introduction

Pricing in the civil aviation market is complex since it has to achieve two contradicting objectives. Maximisation of revenue by selling the perishable good at a profit in a susceptible market on one side and penetrating the market with low prices on the other are the two contradicting objectives. Charging high prices on refundable and flexible tickets, peak-load pricing, charging extra for add-on services, seat selection, etc., are the techniques adopted by airline companies for revenue maximisation (Shapiro, 2008), which creates dynamics in airline pricing. These techniques make the pricing strategy almost equal to first-degree price discrimination. Charging based on each customer's maximum willingness to pay is the philosophy of airline revenue management. It creates dynamics in pricing and complexity in the market. This chapter analyses the extent of price dispersion caused by the airline price dynamics in the Indian domestic airline market.

4.2 Data Set and Tools for Analysis

Time series data of ticket prices quoted by various airlines over selected routes on selected departure dates are analysed in this chapter. The secondary data were collected from published documents of the DGCA and the AAI. The Gini coefficient, Lorenz curve, Herfindahl-Hirschman Index, Kendall's rank correlation, and Pooled OLS are the statistical tools used for analysis. Gretl, an open-source statistical package, is mainly used for econometric analysis.

4.2.1 Gini coefficient - the Measure of Inequality

The measurement of income inequality has been a matter of interest for a long time (Dalton, 1920), and the Gini coefficient has become a widely accepted tool for this measurement of inequality (Gini, 1921). The Gini coefficient is a popular statistical tool used in the literature for measuring the extent of price dispersion in the airline market (Rose & Borenstein, 1994) (Liu, 2003)(Verlinda, 2005)(Kim, 2006)(John, 2007)(Li, 2007)

(Shapiro, 2008)(Chi, 2008)(Cornia et al., 2012)(Gelhausen et al., 2013)(Noughabi et al., 2014)(Djolov, 2014)(Siegert & Ulbricht, 2015).

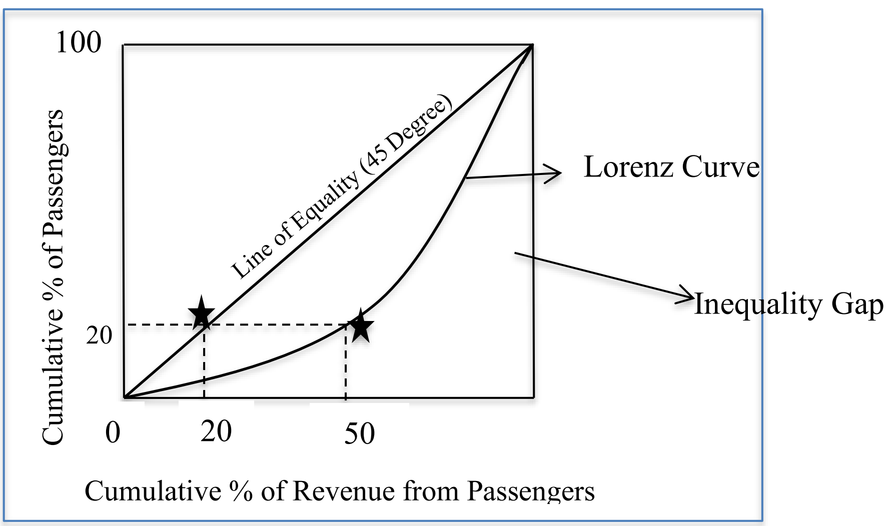
The range of the Gini coefficient is 0 to 1. Zero is no dispersion, and 1 is the highest dispersion (John, 2007). An absolute price difference of 50% of the mean fare is denoted by a Gini coefficient of 0.25 (Shapiro, 2008). The alarming level is 0.4(Tao et al., 2017).

4.2.2 Lorenz Curve

The Lorenz curve plots the cumulative percentages of total revenue received against the cumulative number of passengers, starting with the lowest price (Lorenz, 1905). A 45-degree line of the Lorenz curve shows "perfect" fare distribution. The area generated between the Lorenz curve and the 45-degree line is divided by the area below the 45-degree line (John, 2007). The Gini coefficient is the resulting figure. The value of the Gini coefficient ranges from 0 to 1. The area fenced between the Lorenz curve, and the line of equality denotes the measure of inequality. The larger this area, the larger the inequality (Dalton, 1920).

Figure 4.1

Lorenz Curve



Source: Adapted by the researcher based on (Lorenz, 1905)

In diagram 4.1, the marked point on the line of equality shows that 20 % of the passengers in a flight/route provide 20% of the total revenue of that airline. On the other hand, the marked point on the Lorenz curve shows that 20% of the passengers in a flight/route provide 50% of the airline's total revenue. In other words, the ticket price paid by this 20% of the travellers is much more than the other 80% of travellers, indicating a higher dispersion.

4.2.3 HHI, the Measure of Competition

Herfindahl-Hirschman Index (HHI) is a commonly accepted tool for measuring market concentration (Laine, 1995) (Hannan, 1997)(Chikoto et al., 2015). The Herfindahl Index has been widely used in airline pricing literature to analyse the extent of market competition (Sin, 2005). HHI<0.15 indicate 'un-concentrated markets', HHI between 0.15–0.25 indicates moderately concentrated markets, and HHI >0.25 indicates highly concentrated markets (Naldi & Flamini, 2014). HHI is the sum of the squares of the market share of an operating carrier on a route, calculated based on the number of passenger seats available (Rhoades, 1995).

4.2.4 Kendall's Rank Correlation

Kendall's rank correlation tau is used to test the correlation of two data sets (Kendall, 1938). It is used to compare data in time series data analysis (Martínez-Garcia et al., 2012) and to check internal validity (Yoon et al., 2006).

4.2.5 Ordinary Least Square (OLS)

Ordinary Least Squares regression (OLS) is a statistical regression technique for estimating coefficients of linear regression equations (Harris & Emrich, 2007). It describes the relationship between one or more independent and dependent variables (Sun, 2014). This regression is widely used in the analysis of price dynamics (Morlotti et al., 2017), (Tsui et al., 2021).

4.3 Price Dispersion in the Concentrated Markets

Following the literature, the Gini coefficient is used to measure the extent of price dispersion of airline tickets in this chapter. Price dispersion in the domestic market is analysed in the following dimensions:

1. Price dispersion in the concentrated markets - effect of the monopolistic and duopolistic situations in the same route and the effect of the triopoly situation.
2. Price dispersion in the concentrated markets - between airline companies.
3. Day effect on the price dispersion in the monopoly, partial monopoly, and triopoly situation.

Market concentration is evaluated on the basis of HHI. The total seats available for an airline company on the route for a week are calculated first. Then HHI was calculated by considering the market share of the flight on the route weekly. HHI on these routes ranges from 51 to 100. Route M5 has multiple features. It shows features of monopoly on a few days and duopoly on other days. Indigo operates two flights on Tuesday on route M5. HHI was more than 30% (0.3) for all these routes, showing a concentrated market situation. Table 4.1 shows the characteristics of the six routes selected.

Table 4.1

Concentrated Markets - Route Characteristics

Route Code	Route	Air Distance in Km	Available Seats/day	Market Share (Route)	HHI
M1	**Hyderabad - Nanded**	248			100

	TrueJet		72	100	
M2	**Ahmedabad - Lucknow**	928			100
	Indigo		180	100	
M3	**New Delhi - Dibrugarh**	1761			100
	Indigo		180	100	
M4	**Varanasi - Khajuraho**	305			100
	JetAirways		189		
M5	**Pune - Kochi**	975			51
	Indigo				
	Sunday		180	100	
	Wednesday*		360	66	
	Other days		180	49	
	Spicejet		189		
	Wednesday			34	
	Other days (Except Sunday)			51	
M6	**Mumbai-Thiruvananthapuram**	1258	568		52
	Air India		220	37	

Indigo	180	31
JetAirways	189	32

Source: Secondary Data. Route share and HHI are calculated values.

* Indigo has non-stop and one-stop flights, each with 180 seats.

Route M1 has only 40% of seating capacity compared to others. It is the shortest route taken as a sample in this study. On route M3, Indigo has two flights, one direct and another with a stop. Only direct flights are taken for this analysis. For route M5, Air India was operating on route M4 on Wednesdays and Saturdays. Hence Jet Airways had a monopoly on other days only. For route M5, two airline companies were operating except on Saturday. Hence Indigo has a monopoly only on Saturdays. This route is termed the 'partial monopoly route' in this research. On route M6, Indigo has two flights on Tuesdays. Three airlines have direct flights on this route, resulting in a triopoly situation. The prices were divided by the air distance in km to convert to the price per km. The Gini coefficient and Lorenz Curve were used to explain the extent of price dispersion on the route. To measure the influence of the day of departure, festival day, and neighbouring day prices on airline ticket prices, Kendall's tau rank correlation analysis and OLS regression are used.

4.3.1 Price Dispersion under Monopoly Situation

Routes M1, M2, M3, and M4 have only one direct daily flight. This creates a monopolistic situation. Prices were collected 30 days prior to departure for seven departure dates for all three routes. Route M1 and M4 are short-distanced, M2 is medium-distanced, and M3 is long-distanced. Table 4.2 gives the summary statistics of the three routes.

Table 4.2

Summary Statistics – Monopoly Situation Price in INR

	M1	M2	M3	M4
Brand	TrueJet	Indigo	Indigo	Jet Airways
No. of Observations	300	300	300	210
Air distance in km*	248	928	1761	305
Mean	8.95	13.38	5.25	24.06
Median	7.49	13.74	4.94	18.86
Min Price	4.76	6.92	3.98	8.49
Max Price	32.90	17.50	11.36	53.63
SD	5.320	2.722	1.363	12.276
CV	0.594	0.203	0.260	0.510
Gini coefficient	0.269	0.115	0.133	0.275
Inter Quartile Range	3.329	4.992	1.818	20.830

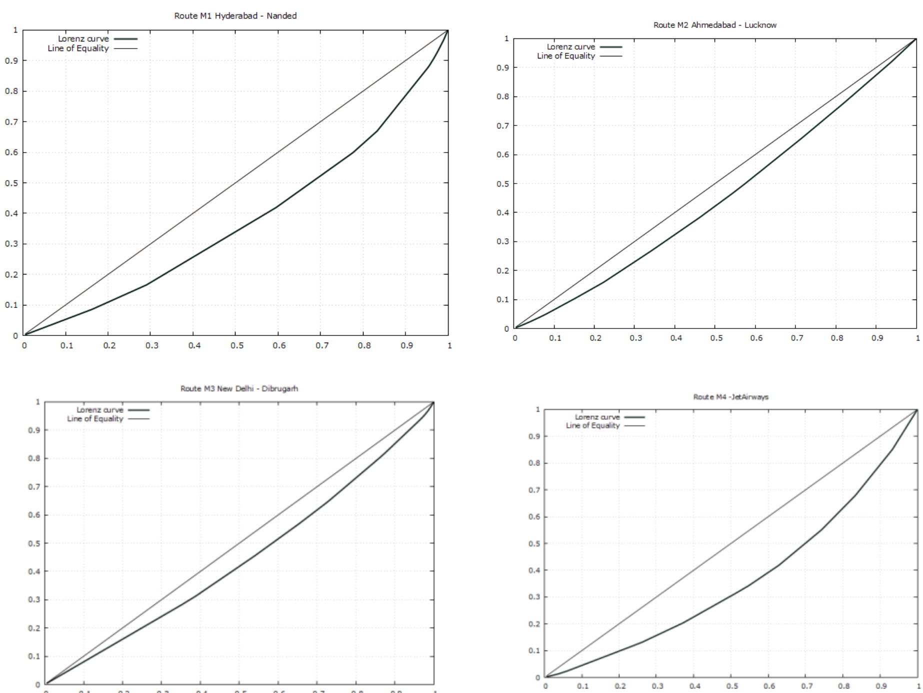
Source: Primary Data * Source: Secondary data

The price per km of Indigo flight decreased with an increase in the air distance of the route. The Gini coefficient increased with an increase in air distance and a price decrease. TrueJet's minimum, maximum, and mean fares were higher than short-distanced Indigo but lesser than medium-distanced Indigo. CV and Gini coefficient also show the same tendency. Other dispersion measures, SD and Inter Quartile Range decrease with an increase in Air distance. HHI is estimated as 100 for all these routes, indicating perfect market concentration. Subject to the limitations of calculated figures, fare and dispersion decreases with the firm's ability to fill the seats. The fares of routes M1 and M4 show a more than 50% difference from the mean fare, as the Gini coefficient is more than 0.25. The Lorenz Curve given in Figure 4.2 explains the dispersion in the monopoly routes.

Monopoly route airfares, especially on routes M1 and M4, exhibit a high degree of variability, suggesting that dynamic pricing is having a significant impact on fare changes throughout the observation period. The Gini coefficients suggest that the highest level of inequality in airfare distribution was observed with route M4.

Figure 4.2

Monopoly Situation - Lorenz Curves



Source: Gretl Output

Lorenz curve explains the dispersion graphically. The area between the line of equality and the Lorenz curve shows the dispersion. It was highest for routes M1 and M4. For M4, 40% of the revenue is contributed by 60% of the passengers. Out of the total revenue of True Jet on Route M1, 40% was collected from 59% of passengers. This means the highest fares contributing 60% of the revenue, are contributed by the remaining 40 to 41% of passengers for Route M1 and M4. Dispersion is less than half on Route M2 and M3. As per the arguments of monotonically increasing and decreasing airfare with closeness to the departure date, the remaining passengers could be either last minute or those booked first (Croix & Liu, 2009). Low bucket and high bucket fare analysis address this question.

4.3.2 Price Dispersion under Partial Monopoly Situation

Route M5 has a duopoly on Saturdays since Spicejet does not operate that day. It creates a partial monopoly situation on the route. Table 4.3 shows the summary statistics of the observations.

Table 4.3

Summary Statistics –Partial Monopoly Situation

Route	M5		
Brand	Indigo	Spicejet	Combined
No. of Observations	330	240	570
Mean	5.14	5.05	5.10
Median	4.80	4.80	4.80
Min Price	3.29	3.67	3.29
Max Price	9.06	9.06	9.06

SD	1.099	0.838	0.998
CV	0.214	0.166	0.195
Gini coefficient	0.105	0.084	0.096
IQ Range	0.661	0.760	0.769

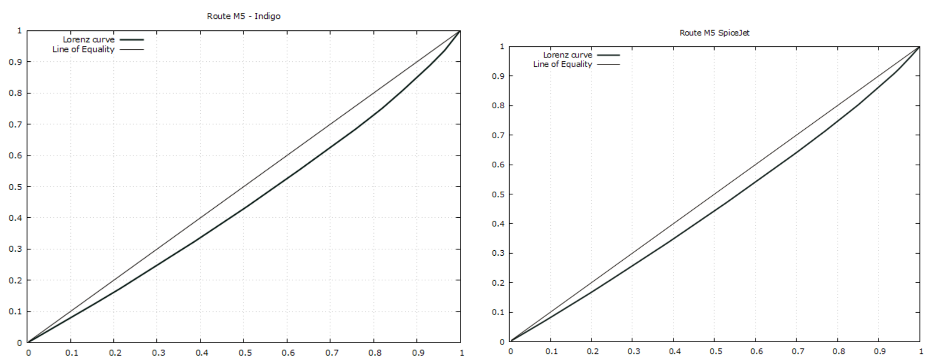
Source: Primary Data

Minimum, maximum and mean price shows similarities between airlines on the same route. This indicates the impact of competition. Changes in the monopolistic and duopolistic situations of the same route require further analysis. HHI was estimated as 51 for route M5, indicating a duopoly market situation.

The airfare dispersion under dynamic pricing on these monopoly routes appears to be relatively consistent, with low levels of inequality and a symmetric distribution. Indigo stands out with higher variability, while Spicejet exhibits lower variability. The Lorenz curve indicating the dispersion is given in Figure 4.3.

Figure 4.3

Partial Monopoly Situation - Lorenz Curves



Source: Gretl Output

The above Lorenz curve of the Gini coefficients of partial monopoly routes explains the dispersion graphically. Here 50% of the revenue is contributed by less than 55% of the passengers.

4.3.3 Price Dispersion under Triopoly Situation

Among the six routes selected from concentrated markets, the Mumbai-Thiruvananthapuram route is characterised by a triopoly situation. All three flights are direct flights. The summary statistics of the observations are given in Table 4.4.

Table 4.4

Summary Statistics - Triopoly Situation

Brand	Indigo	Air India	JetAirways	Combined
No. of Observations	330	330	330	990
Mean	6.96	11.90	7.62	8.83
Median	6.56	8.85	7.62	7.86
Min Price	3.30	0.90	4.85	0.90
Max Price	16.12	21.91	16.28	21.91
SD	2.325	5.314	2.495	4.250
CV	0.334	0.447	0.328	0.482
Gini coefficient	0.178	0.242	0.173	0.247
Inter Quartile Range	2.215	10.308	1.921	3.928

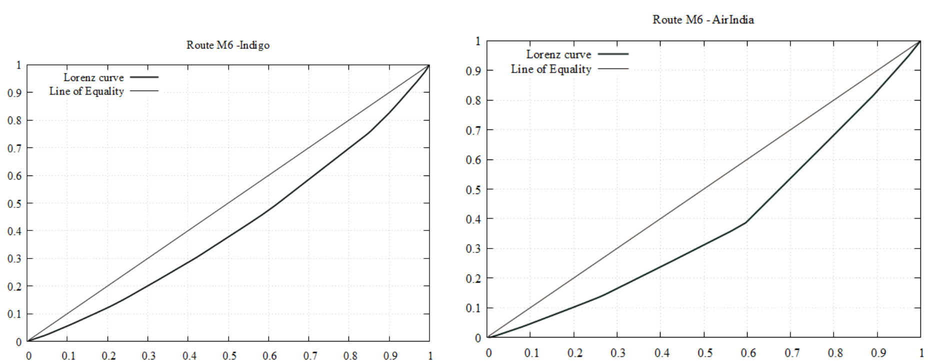
Source: Primary Data

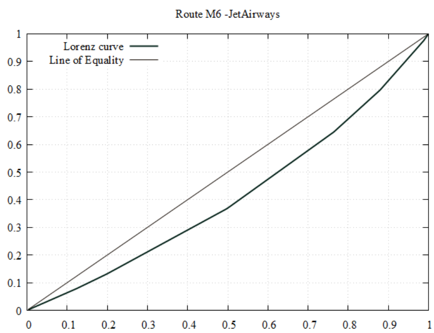
Air India offered the highest mean fare. Both the lowest and highest prices are quoted by the same airline. Their minimum fare offer was 3.5 times lesser than the minimum fare of the other two companies. CV, SD, and Gini coefficient are also the highest for Air India. The mean fares of the other two airlines are less than the combined mean fare of the route. CV is also almost similar to Indigo and Jet Airways. The dispersion of the route is higher than the dispersion of individual flights. The fares of route M4 as a whole show more than a 50% difference from the mean fare, as the Gini coefficient of the whole route is more than 0.25.

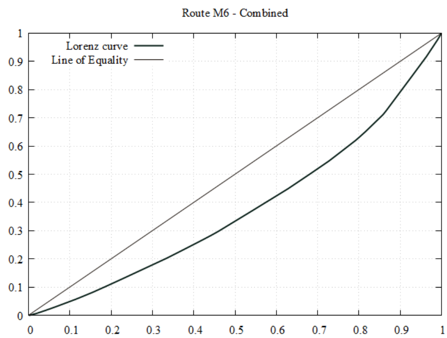
The airfare dispersion under dynamic pricing on these triopoly routes varies across airlines. Air India stands out with higher variability, relative variability, and inequality in airfare distribution. Indigo and JetAirways exhibit lower variability and relative variability. JetAirways has a smaller IQR, suggesting a more concentrated range within the central portion of the distribution.

Figure 4.4

Triopoly Situation - Lorenz Curves







Source: Gretl output

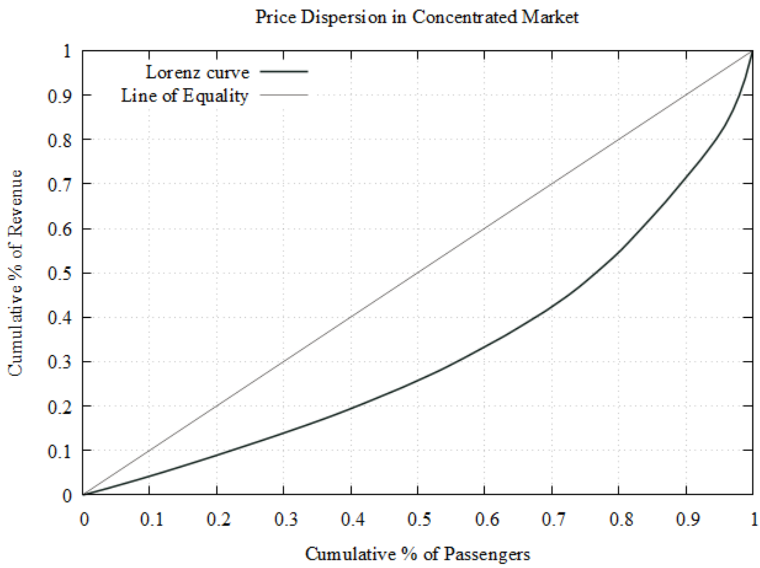
The above Lorenz curve of the Gini coefficients of three flights in route M6 graphically explains the dispersion. The area between the line of equality and the Lorenz curve is larger for Air India. Indigo's 50% revenue was collected from 63% of passengers. Air India collected 39% of their revenue from 60% of its passengers. For Jet Airways, 62% of passengers paid 50% of revenue. For the route as a whole, 68% of passengers paid 50% of revenue. It means that the remaining 50% of the revenue was paid by 32% of passengers.

4.3.4 Overall Dispersion in Concentrated Market

There were 2,880 observations of five airline companies while considering all six sample routes. The minimum price offered within 30 days of departure was ₹0.90 per km. The national carrier Air India offered this fare under the Triopoly market situation. This fare was offered for three days on Sunday departure date before 13 to 11 days to departure. The maximum fare offered for that departure date was ₹17.49 per km. JetAirways made the minimum fare offer under a monopoly situation. This fare was offered for 13 days from 21 days to the departure date. The departure day was Monday. The Mean fare per km and Median fare per km of observations were ₹9.62 and ₹6.56, respectively, with a standard deviation of 7.94. The Gini coefficient calculated was 0.361. The Lorenz curve made from all the observations is given in Figure 4.5

Figure 4.5

Concentrated Markets - Lorenz Curves



Source: Gretl Output

The area between the line of equality and the Lorenz curve given in Figure 4.5 is larger than all the individual airline companies. Fifty per cent of revenue was collected from 76% of passengers. It means that the remaining 50% of the revenue was contributed by 24% of passengers.

Monopoly markets tend to have higher mean airfares, greater variability, higher inequality, and wider spreads of prices compared to partial monopoly and triopoly markets. Route M4 stands out as having the highest mean, highest variability, highest inequality, and the widest spread of prices, suggesting a more dynamic and variable pricing structure. Partial monopoly and triopoly markets show more moderate levels of mean airfares, variability, inequality, and a more concentrated range of prices. Therefore, passengers may experience more predictable and stable airfares in partial monopoly and triopoly markets compared to monopoly markets, where pricing dynamics can be more volatile.

4.3.5 Reasons for Price Dispersion

The above analysis of the extent of price dispersion highlights that the dispersion does not show any similarity with regard to route, competition, or Airline Company. Hence a further analysis is required to explore the nature of price dispersion. Generally, dynamic pricing is used as a tool for revenue maximisation (Feldmann, 2008), and the airline industry is not an exception (Deksnyte, 2012). Since the airline industry deals with a product of a highly perishable nature, demand penetration (Tretheway, 2011) is another objective to be served. Market penetration objective is of more importance for a price-elastic market like India (Wang et al., 2018). Hence the reason for price dispersion is analysed in dimensions of festival day and day of the week.

4.3.5.1 Day of the Week and Festival Effect

It is a well-known phenomenon in the airline industry that the day of the week influences demands. Price dispersion during weekends is more extensive than on weekdays, while the average price stays constant over all days of the week (Mantin & Koo, 2010). Weekday and Weekend differences in airline prices are observed in many cases (Alderighi et al., 2012), (Martínez-Garcia et al., 2012), (Wei & Grubesic, 2016), (Balaiyan et al., 2019). Air travel is more expensive on festival days (Dutta & Santra, 2016) (Mathur, 2020), another observation in the Indian contest. For analysing this phenomenon, route-wise analysis is made in this study. Prices were collected for the departures five days a week, including festival day, and are arranged in a time series formation for every route.

4.3.5.1.1 Monopoly Situations

Price comparisons based on the day of departure are given in Table 4.5 to Table 4.11 for all the six routes under consideration. Route M1 connects Hyderabad in Telangana and Nanded in Maharashtra, air distanced by 248 kms, labelled as short distance in this research. Tuesday and Wednesday, on this data set, were festival days in the destination city. Day of departure wise summary and Gini coefficient are given in Table 4.5.

Table 4.5

Day of Departure Effect – Route M1

	Mean	Median	Min	Max	SD	Gini
Friday	6.43	4.76	4.76	15.67	2.97	0.194
Saturday	13.35	8.95	4.76	32.90	9.84	0.354
Sunday	11.84	8.95	4.76	28.57	6.25	0.277
Monday-Day Before	10.47	8.22	4.76	20.15	4.44	0.227
Tuesday-Festival	12.71	10.08	4.76	28.57	6.22	0.256
Wednesday-Festival	8.33	7.49	4.76	15.67	2.27	0.136
Thursday-Day After	7.05	6.56	4.76	11.20	1.83	0.139
Friday	6.63	7.49	4.76	7.49	1.11	0.083
Saturday	6.08	5.62	4.76	7.49	1.22	0.105
Sunday	6.65	7.49	4.76	8.95	1.21	0.093

Source: Primary Data

The maximum and mean prices offered are highest for Saturday, Sunday, the day before festival day and festival days. SD and Gini coefficient are also higher than other days on these days. This shows that the festival effect on price is evident from the previous Saturday. On the second day of the festival, the price came down. Friday effect is not apparent, either before or after the holidays. Saturday and Sunday (weekend) effects are not evident after the holidays. This can be due to the Holiday season. The Gini coefficient is high from Saturday to the first festival day.

Route M2 Connects Ahmedabad in Gujarat and Lucknow in UP air distanced by 975 kms. This medium-distanced route also has a monopolistic situation. Tuesday and Wednesday, on this data set, were Diwali festival days in the destination city. Day of departure wise summary and Gini coefficient are given in Table 4.6.

Table 4.6

Day of Departure Effect – Route M2

Day	Mean	Median	Min	Max	SD	Gini
Friday	12.84	13.03	10.13	16.18	1.756	0.072
Saturday	16.59	16.18	15.60	17.50	0.785	0.025
Sunday	16.49	16.18	15.01	17.50	0.859	0.027
Monday	12.59	12.62	10.13	17.50	2.106	0.091
Tuesday- Festival Day	14.17	13.74	12.33	16.18	1.143	0.044
Wednesday- Festival Day	11.74	11.47	10.13	15.60	1.593	0.072
Thursday	15.00	15.60	9.23	17.50	1.572	0.048
Friday	12.90	15.01	7.43	16.18	3.122	0.126
Saturday	11.42	12.33	7.43	14.44	2.111	0.094
Sunday	10.05	10.13	6.92	15.6	1.877	0.098

Source: Primary Data

The maximum and mean price offered does not differ much for Sunday, the day before festival days and festival days. The absolute measure of dispersion and the Gini coefficient also shows similarity. The minimum price offered was more on festival days and weekends before the festival. This indicates that the festival's effect on price is evident from the previous Friday. An increase in the maximum prices offered and mean price after the holidays show that demand rose within one month from departure after the holidays. Price-sensitive travellers might have changed their travel dates to subsequent dates, which can be the reason for increased prices after holidays. Friday effect or Saturday and Sunday (weekend) effect are not evident.

Route M3 Connects New Delhi and Dibrugarh in Assam air distanced by 1761 kms. This medium-distanced route also has a monopolistic situation. Tuesday and Wednesday, on this data set, were Diwali festival days in the destination city. Day of departure wise summary and Gini coefficient are given in Table 4.7.

Table 4.7

Day of Departure Effect – Route M3

	Mean	Median	Min	Max	SD	Gini
Friday	5.04	4.43	3.98	11.36	1.582	0.124
Saturday	5.59	4.94	4.43	11.36	1.436	0.114
Sunday	6.14	5.79	4.94	11.36	1.688	0.123
Monday	5.36	4.94	4.66	8.29	0.894	0.077

Tuesday-Festival Day	4.68	4.09	3.98	6.48	0.896	0.098
Wednesday-Festival Day	4.61	3.98	3.98	6.48	0.859	0.092
Thursday	4.58	3.98	3.98	6.48	0.862	0.091
Friday	4.63	3.98	3.98	6.48	0.881	0.094
Saturday	4.74	4.32	3.98	6.48	0.860	0.096
Sunday	7.12	6.82	6.14	9.20	0.802	0.060

Source: Primary Data

Maximum price, minimum price, and mean price offered do not show much difference on the day before or after festival day and festival days. SD and Gini coefficient also show a similarity between Friday and the weekend before festival days; also between other days, including holidays. The table does not show the Friday, weekend, and festival effects. Nevertheless, Sunday offers comparatively higher fares.

Route M4 connects Varanasi in Uttar Pradesh and Khajuraho in Madhya Pradesh air distanced by 305 kms. Table 4.8 explain the basic statistics and Gini coefficient of this route. Tuesday is a festival day in the destination city.

Table 4.8

Day of Departure Effect - Route M4

	Mean	Median	Min	Max	SD	Gini
Friday	14.20	12.83	8.49	19.53	3.124	0.103

Saturday	15.33	18.86	8.49	18.86	4.434	0.146
Sunday	26.55	27.81	12.83	34.00	6.707	0.116
Monday	41.12	34.00	18.86	53.63	12.489	0.159
Tuesday-Festival Day	36.57	41.58	15.76	41.58	9.022	0.106
Wednesday-Festival Day	14.61	15.76	11.11	15.76	1.715	0.055
Thursday	19.80	22.64	12.83	22.64	3.874	0.096
Friday	47.29	53.63	34.00	53.63	8.258	0.087
Saturday	47.23	42.01	41.58	53.63	6.089	0.064
Sunday	35.03	34.00	23.50	41.58	6.086	0.093

Source: Primary Data

The minimum, maximum and mean fares on the festival day and the days before the festival are lower than those after the festival days. Dispersion on and before the festival day was higher than the dispersion after festival days.

4.3.5.1.2 Partial Monopoly Situation

Route M5 connects Pune in Maharashtra and Kochi in Kerala, air distanced by 975 km. For Routes M1 to M4, Diwali was the major festival, whereas it is not a major festival in Kerala. Onam is the major festival of Kerala. It was on Sunday in the year of observation. To have a better understanding of the Saturday and Sunday effects, prices of two weeks were observed. Indigo has got a monopoly on the route on both Saturdays. All other days show a duopolistic tendency. The departure time of Indigo was 02:45 am on all days.

On Tuesday additional flight from Indigo departs at 11.00 am. The departure time of Spicejet was 11.25 am on all days. The summary statistics and Gini coefficient are given in Table 4.9.

Table 4.9

Day of Departure Effect - Route M5

	Mean	Median	Min	Max	SD	Gini
Spicejet						
Friday	5.04	5.04	4.08	6.15	0.622	0.069
Sunday	5.58	5.02	4.58	7.82	0.980	0.091
Monday	4.78	4.58	4.15	6.09	0.542	0.058
Tuesday	4.41	4.37	4.05	4.80	0.200	0.025
Wednesday	5.35	5.28	4.80	6.15	0.361	0.036
Thursday	4.81	4.91	4.32	5.59	0.296	0.032
Friday-Day Before	5.37	5.02	4.58	7.82	1.061	0.087
Sunday-Day After	4.81	4.56	4.15	7.38	0.783	0.077
Monday	4.50	4.57	4.15	4.80	0.195	0.024
Tuesday	4.64	4.68	4.15	4.80	0.188	0.020
Wednesday	4.75	4.37	4.05	7.38	0.989	0.091
Thursday	5.45	4.58	3.94	10.83	2.011	0.166
Friday	4.86	4.91	3.67	7.88	0.755	0.070

Indigo						
Friday	4.79	4.75	3.29	5.55	0.542	0.061
Saturday	6.74	6.58	5.68	9.06	1.110	0.077
Sunday	5.49	5.00	4.51	9.06	1.145	0.099
Monday	4.83	4.51	4.15	9.06	1.044	0.086
Tuesday 2:45	4.64	4.39	3.67	9.06	1.086	0.084
Tuesday 11	4.64	4.39	3.67	9.06	1.086	0.084
Wednesday	5.40	5.17	4.51	9.06	0.915	0.068
Thursday	5.19	4.80	4.15	9.06	1.311	0.112
Friday-Day Before	4.84	4.75	4.26	5.55	0.318	0.034
Saturday-Festival Day	5.51	5.17	5.00	6.58	0.547	0.049
Sunday-Day After	4.50	4.26	4.15	5.55	0.471	0.052
Monday	4.36	4.26	4.15	4.80	0.223	0.027
Tuesday 2:45	4.49	4.51	4.15	4.80	0.179	0.021
Tuesday 11	5.08	4.51	4.15	6.63	0.967	0.092
Wednesday	4.46	4.15	3.67	6.58	0.710	0.076
Thursday	4.23	4.15	3.67	5.00	0.359	0.045
Friday	4.83	4.80	4.37	5.00	0.186	0.018

Source: Primary Data

Fares of the route do not show much difference between weekdays and holidays. The dispersion between airlines and within airlines is comparatively lesser than other concentrated routes - M1, M2, M3, and M4. This indicates the impact of competition. Prices on Saturdays show higher rates indicating the presence of a monopoly situation and weekend effect. But the availability of seats was only half on Saturdays. Monopoly and reduction in supply do not increase the fare.

On the other hand, Tuesdays are marked with an additional flight with a duopoly situation. These do not reduce the price much. Both these situations are either against the 'law of demand and supply' or the effect of a reduction in demand on Saturdays and an increase in demand on Tuesdays. Festival days do not increase the price, showing the lesser impact of festival days. This can indicate the speciality of the route with price-sensitive business travellers.

4.3.5.1.3 Triopoly Situations

Table 4.10 explain the basic statistics of route M6. This route connecting Mumbai and Thiruvananthapuram has an air distance of 1,258 kms. Christmas is a public holiday in Kerala. Schools and colleges used to get one week's holiday with the Christmas Festival. Three airline companies were operating on all days, creating a triopoly situation. Table 4.10 shows the summary statistics and Gini coefficient of three airline companies.

Table 4.10

Day of Departure Effect - Route M6

	Mean	Median	Min	Max	SD	Gini
Indigo						
Saturday	13.89	15.90	11.27	15.90	2.189	0.079

Sunday	10.82	9.94	7.86	16.12	2.238	0.107
Monday-Day Before	7.77	7.86	5.97	14.28	1.670	0.084
Tuesday-Festival Day	7.28	7.86	5.64	9.94	1.245	0.090
Wednesday- Day After	8.79	7.86	5.27	11.61	2.030	0.125
Thursday	7.56	6.56	3.39	12.40	2.817	0.202
Friday	6.71	6.56	5.78	7.86	0.708	0.055
Saturday	6.68	6.76	4.62	7.86	0.955	0.078
Sunday	6.59	6.56	5.14	7.86	0.849	0.070
Monday	4.59	4.30	3.30	6.43	0.845	0.097
Tuesday	4.44	4.30	3.30	6.43	0.886	0.104
Wednesday	5.37	5.14	3.39	7.27	0.980	0.094
Air India						
Saturday	18.67	17.49	13.61	21.91	2.236	0.056
Sunday	17.47	19.62	7.68	21.91	4.781	0.137
Monday-Day Before	16.29	19.45	8.68	21.58	4.756	0.140
Tuesday-Festival Day	14.94	17.32	8.68	19.45	4.216	0.134
Wednesday- Day After	15.81	17.32	6.64	17.32	3.446	0.080
Thursday	12.02	8.68	6.64	17.32	4.777	0.204

Friday	15.87	17.49	6.09	17.49	3.735	0.086
Saturday	9.01	8.85	7.01	17.49	1.667	0.044
Sunday	7.54	6.80	0.90	17.49	3.497	0.207
Monday	6.97	6.64	5.89	8.68	1.191	0.088
Tuesday	6.64	6.64	5.22	8.68	1.074	0.086
Wednesday	8.35	8.68	6.64	9.89	1.417	0.091
Jet Airways						
Saturday	16.22	16.28	12.53	21.31	1.688	0.048
Sunday	12.01	12.53	7.93	16.28	2.289	0.093
Monday-Day Before	7.74	7.93	6.02	12.53	1.269	0.069
Tuesday-Festival Day	7.89	7.93	5.79	10.02	1.360	0.088
Wednesday- Day After	10.60	12.53	6.02	12.53	2.405	0.116
Thursday	8.91	10.02	4.85	10.02	1.879	0.092
Friday	6.72	6.02	6.02	7.93	0.941	0.066
Saturday	7.42	7.93	6.02	7.94	0.863	0.051
Sunday	6.03	6.02	5.35	7.93	0.575	0.035
Monday	5.12	4.85	4.85	6.02	0.503	0.041
Tuesday	5.40	5.35	4.85	6.02	0.462	0.045

Wednesday	5.93	5.68	4.85	7.93	1.113	0.096

Source: Primary Data

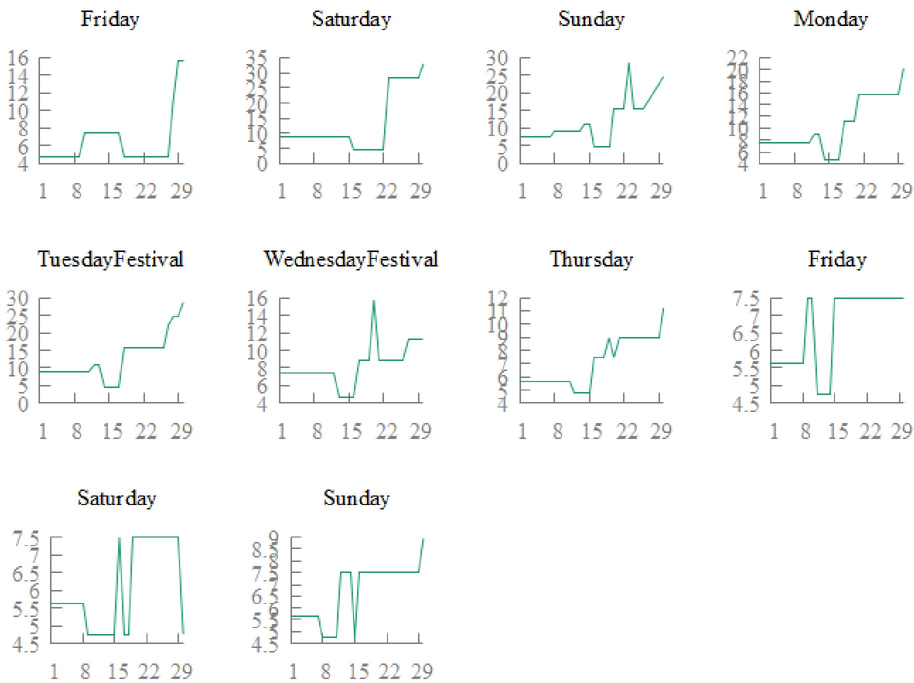
Air India has the highest mean fare, minimum fare and maximum fare, followed by Jet Airways. The mean fares of all the flights were higher during the festival days, the day after and the day before the festival day. At weekends close to the festival day, fares were the highest for all flights. The Saturday and Sunday before the festival day marked the highest price. The Sunday fares after the festival day were nearly half the fares before the festival day for all the flights. The Gini coefficient of Indigo and Air India on Thursday showed a higher dispersion of 0.20. Thursday was the second day of the festival day. Jet Airways also showed a higher dispersion on the day after the festival than on other days. These are all evidence of the festival effect and its impact on adjacent weekends.

4.3.5.2 Out Layers - Low Bucket and High Bucket

Airline companies offer low fares to attract passengers to penetrate demand. Low fares buckets are generally few. On the other hand, since demand is not exactly predictable, it is difficult for companies to charge high fares. So the high fare buckets are also generally few. Reports show that the percentage of seats sold and the percentage of revenue earned in the highest fare buckets were less than 1% on many routes, and they are sometimes zero (DGCA, 2018). The researcher could not find any reports showing the actual seats sold under each fare bucket. Hence, the out layers on each departure day are analysed to better understand the price dynamics and dispersion. Time series plots are used for this analysis. The time series plot for route M1 is given in Figure 4.6.

Figure 4.6

Time Series Plot: Route M1



Source: Gretl Output

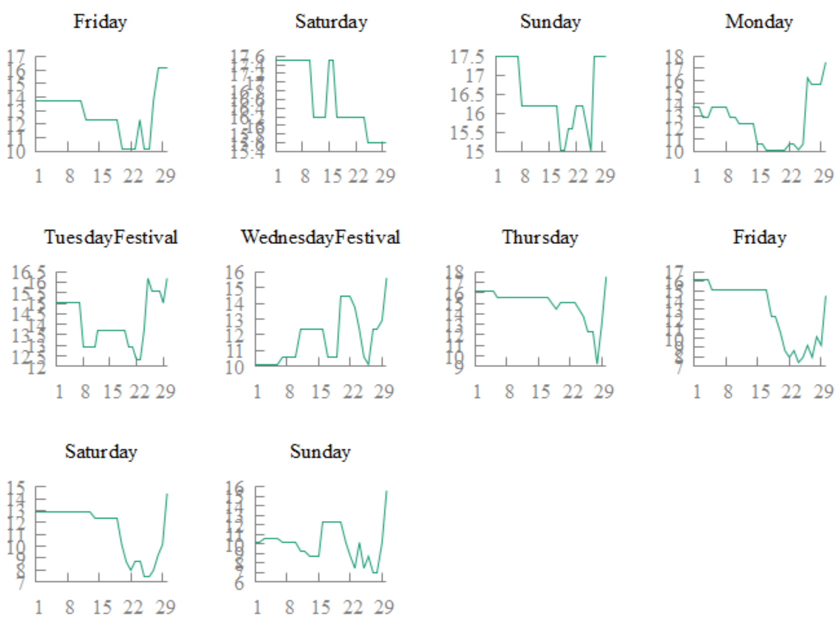
In Figure 4.6, the X-axis indicates observations from the 1st day to the 30th day of the day before departure. '1' indicates the first day of observation. '29' indicates the 29th day of observation. The Y-axis indicates the price of the ticket per km. The last-minute fluctuations in the departure dates were ignored.

On Friday before the festival, the maximum fare was quoted on the last few days of departure with a sudden jump. It shows the presence of an out layer. But since these out layers are quoted for the last few days, it may not make many changes in the revenue because leisure travellers tend to avoid last-minute bookings. The reverse will be the effect if the route has more price-inelastic business travellers (Gillen & Hazledine, 2006).

During festival days, the firm expected a demand hike, which is reflected in the initial minimum prices from 30 days to 15 days of departure. Between 10 to 15 days of departure, a sharp decline is evident on all the days, indicating the penetrating market strategy to induce leisure travellers. Even though the mean price appears to be high during the festival season, the hike is due to the increased price after the above-mentioned decline. The strategy to capture more from the last-minute, time-sensitive travellers tends to increase the dispersion on the route. Before the 15th day of departure, the prices are below ₹10 per km on all days. Only on 'Saturday after the festival' the firm reduced the price. That was also on the day before departure. This analysis also shows that the dispersion indicated by the Lorenz curve does not mean that the highest contributors are not necessarily the last-minute passengers or those who booked first. Figure 4.7 shows the time series plot of Route M2.

Figure 4.7

Time Series Plot: Route M2



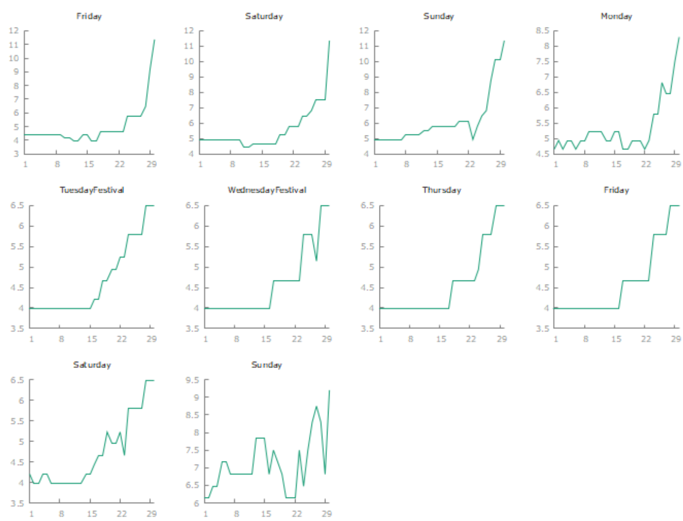
Source: Gretl Output

Figure 4.7 displays the time trend of Route M2 for all the days of departure under observation. The trend shows the demand expectation of the firm. The prices offered during the initial days of observation were high on all days of departure. The minimum fare ranges from ₹10 to ₹17.5 during the initial days. Between 10 to 15 days of departure, a sharp decline is evident on all the days, indicating the penetrating market strategy to induce leisure travellers. The same observation was made in route M1 also. Wednesday, a festival day, seems to be an exception to this sharp decline from the initial price. There also a decline happened to the minimum price of observation. On Saturday before the festival, a sharp increase in the price is not evident. But the minimum fare offered on that date was also high. This analysis also shows that the dispersion indicated by the Lorenz curve does not mean that the highest contributors are not necessarily the last-minute passengers or those who booked first.

The Time Trend of observations on all dates of departure of Route M3 is given in figure 4.8.

Figure 4.8

Time Series Plot: Route M3

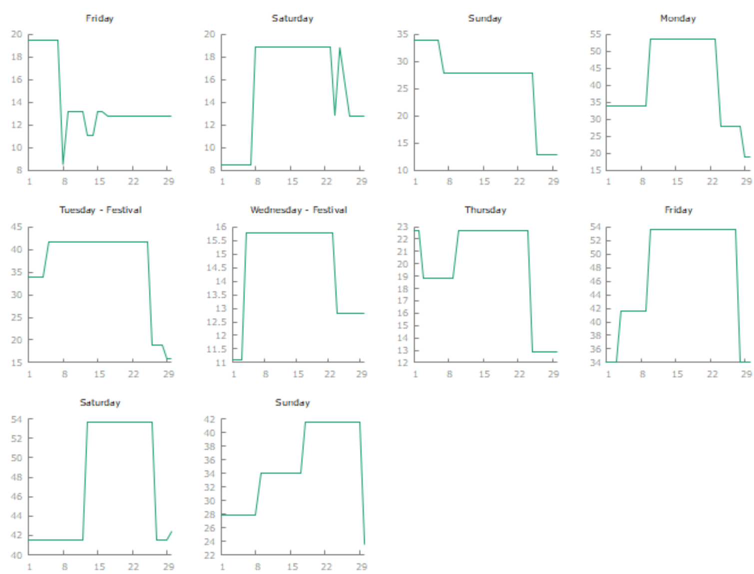


Source: Gretl Output

In the figure 4.8, time trends of 10 departure dates are given. Saturday and Sunday before and after the Diwali festival days are shown. Distinct from Route M1 and M2, the minimum fare offered 30 days before departure was around ₹4 to ₹5 per km. A sharp decline between 10 to 15 days to departure is not evident on this route, except for Sundays. All these days, the common phenomenon of the airline industry, that is, 'price increases with closeness to departure date', is evident. On the Sunday, which came after the festival, the minimum price offered 30 days before departure was above ₹6 per km. A sharp decline of 10 to 15 days before departure is evident on some days of observation. A sharp rise in the fare starts only before the last few days of the departure date. This analysis also shows that the dispersion indicated by the Lorenz curve does not mean that the highest contributors are not necessarily the last-minute passengers or those who booked first. Figure 4.9 display the time trend of Rote M4 for all the days of departure under observation.

Figure 4.9

Time Series Plot: Route M4

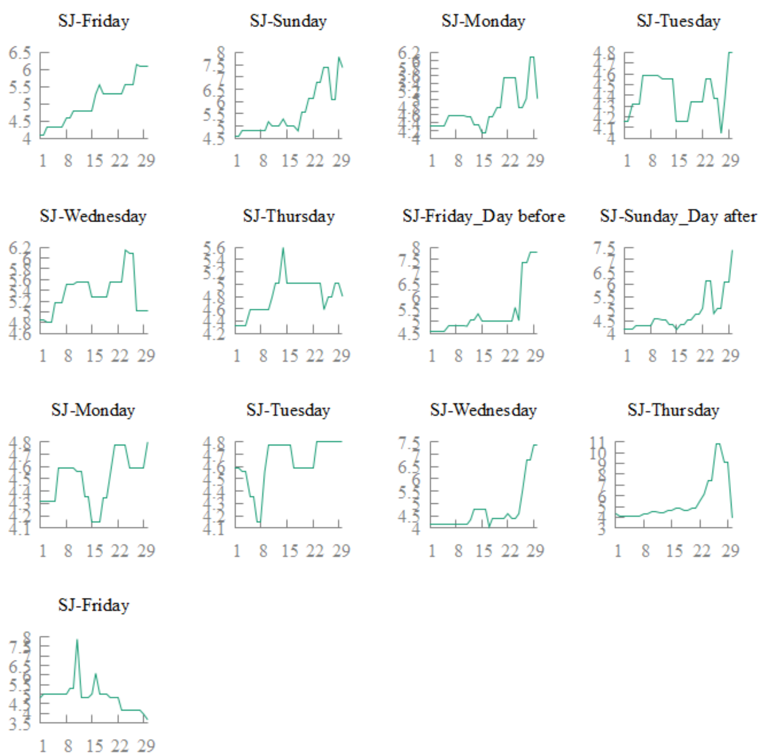


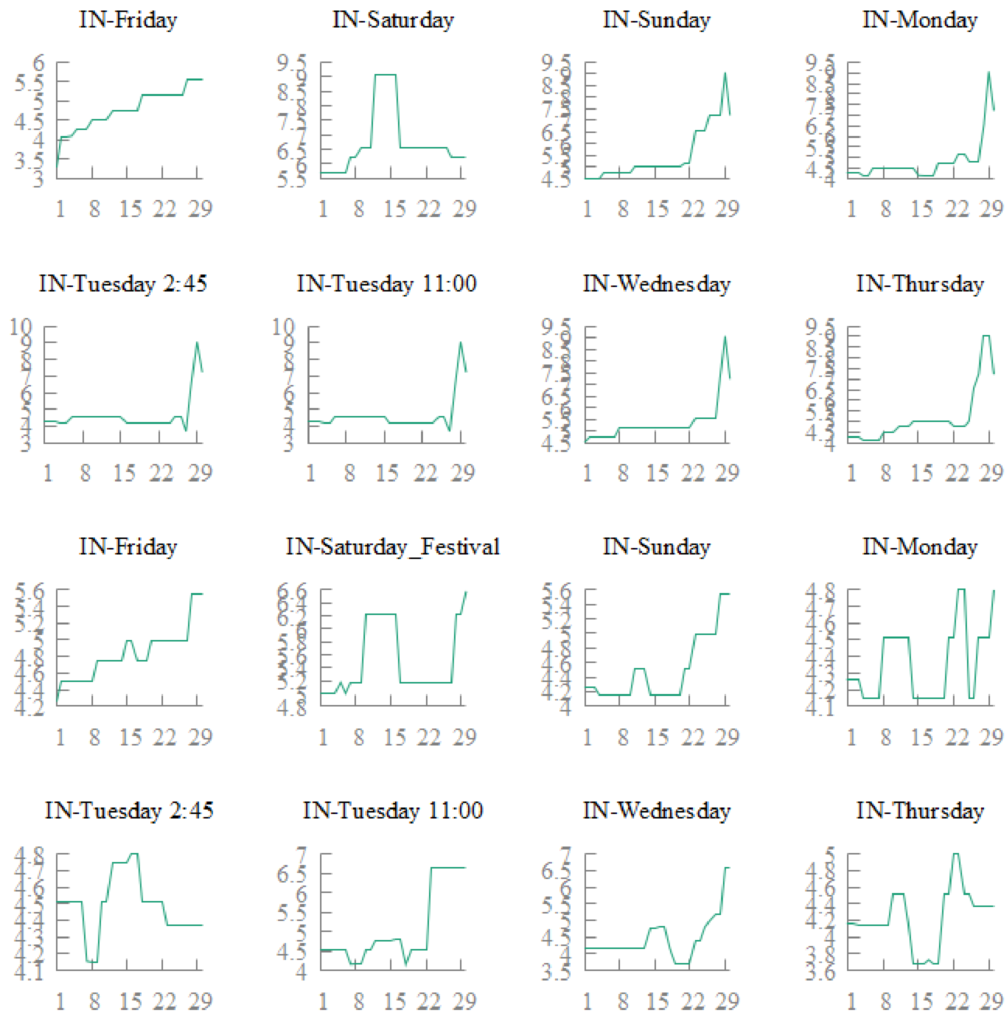
Source: Gretl output

In the figure 4.9, time trends of 10 departure dates are given. Saturday and Sunday before and after the Diwali festival days are shown. The minimum fare offered on the first day of observation of five days was above ₹30, and for another three days, it was above ₹20 per km. This was the highest of all other routes. A sharp decline is evident on this route within ten days of departure. On Friday before the festival, fare decreased sharply on the eighth day of observation. All these days, the common phenomenon of the airline industry, that is, 'price increases with closeness to departure date', is not evident. The figures show a nearly similar movement on all days. This analysis also proves that the dispersion indicated by the Lorenz curve does not mean that the highest contributors are not necessarily the last-minute passengers or those who booked first.

Figure 4.10

Time Series Plot: Route M5





Source: Gretl Output

‘SJ’ indicate Spicejet, ‘IN’ indicate Indigo

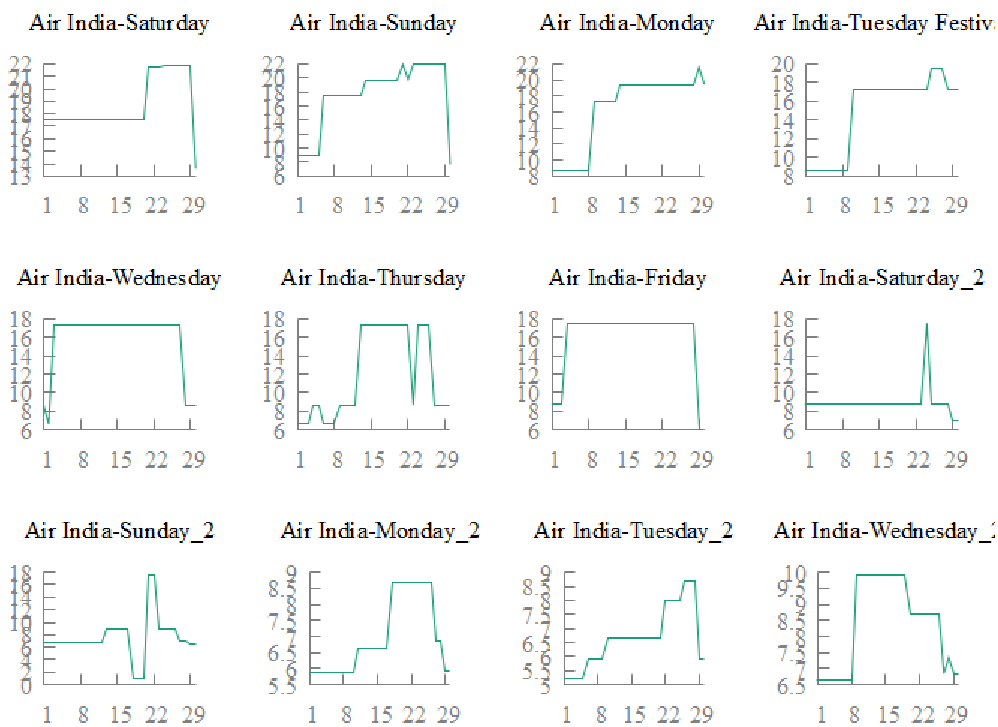
Route M5 is characterised by a duopoly situation six days a week. Figure 4.10 shows the time trend of the two companies on Route M5.

The minimum fare offered on the first day of observation was above ₹4 per km for both companies. A sharp decline is evident on this route within 15 days of departure in most cases. For both companies, the airline industry's common phenomenon, 'price increases with closeness to departure date', is not evident on all days. The figures show a nearly similar movement on all days for both companies.

A triopoly situation characterises route M6 on all days of the week. The time trend of the three companies on Route M6 is given in figure 4.11.

Figure 4.11

Time Series Plot: Route M6



Source: Gretl Output

The minimum fare offered on the first day of observation was above ₹3 per km for all the companies. The maximum fare offered on the first day of observation was the highest for all companies on Saturday before the festival. A sharp decline is evident on this route within 15 days of departure in most cases. For all the companies, the common phenomenon of the airline industry, ‘price increases with closeness to departure date’, is evident on most days of observation, even though monotonic increases are not. The figures show a nearly similar movement on all days for all three companies.

4.3.5.3 Inter-Dependence of Prices

The airline market is characterised mainly by the presence of two types of travellers: Price sensitive leisure travellers and time-sensitive business travellers. Besides price, customers consider brand experience (Zehir & Kitapçı, 2011), especially when they have a choice. Customer orientations to brand experience (Lin, 2015), impulse purchase, trust, and quality influence purchase decisions (Thamizhvanan & Xavier, 2013). Departure time is also an essential factor influencing demand (Button et al., 2007) (Tsai, 2016).

4.3.5.3.1 Prices of Neighbouring Days

The date of travel is vital for business travellers. However, price-sensitive leisure travellers may be ready for flexible travel dates or may change their mode of travel. So it is assumed that he will look for a better price for the next day of travel. If this assumption is correct, there can be a correlation between the price movements of adjacent departure dates. The following hypotheses were formulated for this purpose.

$H_{0\,7}$ Price movements of neighbouring days of departure of the same airline is not significantly correlated under a monopoly situation.

$H_{0\,8}$ Price movements of neighbouring days of departure of the same airline is not significantly correlated under a partial monopoly situation.

$H_{0\,9}$ Price movements of neighbouring days of departure of the same airline is not significantly correlated under a triopoly situation.

'Kendall's rank correlation tau' is used to test the significance at 0.05 levels (2-tailed) of correlation between two adjacent days of departure. The test assumes the null hypothesis of no correlation. Table 4.11 shows the results of routes with a single flight, i.e., monopoly situation.

Table 4.11

Correlation- Single Flight Routes

		M1	**M2**	**M3**	**M4**
Friday	Saturday	0.169	0.236	0.830	-0.499
		(>0.05)	**(>0.05)**	(<0.05)	(<0.05)
Saturday	Sunday	0.568	0.260	0.421	-0.233
		(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Sunday	Monday	0.572	0.629	0.493	0.176
		(<0.05)	(<0.05)	(<0.05)	**(>0.05)**
Monday	Tuesday – Festival	0.943	0.523	0.403	0.685
		(<0.05)	(<0.05)	(<0.05)	(<0.05)
		0.770	-0.324	0.940	0.670

Tuesday - Festival	Wednesday-Festival	(<0.05)	(<0.05)	(<0.05)	(<0.05)
Wednesday-Festival	Thursday	0.764	-0.314	0.947	0.411
		(<0.05)	(<0.05)	(<0.05)	(<0.05)
Thursday	Friday	0.710	0.717	0.956	0.501
		(<0.05)	(<0.05)	(<0.05)	(<0.05)
Friday	Saturday	0.472	0.720	0.882	0.644
		(<0.05)	(<0.05)	(<0.05)	(<0.05)
Saturday	Sunday	0.398	0.332	0.218	0.489
		(<0.05)	(<0.05)	**(>0.05)**	(<0.05)

Source: Gretl Output

* Figures in bracket indicate P value significance

It is seen from the above table that there exists a significant correlation between the price movements in most cases ($p<0.05$). Hence the null hypothesis $H_{0\,7}$ is rejected in most cases. For Route M1, price movements of all neighbouring days are significantly correlated, except for the Friday before the festival. On route M2, except for Friday, Saturday, and Sunday before the festival, all adjacent days shows a significant correlation. For Route M3, a significant correlation exists, except between the last days of observation. A significant correlation exists between the price movements of all adjacent days of Route M4, except for the first two pairs. There are occurrences of positive and negative correlations. A negative correlation reflects that an increase in one-day prices decreases the prices of an adjacent day and vice versa. In other words, an increase in the demand for tickets for one day decreases the demand for an adjacent day. This strongly supports the argument of the presence of co-existence of price-sensitive and time-sensitive travellers on the route. Airline companies decrease the price to attract price-sensitive travellers to dates with low demand. Of the 36 pairs tested for correlation, 30 (83.3%) show significant correlation. Of the statistically significant correlated pairs, 90% are positively correlated. In the case of the remaining 10%, a negative correlation is evident on Fridays, weekends and festival days. In short the price movement of neighbouring days of departure of the same airline is correlated under a monopoly situation.

Table 4.12 shows the correlation of price movements of neighbouring days of departures of the partial monopoly and triopoly routes.

Table 4.12

Correlation - Partial Monopoly & Triopoly Routes

		Spicejet	Indigo	Indigo	Air India	Jet Airways
		M5	M5	M6	M6	M6
Friday	Saturday		0.214			
			(>0.05)			
Friday	Sunday	0.714				
		(<0.05)				
Saturday	Sunday		0.234	0.115	0.765	0.302
			(>0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Sunday	Monday	0.594	0.650	0.264	0.738	0.325

		(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	(<0.05)
Monday	Tuesday	0.329	0.246	0.486	0.748	0.236
		(<0.05)	**(>0.05)**	(<0.05)	(<0.05)	**(>0.05)**
Tuesday	Wednesday	0.183	0.145	0.413	0.152	0.223
		(>0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	**(>0.05)**
Wednesday	Thursday	0.466	0.737	0.078	0.374	0.657
		<0.05)	<0.05)	**(>0.05)**	(<0.05)	(<0.05)
Thursday	Friday	0.558	0.772	-0.008	0.413	0.077
		(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Friday	Saturday		0.503	-0.080	0.566	0.204
			(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Friday	Sunday	0.577				
		(<0.05)				
Saturday	Sunday		0.187	-0.253	0.358	0.309
			(>0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**
Sunday	Monday	0.654	0.617	0.658	0.319	0.172
		(<0.05)	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**
Monday	Tuesday	0.279	-0.316	0.804	0.754	0.306

		(>0.05)	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**
Tuesday	Tuesday		0.040			
-Flight 1	-Flight 2		**(>0.05)**			
Tuesday	Wednesday		0.640	0.411	0.346	0.466
-Flight 2			(<0.05)	(<0.05)	(<0.05)	(<0.05)
Tuesday	Wednesday	0.63	-0.301			
-Flight 1		(<0.05)	**(>0.05)**			
Wednesday	Thursday	0.492	-0.065			
		(<0.05)	**(>0.05)**			
Thursday	Friday	-0.501	-0.504			
		(<0.05)	(<0.05)			

Source: Gretl Output

* Figures in bracket indicate P value significance

Table 4.12 shows that 91.7% of the observations are significantly correlated for Spicejet and 75% for Indigo in Route M5 ($p<0.05$). Hence the null hypothesis $H_{0\ 8}$ is rejected in most cases. In Route M6, 91% of the observations are significantly correlated for Air India, 72.7% for Indigo and 63.6% for Jet Airways ($p<0.05$). Hence the null hypothesis $H_{0\ 9}$ is rejected in most cases. There are occurrences of seven negative correlations, indicating the presence of the co-existence of price-sensitive and time-sensitive travellers on the route.

For all the routes under concentrated markets, price movements of 83.5% of the adjacent days were significantly correlated. Out of the significantly correlated adjacent days, 91.6% were positively correlated. Hence it is concluded that the price movement of neighbouring days of departure of the same airline is correlated under monopoly, partial monopoly and triopoly situations. The presences of price sensitive travellers tend to change their travel date to the next day if that date has a favourable price. Hence the demand of one day and the subsequent change in price influence the demand and prices of the next day.

4.3.5.3.2 Prices of Competing Airlines

A brand-loyal customer may try to choose his favourite airline company, irrespective of the price. On the other hand, price-sensitive customers, both business and leisure travellers, may compare the price of alternative flights on the same day. Time preference will also be a factor here. Hence the price of competing airlines will tend to be correlated. The following hypotheses are formulated with this objective.

$H_{0\ 10}$ Price movements of competing airlines on the same day is not significantly correlated under a partial monopoly situation.

$H_{0\ 11}$ Price movements of competing airlines on the same day is not significantly correlated under a triopoly situation.

Kendall's rank correlation tau is used to test the significance at 0.05 levels (2-tailed) of correlation between the price movements of competing airlines. The test assumes the null hypothesis of no correlation. Table 4.13 show the results of routes with more than one flight.

Table 4.13

Correlation- Price Movements of Competing Airlines

Day	M5	M6					
	Indigo	Indigo		Air India		Jet Airways	
	Spice Jet	Air India	Jet Airways	Indigo	Jet Airways	Indigo	Air India
Friday	0.834						
	(<0.05)						
Saturday		0.193	0.023	0.193	-0.292	0.023	-0.292
		(>0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**	**(>0.05)**	**(>0.05)**
Sunday	0.826	0.046	-0.105	0.046	-0.688	-0.105	-0.688
	(<0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**	(<0.05)	**(>0.05)**	(<0.05)
Monday	0.802	0.184	0.807	0.184	0.119	0.807	0.119
	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	**(>0.05)**	(<0.05)	**(>0.05)**
Tuesday	0.55	0.386	0.645	0.386	0.151	0.645	0.151
	(<0.05)	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Wednesday	0.331	0.056	0.168	0.056	0.402	0.168	0.402
	(<0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**	(<0.05)	**(>0.05)**	(<0.05)
Thursday	0.375	0.394	-0.495	0.394	0.088	-0.495	0.088
	(<0.05)	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**

Friday	0.706	0.385	0.352	0.385	0.382	0.352	0.382
	(<0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)
Saturday		-0.249	0.217	-0.249	0.164	0.217	0.164
		(>0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**	**(>0.05)**	**(>0.05)**
Sunday	0.451	0.307	-0.171	0.307	0.199	-0.171	0.199
	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**
Monday	0.53	0.524	0.602	0.524	0.158	0.602	0.158
	(<0.05)	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Tuesday	0.802	0.630	-0.131	0.630	-0.263	-0.131	-0.263
	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**
Wednesday	0.372	-0.286	0.570	-0.286	-0.425	0.570	-0.425
	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	(<0.05)	(<0.05)	(<0.05)
Thursday	0.211						
	(<0.05)						
Friday	0.55						
	(<0.05)						

Source: Gretl Output

* Figures in bracket indicate P value significance

The results show a significant correlation between the fares of Indigo and Spicejet (Route M5) on all days of observation ($p<0.05$). Hence the null hypothesis $H_{0\ 10}$ is rejected in all cases. Between Indigo, Air Asia, and Jet Airways (Route M6) percentage of significantly correlated pairs are comparatively less. Out of the 72 pairs of observation, 44% are significantly correlated, while 66% are not ($p>0.05$). Hence the null hypothesis $H_{0\ 11}$ is accepted in all cases. Price movements of competing airlines on the same day are significantly correlated under the partial monopoly situation and are not correlated under the Triopoly situation in concentrated markets.

The reason for this difference needs further analysis. Traffic density on the route would naturally increase the number of category of passengers on the route. This may give more importance to the time of departure and brand preferences. The number of passengers travelled on the route during the month of observation is 3,693 in Route M5 and 12,928 in Route M6, as per the published records (DGCA, 2019b).

4.3.5.4 Time of Booking

It is a well-known fact that the time of booking and the dates of departure is one of the critical tools used by airline companies to distinguish travellers as time-sensitive and price-sensitive (Graf, 2005). Generally, price increases with proximity to the departure date (Martínez-Garcia et al., 2012). Therefore, the following hypotheses were formed.

$H_{0\ 12}$ Booking Prices are not significantly correlated to the time gap to the departure date under a monopoly situation.

$H_{0\ 13}$ Booking Prices are not significantly correlated to the time gap to the departure date under a partial monopoly situation.

$H_{0\ 14}$ Booking Prices are not significantly correlated to the time gap to the departure date under a triopoly situation.

Assuming the null hypothesis of no correlation, Kendall's rank correlation tau is used to test the significance at 0.05 levels (2-tailed) of correlation between the price movements of competing airlines. Table 4.14 show the results.

Table 4.14

Correlation: Price and Time of Booking

	M1	M2	M3	M4	M5 Indigo	M5 Spicejet	M6 Indigo	M6Air India	M6 Jet Airway
Friday	-0.235	0.311	-0.562	0.545	-0.920	-0.827			
	(>0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)			
Saturday	-0.220	0.768	-0.516	-0.17	-0.197		-0.588	-0.538	0.161
	(>0.05)	(<0.05)	(<0.05)	**(>0.05)**	**(>0.05)**		(<0.05)	(<0.05)	**(>0.05)**
Sunday	-0.600	0.301	-0.839	0.741	-0.903	-0.772	-0.261	-0.740	0.451
	(<0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	(<0.05)
Monday	-0.603	0.182	-0.483	0.125	-0.590	-0.558	-0.092	-0.792	0.001
	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**
Tuesday	-0.607	-0.028	-0.854	0.154	0.019	-0.068	-0.477	-0.692	-0.409
	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**	(<0.05)	(<0.05)	(<0.05)
Wednesday	-0.549	-0.548	-0.797	0.19	-0.830	-0.260	-0.113	0.097	0.111
	(<0.05)	(<0.05)	(<0.05)	**(>0.05)**	(<0.05)	**(>0.05)**	**(>0.05)**	**(>0.05)**	**(>0.05)**

Thursday	-0.622 (<0.05)	0.708 (<0.05)	-0.799 (<0.05)	0.157 **(>0.05)**	-0.746 (<0.05)	-0.345 (<0.05)	-0.649 (<0.05)	-0.427 (<0.05)	0.477 (<0.05)
Friday	-0.511 (<0.05)	0.720 (<0.05)	-0.809 (<0.05)	-0.326 (<0.05)	-0.839 (<0.05)	-0.704 (<0.05)	-0.108 **(>0.05)**	-0.080 **(>0.05)**	-0.362 (<0.05)
Saturday	-0.301 (<0.05)	0.628 (<0.05)	-0.757 (<0.05)	-0.394 (<0.05)	-0.364 (<0.05)		0.254 **(>0.05)**	0.195 **(>0.05)**	0.457 (<0.05)
Sunday	-0.562 (<0.05)	0.239 **(>0.05)**	-0.351 (<0.05)	-0.678 (<0.05)	-0.370 (<0.05)	-0.706 (<0.05)	-0.672 (<0.05)	-0.172 **(>0.05)**	0.169 **(>0.05)**
Monday					-0.104 **(>0.05)**	-0.365 (<0.05)	-0.820 (<0.05)	-0.588 (<0.05)	-0.508 (<0.05)
Tuesday					0.222 **(>0.05)**	-0.547 (<0.05)	-0.804 (<0.05)	-0.691 (<0.05)	0.144 **(>0.05)**
Wednesday					-0.280 (<0.05)	-0.651 ((<0.05))	-0.441 (<0.05)	-0.069 **(>0.05)**	-0.053 **(>0.05)**
Thursday					-0.171 **(>0.05)**	-0.733 (<0.05)			
Friday					0.331 (<0.05)	0.620 (<0.05)			

Source: Gretl Output
* Figures in bracket indicate P value significance

Table 4.14 indicates that 75% of the observations under monopoly and partial monopoly situations are significantly correlated with the booking date. Under triopoly, the significant correlations are 54%. Hence the null hypotheses $H_{0\,12}$, $H_{0\,13}$, and, $H_{0\,14}$ are rejected ($p<0.05$). It is concluded that the time gap between the date of departure and the date of booking significantly influences the price of a ticket.

4.3.6 Interdependence of Prices - OLS Regression Analysis

For Indians, the Diwali festival is of most importance (Mathur, 2020). The prices of neighbouring days or the season may influence the festival day prices. In this research, this influence is assumed for four days before and after the festival. If Tuesday is the festival, the impact is assessed from four days before to two days after. That means if Tuesday is a festival, the impact of prices of the previous Friday to next Thursday. Regression analysis was made separately for monopoly, partial monopoly and triopoly situations.

4.3.6.1 OLS Regression Analysis – Monopoly Routes

In order to assess the impact of these neighbouring day prices on the festival day prices, the following hypothesis was formulated.

$H_{0\,15}$ Neighbouring day prices does not significantly influence the festival day prices under a monopoly situation.

OLS regression model equation formed to test the hypothesis was:

$$Y_j = \beta_0+\beta_1*i_1+\beta_2*i_2+\beta_3*i_3+\beta_4*i_4+\beta_5*i_5+\beta_6*i_6$$

Where:

Y = Dependent variable (Prices of Festival Day)

β = Regression coefficient

i_1= Price of Four days before the festival

i_2= Price of Three days before the festival

i_3= Price of Two days before the festival

i_4= Price of One day before the festival

i_5= Price of One day after the festival

i_6= Price of Two days after the festival

All observations of the independent variable are indexed as i=1…..n

The OLS regression results of the models are given in Table 4.15. The models were selected after different trial and error methods. Models showing the lowest values as per the Akaike criterion, Schwarz criterion, and Hannan-Quinn are selected after ensuring that the OLS assumptions are satisfied.

Table 4.15

OLS Regression – Monopoly Routes

Variables	coefficient	std. error	t-ratio	p-value	Adjusted R-squared	Durbin-Watson
Route M1						
const	−5.0545	0.9552	−5.292	<0.01		
i1	0.6154	0.0705	8.733	<0.01		
i2	0.0534	0.0604	0.884	**>0.05**		
i3	−0.2324	0.1018	−2.282	<0.05	0.94	1.746
i4	1.3096	0.1859	7.044	<0.01		
i5	0.7458	0.1474	5.061	<0.01		
i6	−0.5787	0.2446	−2.366	<0.05		

Route M2						
const	18.856	6.1561	3.063	<0.01		
i1	−0.1288	0.1270	−1.014	**>0.05**		
i2	−0.8810	0.4587	−1.921	**>0.05**		
i3	0.7789	0.3070	2.537	<0.05	0.59	1.5
i4	0.1927	0.0698	2.762	<0.05		
i5	−0.3935	0.1585	−2.483	<0.05		
i6	0.0621	0.1270	0.489	**>0.05**		
Route M3						
const	0.049	0.284	0.173	**>0.05**		
i1	−0.093	0.068	−1.368	**>0.05**		
i2	0.171	0.070	2.430	<0.05		
i3	−0.037	0.054	−0.681	**>0.05**	0.97	1.7
i4	−0.134	0.099	−1.360	**>0.05**		
i5	0.527	0.140	3.774	<0.05		
i6	0.581	0.171	3.404	<0.05		
Route M4						
const	−24.982	11.594	−2.155	<0.05	0.91	1.8

i1	−0.037	0.477	−0.077	**>0.05**
i2	0.833	0.268	3.107	<0.05
i3	1.026	0.200	5.133	<0.05
i4	−0.158	0.139	−1.140	**>0.05**
i5	1.410	0.528	2.670	<0.05
i6	0.403	0.366	1.102	**>0.05**

Source: Gretl Output

Five neighbouring day prices significantly influence festival day prices in the case of Route M1 and three in the case of Route M2, M3 and M4. Hence the null hypothesis $H_{0\ 15}$ is rejected. It is concluded that price movements on the festival day are significantly influenced by the prices of neighbouring days. Adjusted R^2 values of 93.8% (Route M1), 58.6% (Route M2), 96.6% (Route M3), and 90.7% (Route M4) indicate the percentage influence of neighbouring day prices on the festival day price.

Regression equations of the models are:

Route M1

$$\hat{Y}_i = -5.05 + 0.615^* i_1 + 0.0534^* i_2 - 0.232^* i_3 + 1.31^* i_4 + 0.746^* i_5 - 0.579^* i_6$$

(0.955) (0.0705) (0.0604) (0.102) (0.186) (0.147) (0.245)

T = 30, R-squared = 0.951

(standard errors in parentheses)

Route M2

$$\hat{Y}_i = 18.9 - 0.129^* i_1 - 0.881^* i_2 + 0.779^* i_3 + 0.193^* i_4 - 0.394^* i_5 + 0.0621^* i_6$$

(6.16) (0.127) (0.459) (0.307) (0.0698) (0.158) (0.127)

T = 30, R-squared = 0.672

(standard errors in parentheses)

Route M3

$$\hat{\hat{Y}}i = 0.0490 - 0.093^* i_1 + 0.171^* i_2 - 0.037^* i_3 - 0.134^* i_4 + 0.527^* i_5 + 0.581^* i_6$$

(0.284) (0.0681) (0.0703) (0.0535) (0.0986) (0.140) (0.171)

T = 30, R-squared = 0.973

(standard errors in parentheses)

Route M4

$$\hat{\hat{Y}}i = -25.0 - 0.0369^* i_1 + 0.833^* i_2 + 1.03^* i_3 - 0.158^* i_4 + 1.41^* i_5 + 0.403^* i_6$$

(11.6) (0.477) (0.268) (0.200) (0.139) (0.528) (0.366)

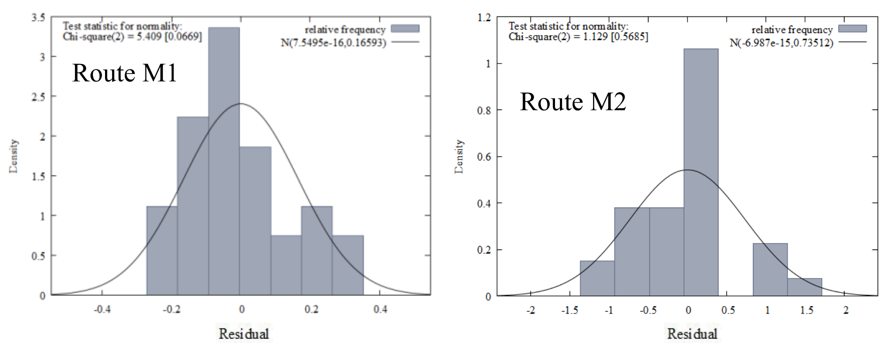
T = 30, R-squared = 0.926

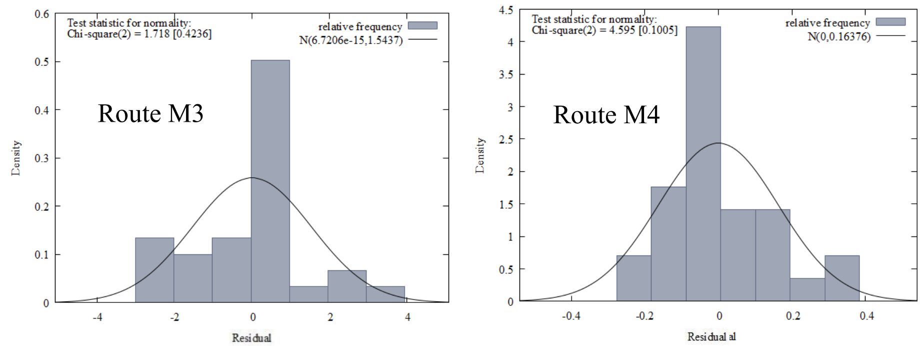
(standard errors in parentheses)

Models satisfy the OLS assumptions of independence of observation, linear relationship, no autocorrelation, homoscedasticity, and normality of residuals. A graphical representation of the normality of the residual is given in Figure 4.12.

Figure 4.12

Monopoly Routes - Normality of Residuals





Source: Gretl Output

Test for the null hypothesis of normal distribution in the gretl procedure has given the Chi-square(2) value with p-values >0.05, and it is concluded that all models satisfy the normality assumption.

4.3.6.2 OLS Regression Analysis – Partial Monopoly Route

In order to assess the impact of these neighbouring day prices on the festival day prices, the following hypothesis was formulated.

> $H_{0\,16}$ Neighbouring day prices does not significantly influence the festival day prices under a partial monopoly situation.

OLS regression model equation formed to test the hypothesis was:

$$Y_j = \beta_0+\beta_1*i_{a1}+\beta_2*i_{a2}+\beta_3*i_{a3}+\beta_4*i_{a4}+\beta_5*i_{a5}+\beta_6*i_{a6}+\beta_1*i_{b1}+\beta_2*i_{b2}+\beta_3*i_{b3}+\beta_4*i_{b4}+\beta_5*i_{b5}+\beta_6*i_{b6}$$

Where:

Y = Dependent variable (Price on Festival Day)

β = Regression coefficient

i_{a1}= price of flight 1 before four days of the festival

i_{a2}= price of flight 1 before three days of the festival

i_{a3}= price of flight 1 before two days of the festival

i_{a4}= price of flight 1 before one day of the festival

i_{a5}= price of flight 1 after one day of the festival

i_{a6}= price of flight 1 after one day of the festival

i_{b1}= price of flight 2 before four days of the festival

i_{b2}= price of flight 2 before three days of the festival

i_{b3}= price of flight 2 before two days of the festival

i_{b4}= price of flight 2 before one day of the festival

i_{b5}= price of flight 2 on next day of the festival

i_{b6}= price of flight 2 on second day after the festival

All observations of the independent variable are indexed as ia/ib=1…..n

The OLS regression result of the model is given in Table 4.16. The model was selected after different trial and error methods. Models showing the lowest value as per the Akaike criterion, Schwarz criterion, and Hannan-Quinn are selected, after ensuring that the OLS assumptions are satisfied.

Table 4.16

OLS Regression – Partial Monopoly Route

Variables	coefficient	std. error	t-ratio	p-value	Adjusted R-squared	Durbin-Watson
Route M5						
Const	−6.386	1.637	−3.901	<0.05		
i_{a1}	0.580	0.166	3.501	<0.05	0.73	2.34
i_{a2}	−1.194	0.253	−4.715	<0.05		

i_{a3}	0.159	0.203	0.779	**>0.05**
i_{a4}	1.991	0.344	5.794	<0.05
i_{a5}	0.241	0.248	0.971	**>0.05**
i_{a6}	1.573	0.296	5.304	<0.05
i_{b1}	1.509	0.428	3.525	<0.05
i_{b2}	0.053	0.218	0.244	**>0.05**
i_{b3}	0.390	0.202	1.936	**>0.05**
i_{b4}	0.033	0.146	0.225	**>0.05**
i_{b5}	−0.4019	0.144	−2.798	<0.05
i_{b6}	−2.1840	0.381	−5.736	<0.05

Source: Gretl Output

Saturday was the festival day of this route, where only one company was operating. On the other days, two companies were operating flights. Festival day prices of the airline company were significantly influenced by four neighbouring day prices of the same airline company and three neighbouring day prices of the competing airline company. Out of 12 independent variables, seven significantly influenced the prices on festival day. Hence the null hypothesis is rejected; it is concluded that price movements on a festival day are significantly influenced by the prices of neighbouring days under a partial monopoly situation. Adjusted R^2 values of 73% indicate the percentage influence of neighbouring day prices of airline companies on the festival day price.

The regression equation of the model is:

$\hat{}Y_j = -6.39 + 0.580^* i_{g1} - 1.19^* i_{g2} + 0.159^* i_{g3} + 1.99^* i_{g4} + 0.241^* i_{g5} + 1.57^* i_{g6} +$

(1.64) (0.166) (0.253) (0.203) (0.344) (0.248) (0.296)

$1.51^* i_{s1} + 0.0530^* i_{s2} + 0.390^* i_{s3} + 0.0328^* i_{s4} - 0.402^* i_{s5} - 18^* i_{s6}$

(0.428) (0.218) (0.202) (0.146) (0.144) (0.381)

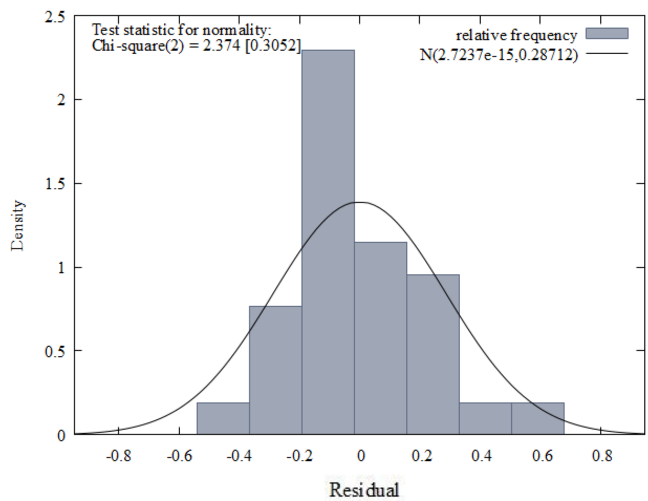
T = 30, R-squared = 0.839

(standard errors in parentheses)

The model satisfies the OLS assumptions of independence of observation, linear relationship, no autocorrelation, homoscedasticity, and normality of residuals. A graphical representation of the normality of the residual is given in Figure 4.13.

Figure 4.13

Partial Monopoly Route - Normality of Residuals



Source: Gretl Output

Test for the null hypothesis of normal distribution in the Gretl procedure has given the Chi-square (2) value as 2.374 with a p-value 0.30515, which is >0.05, and it is concluded that the model satisfies the normality assumption.

4.3.6.3 OLS Regression Analysis – Triopoly Route

In order to assess the impact of these neighbouring day prices on the festival day prices under triopoly, the following hypothesis was formulated.

> $H_{0\ 17}$ Neighbouring day prices does not significantly influence the festival day prices under a triopoly situation.

OLS regression model equations formed to test the hypothesis was:

$$Y= \beta_0+\beta_1*ia_1+\beta_2*ib_1+\beta_3*ic_1+ \beta_1*ia_2+\beta_2*ib_2+\beta_3*ic_2+ \beta_1*ia_3+\beta_2*ib_3+\beta_3*ic_3+ +\beta_2*ib_4+\beta_3*ic_4+ \beta_1*ia_5+\beta_2*ib_5+\beta_3*ic_5+ \beta_1*ia_6+\beta_2*ib_6+\beta_3*ic_6$$

Where:

Y = Dependent variable (Prices on Festival Day of Flight x)

β = Regression coefficient

i_{a1}= price of flight 1 before three days of the festival

i_{b1}= price of flight 2 before three days of the festival

i_{c1}= price of flight 3 before three days of the festival

i_{a2}= price of flight 1 before two days of the festival

i_{b2}= price of flight 2 before two days of the festival

i_{c2}= price of flight 3 before two days of the festival

i_{a3}= price of flight 1 before one day of the festival

i_{b3}= price of flight 2 before one day of the festival

i_{c3}= price of flight 3 before one day of the festival

i_{b4}= price of flight 2 on festival day

i_{c4}= price of flight 3 on festival day

i_{a5}= price of flight 1 on next day of the festival

i_{b5}= price of flight 2 on next day of the festival

i_{c5}= price of flight 3 on next day of the festival

i_{a6}= price of flight 1 on second day after the festival

i_{b6}= price of flight 2 on second day after the festival

i_{c6}= price of flight 3 on second day after the festival

All observations of the independent variable are indexed as ia/ib/ic=1…..n

a= flight a, b= fight b, c=flight c

The OLS regression results of the model are given in Table 4.16. The models were selected after different trial and error methods. Models showing the lowest value as per the Akaike criterion, Schwarz criterion, and Hannan-Quinn are selected. None of the regression models run and tested by the researcher with Air India prices as a dependent variable could satisfy the regression criterion, and hence they have been excluded from the study.

Table 4.17

OLS Regression – Triopoly Route

Variables	coefficient	std. error	t-ratio	p-value	Adjusted R-squared	Durbin-Watson
Dependent Variable:	**Prices of Indigo Airlines (Model 1)**					
const	−1.785	2.493	−0.716	**>0.05**		
ia_1	0.075	0.118	0.639	**>0.05**	0.84	2.287
ib_1	−0.033	0.074	−0.455	**>0.05**		

ic_1	0.167	0.042	3.975	<0.01		
ia_2	0.057	0.025	2.234	<0.01		
ib_2	−0.084	0.027	−3.141	<0.01		
ic_2	−0.018	0.105	−0.171	**>0.05**		
ia_3	1.462	0.305	4.800	<0.01		
ib_3	−0.111	0.028	−3.974	<0.01		
Ic_3	−1.877	0.456	−4.114	<0.01		
ib_4	0.184	0.040	4.658	<0.01		
ic_4	0.361	0.082	4.387	<0.01		
ia_5	0.060	0.066	0.898	**>0.05**		
ib_5	−0.112	0.061	−1.822	**>0.05**		
ic_5	0.036	0.072	0.499	**>0.05**		
ia_6	0.267	0.099	2.704	<0.01		
ib_6	−0.036	0.045	−0.799	**>0.05**		
ic6	0.634	0.188	3.363	<0.01		
Dependent Variable:	**Prices of Jet Airways (Model 2)**					
const	−4.410	6.776	−0.651	**>0.05**	0.57	2.576
ia_1	0.231	0.132	1.751	**>0.05**		

ib_1	0.132	0.190	0.693	**>0.05**
ic_1	−0.068	0.151	−0.451	**>0.05**
ia_2	−0.007	0.039	−0.191	**>0.05**
ib_2	0.164	0.055	2.987	<0.01
ic_2	0.034	0.297	0.115	**>0.05**
ia_3	−2.192	0.349	−6.291	<0.01
ib_3	0.128	0.050	2.589	<0.01
Ic_3	3.044	0.425	7.157	<0.01
ib_4	1.167	0.162	7.185	<0.01
ic_4	−0.263	0.046	−5.670	<0.01
ia_5	−0.128	0.075	−1.694	**>0.05**
ib_5	0.229	0.128	1.789	**>0.05**
ic_5	−0.053	0.131	−0.404	**>0.05**
ia_6	−0.279	0.128	−2.174	**>0.05**
ib_6	−0.019	0.041	−0.469	**>0.05**
ic6	−0.924	0.308	−2.997	<0.01

Source: Gretl Output

Tuesday was the festival day of this route, where three companies were operating on all days. As the regression result of the first model shows, festival day prices of the airline company Indigo were significantly influenced by neighbouring day prices of airline companies. Out of 17 independent variables, ten significantly influenced the dependent variable. Seven of the 12 independent variables in the second model significantly influenced the dependent variable. Hence, the null hypothesis $H_{0\ 17}$ is rejected and it is concluded that neighbouring day prices significantly influence the festival day prices under a triopoly situation.

Regression equations of the models are:

Model 1

^Y= -1.79 + 0.0755* ia_1 - 0.0334* ib_1 + 0.167* ic_1+ 0.0567* ia_2- 0.0840* ib_2 -

(2.49) (0.118) (0.0735) (0.0421) (0.0254) (0.0267)

0.0181* ic2 + 1.46* ia_3 - 0.111* ib_3 - 1.88* ic_3+ 0.184* ib_4 + 0.361* ic_4 +

(0.105) (0.305) (0.0280) (0.456) (0.0395) (0.0824)

0.0595* ia_5 - 0.112* ib_5 + 0.0359* ic_5+ 0.267* ia_6 - 0.0359* ib_6 + 0.634* ic_6

(0.0663) (0.0612) (0.0719) (0.0988) (0.0449) (0.188)

T = 30, R-squared = 0.934

(standard errors in parentheses)

Model 2

^Y= -4.41 + 0.231* ia_1 + 0.132* ib_1 - 0.0681* ic_1- 0.00736* ia_2+ 0.164* ib_2 +

(6.78) (0.132) (0.190) (0.151) (0.0386) (0.0550)

0.0342* ic2 - 2.19* ia_3 + 0.128* ib_3 + 3.04* ic_3+ 1.17* ib_4 - 0.263* ic_4

(0.297) (0.349) (0.0494) (0.425) (0.162) (0.0463)

-0.128* ia_5 + 0.229* ib_5 - 0.0527* ic_5- 0.279* ia_6 - 0.0194* ib_6 - 0.924* ic_6

(0.0754) (0.128) (0.131) (0.128) (0.0415) (0.308)

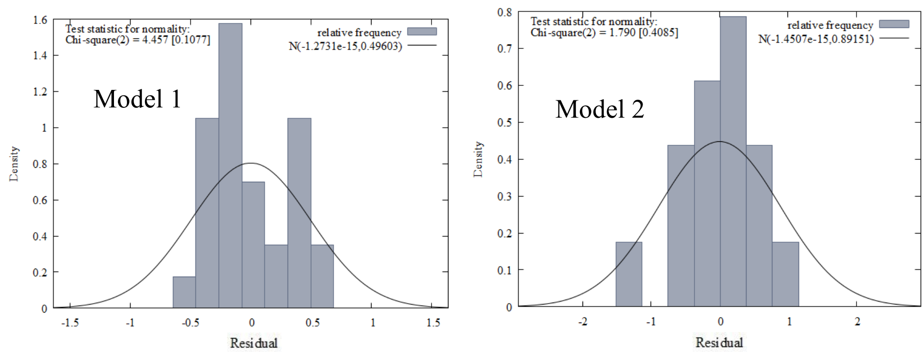
T = 30, R-squared = 0.822

(standard errors in parentheses)

The model satisfies the OLS assumptions of independence of observation, linear relationship, no autocorrelation, homoscedasticity, and normality of residuals. A graphical representation of the normality of the residual is given in Figure 4.14.

Figure 4.14

Triopoly Route - Normality of Residuals



Source: Gretl Output

Test for the null hypothesis of normal distribution in the Gretl procedure has given the Chi-square(2) values as 4.457 with a p-value of 0.108 for Model 1 and 1.790 with a p-value of 0.409 for Model 2. Since the P values are >0.05, the model satisfies the normality assumption. Hence the results of the OLS regression model are statistically reliable.

4.4 Discussion of the Results and Interpretation

The chapter discussed the price dispersion in the concentrated markets of India with the tools Gini coefficient and Lorenz curve. Overall dispersion indicated by the Gini coefficient ranges from 0.115 to 0.275 under monopoly routes, 0.084 to 0.105 under partial monopoly routes and 0.173 to 0.247 under triopoly routes. Overall dispersion in the concentrated market was 0.361, which is close to the alarming rate of 0.40.

The study finds statistical evidence for the impact of the day of departure and festival day on the prices of airline tickets. Price fluctuations are also used as a tool to penetrate the demand for an airline ticket. As a result, low bucket fares are offered. In many cases, a sharp reduction is observed between 10 to 15 days before the departure date. High bucket fares are offered not only at the time of closeness to departure but even 20 to 15 days before departure. The time trends of routes M2, M3, M5, and M6 provide ample evidence for this phenomenon. This contradicts the findings of Alderighi that fares increase monotonically over the last three weeks before departure (Alderighi et al., 2012); and supports the findings of Urday Escobari that the increase is not necessarily monotonic (Urday, 2008). There is also evidence of the impact of neighbouring day prices on the prices of a day. This interdependence of prices was evident in the prices of adjacent day and competing airlines. The date of booking also influences the prices. In the majority of observations, the time gap between the date of departure and the date of booking significantly influenced the price of a ticket. OLS regression analysis supported this argument of the interdependence of prices with an adjusted R square of more than 70% in most cases.

Chapter 5

Price Dynamics in Moderately Concentrated Markets

5.1 Introduction

Chapter four discussed the dynamic pricing of six concentrated market routes having nine direct flights. Those six routes had characteristics of monopoly, partial monopoly, and triopoly situations. This chapter discusses the oligopolistic situation with five to seven airline companies with 10 to 36 flights. There were no civil aviation routes where HHI<0.15 reflected the 'un-concentrated markets' situation in India's domestic civil aviation segment. There were routes with HHI between 0.15–0.25, indicating moderately concentrated markets, and HHI >0.25, indicating highly concentrated markets. Hence Indian civil aviation market consisted of two types of routes - concentrated routes and moderately concentrated routes. Under all observations of highly concentrated markets, the number of operators on a route ranges from five to seven, creating an oligopolistic situation.

Five routes were selected and observed to evaluate the price dispersion of Moderately Concentrated Routes (MCR). Only economy classes of travel are considered for this analysis. Five airline companies were operating for all routes, except for route Delhi-Kolkota, where seven companies were present. Market share was calculated by considering the total seat availability of an airline company in a week of seven days. The route characteristics are given in Table 5.1.

Table 5.1

Route Characteristics – MCR

Route Code	Route	Air Distance in Km	No. of Airline Companies	No. of Flights	Average Seats per Day	HHI
O1	Port Blair - Kolkata	1,303	5	6	1,021	0.24

O2	Chennai - Port Blair	1,791	5	6	1,065	0.22
O3	Delhi-Kochi	2,049	5	10	1,477	0.24
O4	Delhi-Kolkata	1,313	7	30	5,120	0.22
O5	Mumbai-Bangalore	835	5	34	5,562	0.25

Source: Compiled by the researcher from airline websites

As per Table 5.1, the market concentration of the selected routes varies from 0.22 to 0.25. Routes O4 and O5 had the highest traffic density attracting 30 or more flights a day; HHI just crossed the boundary of a concentrated market to designate as a moderately concentrated market. The HHI of other routes were also very close to the upper boundary of the concentrated market (0.22 and 0.24). For the calculation of HHI, market share was calculated based on the total seat availability of the week. The limited number of airline companies (5 to 7) creates an oligopolistic situation in the Indian airline market. Table 5.2 outlines airline companies and the number of flights operating on these selected routes.

Table 5.2

Airline Companies and Number of Flights

Route Code	Air India	Indigo	Spice Jet	GoAir	Vistara	Air Asia	Jet Airways	Total
O1	1	2	1	1	1			6

O2	1	2	1	1	1			6
O3	3	3	1		2		1	10
O4	4	11	3	3	3	2	4	30
O5	4	12	3	4			11	34

Source: Compiled by the researcher from travel agency websites

As Table 5.2 shows, there were six flights each for routes O1 and O2 and ten flights for route O3. Route O4 has 30 flights a day, and O5 has 34 flights. Hence the data include prices of 86 flights from seven airline companies. Five airline companies were operating on all routes, except on route O4 with seven airline companies. Indigo operates the highest number of flights on all routes. Indigo, Air India, and Spicejet were present on all selected sample routes. Indigo has the highest market share, while Air India had the National carrier flag at the time of observations (MCA, 2019).

5.2 Data Set and Data Classification

Unlike the previous chapter, comparing the situation by taking the whole flight may not be suitable. Since there are more flights on the same day, travellers get more flight choices. Hence the researcher assumes the presence of more time-sensitive travellers on the routes. Therefore, the researcher takes a different approach to identify the competition and its influence on prices. The sample routes were grouped into two: Group-I consists of three routes with ten or lesser number of direct flights, and group-II consists of the two routes with more than 30 direct flights daily. Group-I flights were grouped into Forenoon flights and Afternoon Flights. Forenoon flights (FN) consist of flights from 0:00 hours to noon. Afternoon flights (AN) consist of flights from 12:01 to 24:00 midnight. Group-II flights were classified into five segments: Early Morning (from

0:00 hours to 6:00 hours), Forenoon (6:01 hours to noon), Afternoon (12:01 hours to 17:00 hours), Evening (17:01 hours to 20:00 hours), Late Night flights (20:01 hours to 24:00 hours).

5.3 Price Dispersion in MCR

Price Dispersion in the MCR is analysed in the following dimensions in this chapter: The extent of price dispersion and the reasons for price dispersion. The extent of price dispersion and variability are measured with the help of SD, CV, IQR, and Gini coefficient. Antecedents of dispersion are evaluated with the help of correlation analysis and Exploratory Data Analysis such as OLS and Panel Data Analysis.

5.3.1 Gini coefficient and Lorenz Curve

Following the literature (Rose & Borenstein, 1994) (Q. Liu, 2003)(Verlinda, 2005)(Kim, 2006)(John, 2007)(Li, 2007)(Shapiro, 2008)(Chi, 2008)(Cornia et al., 2012)(Gelhausen et al., 2013)(Noughabi et al., 2014)(Djolov, 2014)(Siegert & Ulbricht, 2015), this chapter also use the Gini coefficient, along with SD, CV, and IQR, to measure the extent of price dispersion of airline tickets. Table 5.3 shows the summary statistics of all five routes, along with the corresponding Gini coefficient.

Table 5.3

Summary Statistics and Gini – MCR

Route Codes	**O1**	**O2**	**O3**	**O4**	**O5**	**Total**
Number of Observations	1,800	1,800	4,200	8,880	12,000	28,680
Number of Flights	6	6	10	30	34	86
Number of Airline Companies	5	5	5	7	5	7

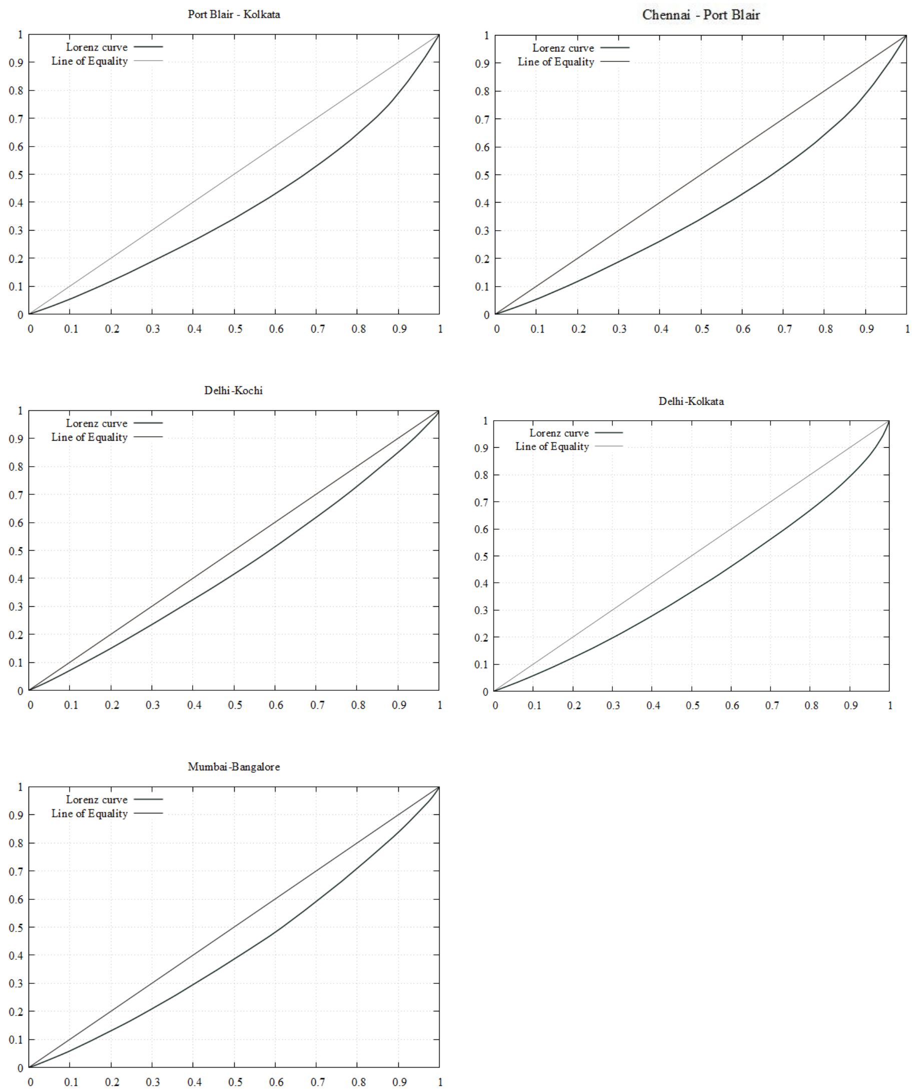
Mean	9.31	6.82	3.13	5.36	7.70
Median	7.62	5.91	2.94	4.88	7.18
Minimum	4.25	3.10	1.76	2.48	2.96
Maximum	23.89	17.43	17.49	24.27	24.46
SD	4.270	3.135	0.844	2.481	2.347
CV	0.459	0.460	0.270	0.463	0.305
Inter Quartile Range	3.69	2.91	0.78	1.83	2.71
Gini	0.233	0.233	0.122	0.204	0.163

Source: Primary Data

As per Table 5.3, altogether, 28,680 observations on prices were collected and analysed on 86 flights of seven airline companies. Since the number of flights differs with routes, the number of observations also differs. Mean fare, minimum fare, and SD were the highest for route O1 and lowest for route O3. The maximum price was highest for route O5 and lowest for route O2. But the dispersion indicated by the Gini coefficient is highest for Routes O1 and O2. The Gini coefficient of 0.233 indicates that 46.6% price difference from the mean fare (Shapiro, 2008). The Gini coefficient was lowest for route O3. The coefficient of variation (CV) is also the lowest for O3. Route O5 also shows comparatively less dispersion than routes O1, O2, and O4. This variation also indicates that dispersion is lower for routes O3 and O4. Price dispersion reflected in Inter Quartile Range shows the same result pattern. In other words, even though dispersion is comparatively less under oligopoly, dispersion doesn't follow a specific pattern. The Lorenz Curve indicating the price dispersion is given in Figure 5.1. In all the graphs, the X-axis denotes the cumulative percent of revenue, and the Y-axis denotes the cumulative percent of passengers.

Figure 5.1

Lorenz Curve - MCR



Source: Primary Data, Gretl Output

The figure also indicates that dispersion is lowest for route O3 (Delhi-Kochi) and highest for routes O1 and O2. For route O3, having the least rate of dispersion, 61% of the travellers contribute 50% of the revenue. In other words, the next 39% of the travellers contribute the remaining 50% of the revenue. For routes O1 and O2, 32 % of the travellers contribute 50% of the revenue. For route O4, 37% of the travellers contribute 50% of the revenue. Delhi- Kolkata route (Route O4) collected 50% of their revenue from 62% of the population. Table 5.4 shows the summary statistics and Gini coefficient of group-1 routes.

Table 5.4

Summary Statistics and Gini – Route O1, O2, and O3

Indicators	Port Blair - Kolkata			Chennair - Port Blair			Delhi-Kochi		
No. of Observations	1800	1200	600	1800	1200	600	4200	1800	2400
No. of Flights	6	4	2	6	4	2	10	4	6
No. of Airline Companies	5	3	2	5	3	2	5	4	5
Departure Time	All	FN	AN	All	FN	AN	All	FN	AN
Mean	9.31	9.78	8.37	6.82	7.16	6.14	3.13	2.96	3.26
Median	7.62	8.12	7.54	5.91	5.93	5.50	2.94	2.82	3.10
Minimum	4.25	4.25	4.39	3.10	3.10	3.21	1.76	1.95	1.76

Maximum	23.89	23.89	19.42	17.43	17.43	14.17	17.49	5.21	17.49
SD	4.27	4.84	2.56	3.13	3.55	1.88	0.84	0.52	1.01
CV	0.46	0.49	0.31	0.46	0.50	0.31	0.27	0.18	0.31
IQ Range	3.69	4.05	3.79	2.91	2.96	2.76	0.80	0.66	1.12
Gini	0.233	0.253	0.170	0.233	0.253	0.171	0.122	0.097	0.135

Source: Primary Data

The number of observations on the routes changes only because of the increased number of flights. All the routes have observations of 30 days on ten departure dates. The minimum, maximum, SD, Gini coefficients, and IQ ranges differ between After Noon and Forenoon flights. For Route O1 (Port Blair - Kolkata) and route O2 (Chennai –Port Blair), the Gini coefficient is higher for morning flights than for noon flights. For route O3 (Delhi-Kochi), afternoon flights showed more dispersion. Dispersion indicated by the Gini coefficient and inter-quartile range seems to increase as the number of flights of the segment of a route increases. But it seems to decrease as the total number of flights on a route increases. Mean, minimum, and maximum fare decreases as the number of flights on a route increases. It is also evident from the values of CV and Gini that the dispersion varies between AN and FN flights. Morning flights show more dispersion for routes O1 and O2, while in route O3, afternoon flights show more dispersion.

Tables 5.5 and 5.6 show the summary statistics of routes O4 and O5, respectively. The number of observations on the routes changes only because of the increased number of flights. All the routes have observations of 30 days before ten departure dates. Since the numbers of flights are 30, they are grouped into five segments based on departure time.

Table 5.5

Summary Statistics and Gini – Route O4

Route O4	Delhi-Kolkata					
No. of Observations	8880	1800	2070	1710	1800	1500
No. of Flights	30	6	7	6	6	5
No. of Airline Co.	7	5	5	3	6	4
Departure Time	All	EM	FN	AN	EV	LN
Mean	5.36	4.84	5.29	5.78	5.62	5.31
Median	4.88	4.62	4.88	5.28	4.96	4.89
Minimum	2.48	2.72	2.58	2.72	2.71	2.48
Maximum	24.27	24.27	24.27	24.27	24.27	19.23
SD	2.481	2.013	2.339	2.996	2.555	2.314
CV	0.463	0.416	0.442	0.518	0.455	0.435
IQ Range	1.804	1.5923	1.5209	1.5362	2.5034	2.1599
Gini	0.204	0.174	0.187	0.209	0.221	0.211

Source: Primary Data

The maximum fare collected by all segments, such as early morning (EM), forenoon (FN), afternoon (AN), evening (EV), and late night (LN) flights, were the same. It was nearly ten times more than the minimum prices on all observations. Price dispersion was more for the afternoon, evening and late night flights. It was the least for early morning flights.

The mean fare was also least for forenoon flights. The minimum price is lesser than that of monopoly routes discussed in chapter four (Page 115, Table 4.2). Dispersion indicated by the Gini coefficient and IQR is lesser than that of Group-1 oligopoly routes. The dispersion indicated by CV shows a low variability between the time segments. The variation is comparatively greater for the afternoon flights. The minimum fare is also much lower than that of monopoly, triopoly, and Group-1 oligopoly routes, except for O3. Table 5.6 shows the summary statistics of route O5.

Table 5.6

Summary Statistics and Gini – Route O5

Indicators	Mumbai - Bangalore					
No. of Observations	12000	1260	3600	2160	2100	2880
No. of Flights	34	4	10	6	6	8
No. of Airline Cos.	5	4	4	5	3	4
Departure Time	All	EM	FN	AN	EV	LN
Mean	7.70	6.81	8.01	8.60	7.37	7.26
Median	7.18	6.62	7.18	8.46	7.08	6.89
Minimum	2.96	3.08	3.34	4.22	3.15	2.96
Maximum	24.46	17.75	21.88	24.46	19.34	13.58
SD	2.347	1.916	2.487	2.418	2.220	2.072
CV	0.305	0.281	0.310	0.281	0.301	0.285

IQ Range	2.708	1.95	3.156	2.793	3.207	3.207
Gini	0.163	0.146	0.164	0.144	0.161	0.161

Source: Primary Data

The maximum fare collected by all segments, such as early morning (EM), forenoon (FN), afternoon (AN), evening (EV), and late night (LN) flights, were different. It was nearly eight times more than the minimum price for the route. But for the various segments, these differences vary from 4.5 times to 6.5 times the corresponding minimum prices. This reduces the price dispersion on the route. Price dispersion ranges from 0.144 to 0.164. The minimum price is lesser than that of monopoly routes discussed in chapter four. Dispersion indicated by the Gini coefficient and IQR is lesser than that of Group-1 oligopoly routes. The dispersion indicated by CV shows a low variability between the time segments. Variation is comparatively more for the FN and EV flights. The minimum fare offered was also much lower than that of monopoly, triopoly and Group-1 oligopoly routes, except route O3.

5.3.2 Overall Dispersion in MCR

There were 28,680 observations of seven airline companies while considering all five sample routes. These seven companies together had 86 direct flights on the sample routes. The minimum price offered within 30 days of departure was ₹1.76 per km. The Vistara airline company offered this fare on route O3. This fare was offered for one day on the festival day departure date, 27 days prior to departure. The maximum fare offered for that departure date was ₹24.46 per km. Air India made the maximum fare offer on route O5. This fare was offered for six days from six days to the departure date. The departure day was Saturday. The mean fare and median fare of observations were ₹6.35 and ₹5.70, respectively, with a standard deviation of 3.04. The Gini coefficient calculated was 0.250. Table 5.7 shows the minimum and maximum price details over the sample routes.

Table 5.7

Maximum and Minimum Fare Distribution

Route	Price	Airline Co.	F D	D B	D A	Friday	Saturday	Sunday	OD	Day
Minimum Price per Km										
O1	4.25	GoAir	Y		Y	Y				30
O2	3.10	GoAir	Y			Y				30
O3	1.76	Vistara	Y				Y			27
O4	2.48	Indigo			Y				Y	30
O5	2.96	Indigo							Y	27
Maximum Price per Km										
O1	23.89	Air India						Y		10
O2	17.43	Air India						Y		9
O3	17.49	Air India					Y			2
O4	24.27	Jet Airways	Y	Y		Y	Y	Y		4
O5	24.46	Air India					Y	Y		4

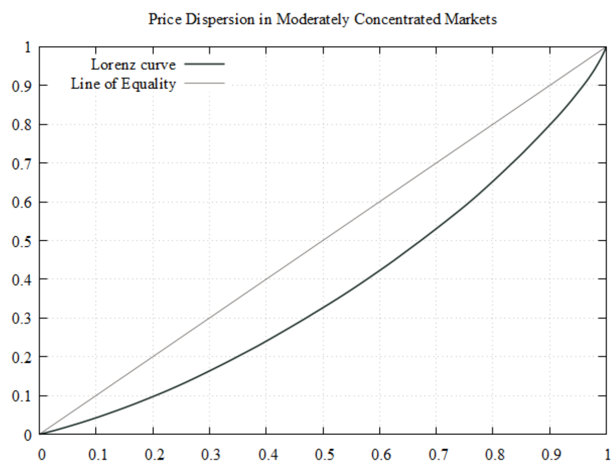
Source: Primary Data

‘Y’ means the days on which the fare was offered, ‘Day’ means the number of days to departure on which the price was offered.

The minimum price offer was made at least 27 days before departure on all the routes. It is also evident that this minimum fare was mostly offered either during the festival season: the day before (DB), day after (DA), on festival day (FD) or during weekends (Friday, Saturday and Sunday). Route O4 and O5 were exceptions. These routes offered minimum fares on other days (OD) also. The maximum fare on all routes was offered either during the festival season or on weekends. The maximum fare was raised close to the departure date and lasted till the departure date. The Gini coefficient of all the observations considering routes O1 to O5 was 0.250. The Lorenz curve made from all the observations is given in Figure 5.2. The X-axis denotes the cumulative percent of revenue, and the Y-axis denotes the cumulative percent of passengers.

Figure 5.2

Lorenz Curves - Combined



Source: Primary Data

The area between the line of equality and the Lorenz curve given in Figure 5.2 is more extensive than all the individual routes. Fifty per cent of revenue was collected from 68% of passengers. It means that the remaining 50% of the revenue was contributed by 32% of passengers who booked near to departure date.

The range of prices (difference between maximum fare on a route and minimum fare on the route) is ₹19.64, ₹14.33, ₹15.73, ₹21.79, and ₹21.5, respectively, for routes O1, O2, O3, O4, and O5. This means that price discrimination between the luckiest and unlucky passengers was ₹25,591, ₹25,665, ₹32,231, ₹28,610, and ₹17,952, respectively, for routes O1 to O5 during the days of observation. The literature says that this dispersion is due to the market penetration strategies of LCCs, mainly through internet penetration (Lee, 2010) (Mahendra, 2014). Hence further analysis is conducted to explore the price penetration strategies leading to price discrimination and price dispersion, which in turn creates price dynamics in the market.

5.3.3 Significance of Price Dispersion – MCR

Mean fare were highest for Port Blair - Kolkata route (Route O1), followed by Mumbai - Bengaluru route (Route O5). It was least for Delhi - Kochi route (Route O3). The mean and median are relatively close, suggesting a roughly symmetric distribution of airfare prices, though the median values are lower than the mean for all routes, indicating slight potential right-skewness in the distribution of airfares. This indicates that, in general, price increases with closeness to departure. Routes O4 (Delhi - Kolkata) and O5 have the widest price ranges, whereas O3 has the narrowest price range.

Routes O1 and O2 (Chennai – Port Blair) have relatively high variability in prices, as indicated by higher standard deviations (SD) and coefficients of variation (CV). Route O3 has the lowest variability in airfares. Routes O4 and O5 have moderate variability. Routes O1, O2, and O4 have Gini coefficients indicating the highest level of inequality. Route O3 has the lowest SD, CV, and Gini coefficient, suggesting more stable and evenly distributed airfares in this market. Route O1 has the largest IQR, suggesting a wider spread of prices within the central 50% of airfares. Route O3 has the smallest IQR, indicating a more concentrated range of prices. Routes O1 and O2 exhibit higher variability and inequality in airfare distribution, which could be indicative of a more competitive oligopoly market with frequent adjustments to pricing. Route O3, with lower variability and a more stable distribution of airfares; suggest a less dynamic pricing environment or a market with more coordinated pricing strategies among the airlines.

5.4 Antecedents of Price Dispersion

Dynamic pricing and demand penetration are used for revenue maximization (Feldmann, 2008) (Tretheway, 2011). However, these revenue maximization and market penetration techniques adopted by airline companies make seasonal fluctuations, including weekend effects (Mantin & Koo, 2010), time of booking effects (Ahmed Abdella et al., 2019), and competition effects in the prices (Dutta & Santra, 2016). The antecedents of price dispersion are discussed with the help of correlation analysis, OLS analysis, and panel data analysis under the following dimensions:

1. Influence of the price of morning flights on afternoon flights and vice versa for routes O1 to O3.
2. Inter influence of early morning flights (EM), forenoon flights (FN), afternoon flights (AN), evening flights (EV), and late night flights (LN) for routes O4 and O5.
3. Inter influence of the prices of competing airlines.
4. Inter influence of the prices of the same airline company.

5.4.1 Correlation Analysis

The researcher uses correlation analysis to evaluate the influence of the prices of competing flights. Kendall's rank correlation tau is a tool used in the Gretl procedure to examine the correlation significance (Coeerell & Lucchetti, 2020). Group-I MCR has two time segments: Forenoon Flights and Afternoon Flights. The data collected on each route was set in panel data formation so that the data sets of different departure dates do not change. The researcher conducted the test on the following null hypothesis:

$H_{0\ 18}$ The prices of forenoon fights are not significantly correlated to the prices of afternoon flights.

Table 5.8 show the test results.

Table 5.8

Correlation Significance: Group-I Flights

Route	Kendall's tau	z-score	p-value	Decision
Route O1	0.062	2.192	<0.05	Reject H_0
Route O2	0.08281	2.93505	<0.05	Reject H_0

Source: Primary Data, Gretl Output

Since the $p<0.05$, the null hypothesis is rejected, and it is concluded that prices of the FN flights significantly influences the prices of AN Flights. The prices of competing flights on a day significantly influence the prices of that day, influencing the price dispersion.

Group-II MCR has five time segments: EM, FN, AN, EV, and LN. The researcher conducted the test on the following null hypothesis:

$H_{0\ 19}$ The prices of one-time segment are not significantly correlated to the prices of other time segments.

Table 5.9 show the test results of Kendall's rank correlation tau.

Table 5.9

Correlation Significance: Group-II Flights

Route		O5			O4			Decision
Group		Kendall's tau	z-score	p-value	Kendall's tau	z-score	p-value	
EM	FN	0.53232	27.0391	<0.05	0.5754	35.5307	<0.05	Reject H_0
EM	AN	0.20266	10.1532	<0.05	0.3971	24.0053	<0.05	
EM	EV	0.30073	14.9365	<0.05	0.4691	29.2606	<0.05	
EM	LN	0.29257	14.9566	<0.05	0.51257	29.0091	<0.05	
FN	AN	0.34696	23.1848	<0.05	0.36775	22.0977	<0.05	
FN	EV	0.38503	25.2888	<0.05	0.39437	24.4469	<0.05	
FN	LN	0.3666	28.369	<0.05	0.50775	28.5114	<0.05	
AN	EV	0.44609	29.3381	<0.05	0.38317	23.2572	<0.05	
AN	LN	0.33676	22.5277	<0.05	0.35568	19.5677	<0.05	
EV	LN	0.51273	33.6946	<0.05	0.55995	31.9127	<0.05	

Source: Primary Data

The null hypothesis is rejected for all observations ($p<0.05$), and it is concluded that the prices of one segment significantly influence the prices of other segments. In other words, the prices of competing flights on a day significantly influence the prices of that day, influencing the price dispersion.

5.4.2 Exploratory Data Analysis

Traditional/classical data analysis follows five steps: identification of the problem, collection of data, framing a suitable model, data analysis, and conclusions. Here the assumption is to select a model that the data follow. Exploratory Data Analysis (EDA) is a new philosophical approach for conducting a data analysis that follows the five steps but in a different sequence: identification of the problem, collection of data, data analysis, framing and selection of a suitable model, and conclusions. Here the assumption is a more direct approach of allowing the data to reveal its underlying structure and model (NIST, 2012). In short EDA approach suggests admissible models that best fit the data. The procedure applied for the selection of the model is explained below.

The data collected for this analysis consists of time series data of airline prices of various airlines on selected routes starting from 30 days before departure. Hence there are observations on a set of units (multiple airlines on the same route) at a common point in time, constituting time series and cross-sectional data at a time. There are seven sets of observations on various departure dates. Following Lucchetti, the researcher arranged the data into a panel of stacked time series; the successive vertical blocks each comprise a time series for a given unit (Cottrell & Lucchetti, 2022). There are 30 time periods with the 'n' number of cross-sectional units. The panel time dimension is given as 'undated'. In other words, the airfare of Airline-1 is taken as an explained variable, and Airline 2, Airline 3, etc., are born as the explanatory variables, as done by Sandra and Dutta in their panel set formation (Santra & Dutta, 2015).

Model Selection

Estimation of panel models includes Pooled Ordinary Least Square (PO), Fixed Effect Model (FE) and Random Effect Model (RE), and Weighted Least Square Model (WLS). Fixed effect regression analysis is based on the assumption that the regressors are nonstochastic and assume fixed values in repeated sampling, whereas random effects are not (Gujarati & Porter, 2009). Greene (Greene, 2022) proposes that the model with the highest adjusted R^2 for small samples and models with the lowest values of Akaike information criterion (AIC), Schwarz information Criterion (SIC) as the samples size increases, can be taken as a criterion for model selection. Gujarati (Gujarati & Porter, 2009) also proposes the same criteria for selecting the best-fit model. AIC (Akaike & Akaike, 1998) is based on the maximum log-likelihood as a function of the vector of parameter estimates and the number of independently adjusted parameters (k) within the model; BIC (Schwarz et al., 1978) modifies it by the multiplication of k by log n; Hannan-Quinn Criterion-HIC (Hannan et al., 1993) is based on the law of the iterated logarithm (Coeerell & Lucchetti, 2020). Best fit models are those having the lowest values of AIC, BIC, and HQC (NIST, 2012) (Cottrell & Lucchetti, 2022).

1. Panel Specification Test (F-Test)

First, the researcher ran a Pooled OLS (POLS) and conducted a panel specification test following the Gretl procedure. This POLS is an F-test joint significance of differing group means with a null hypothesis that the POLS model is adequate than the fixed effects alternative. A low p-value ($p<0.05$) counts against the null hypothesis and concludes that the fixed effects alternative is more suitable for the model at a 5% confidence level (Cottrell & Lucchetti, 2022).

2. Hausman Test

Following Gujarathy, the researcher used the Hausman test to choose between Fixed Effect and Random Effect (Gujarati & Porter, 2009). A rejection using the Hausman test is taken to mean that the key random effect assumption is false, and then the fixed effect estimates are more suitable. If $p<0.05$, then the fixed effects model is more appropriate. A rejection using the Hausman test is taken to mean that the key RE assumption is false, and then the FE estimates are used (Wooldridge, 2013). The Hausman test is based on the idea that under the hypothesis of no correlation, OLS in the LSDV model and GLS are consistent, but OLS is inefficient (Greene, 2022). This method is also suggested by Cottrell & Lucchetti (Cottrell & Lucchetti, 2022) and Wooldridge (Wooldridge, 2013). Many researchers used this test to choose their best-fit model (Papatheodorou & Lei, 2006)(John, 2007)(Das & Saha, 2017)(Grabovskaia, 2020). For the RE models using Nerlove's transformation (Nerlov, 1971).

The models were also evaluated based on information criterion as suggested by Cottrell and Lucchetti (Cottrell & Lucchetti, 2022). The researcher followed the rule of thumb given by Granger and Newbold (Granger & Newbold, 1973) to deal with the chances of spurious regression results. Accordingly, an $R^2 > d$ is a good rule of thumb to suspect that the estimated regression is spurious (Gujarati & Porter, 2009). All the models are robust with errors, using White's heteroscedasticity-corrected standard errors for handling autocorrelation as prescribed by Cottrell (Cottrell & Lucchetti, 2022).

The equation of the model formation of all models is:

$P_{jt}= \beta_0+\beta_{j1t}*i_{j1t}+\beta_{j2t}*i_{j2t}+\beta_{j3t}*i_{j3t}+\ldots\ldots\ldots.\ \beta_{jnt}*i_{jnt}$

Where:

P = Dependent variable (Prices of Airline j)

j = Set of Airlines, j=1,2,3 …….n

t = Set of days prior to departure, t= 1,2,…30

β = Regression coefficient

β_{j1} = Regression coefficient of j^{th} Airline

i_{jt}= Airfare (Price) j^{th} Airline

The airline company name is given in all models instead of codes assigned to identify the results. This is because the dependent and independent variables vary in all models.

5.4.2.1 EDA- Routes with Ten or Fewer Flights

Three sample routes of moderately concentrated markets come under this analysis. Route O1 and O2 had six direct flights each, and route O3 had ten direct flights. Five airline companies operated these flights. The present EDA analysis aims to identify the influence of brand and time on airline prices. Since the combined data set of Routes O1 and O2 violated the assumptions of EDA, the data set are converted into panel data sets of festival season and other days. Since the second data set violated the assumptions of normality, it was excluded from EDA analysis. In the case of Route O3, the entire data set satisfied the assumptions of EDA, and hence the researcher made no elimination of observations.

5.4.2.1.1 EDA- Models 1 & 2

The data of Route O1 and O2 are combined to make the panel data. Only those models that satisfied the criterion of normality are considered for analysis. The regression assumptions were satisfied when the Air India and Spicejet data were set as dependent variables. They respectively constitute model 1 and model 2. The following null hypotheses are considered for analysis.

$H_{0\ 20}$ The prices of other flights on the route does not significantly influence the prices of a flight on the routes O1 and O2.

$H_{0\,21}$ Time of booking does not significantly influence the prices of airlines on the routes O1 and O2.

Time dummies were included to evaluate the time effect on prices. The results of the best-fit models only are taken in this analysis. Table 5.10 shows the results of the model selection tests.

Table 5.10

Model Selection Test Results –Models 1 & 2

Models	1	2
Panel Model Specification Test		
F	29.186	9.317
P	1.91E-27	5.79E-10
Decision	FE	FE
Hausman Test		
Chi-square	6.655	6.362
P Value	0.248	0.027
Decision	RE	FE
Test for Normality of Residual		
Chi-square	12.587	1.968
p-value	0.002	0.374
Final Decision	WLS	FE

Source: Primary Data, Gretl Output

Since the panel specification test favoured Fixed Effects, the researcher conducted Hausman test to choose between FE and RE. The test results preferred RE for model one, but the RE model violated the normality assumption. Hence the researcher chose the Weighted Least Square for panel data modelling, which satisfied the assumptions. Test results preferred FE for model two. The results of the analysis are given in Table 5.11.

Table 5.11

Regression Model Fit – Models 1 & 2

Model Number	1	2	
Dependent Variable	Air India	Spicejet	
Model	WLS	Fixed Effect	
No. of Observations	240	240	
Mean dependent var*	12.277	5.513	
SD dependent var	4.636	1.384	
Sum squared resid	1843.14	65.179	
SE of regression	2.998	0.574	
Log-likelihood	−337.757	−184.125	
R-squared	0.685	0.858	(LSDV R-squared)
Adjusted R-squared	0.633	0.557	(Within R-squared)
rho		0.570	

F (34, 205)	13.110	
P-value (F)	2.41E-35	
AIC	745.51	452.25
SIC	867.34	598.44
HIC	794.60	511.15

Source: Primary Data, Gretl Output

*var denotes vector auto-regression

As Table 5.11 indicates, model-1 is fit as the R-Squared is 0.685. It means the prices of Indigo_EM, Indigo_FN, GoAir, and Vistara, along with the time of booking; explain 68.5% of the changes in the prices of Air India. Since the P-value is less than 0.05% for F-statistic, all the variables jointly significantly affect the dependent variable at a 5% significance level. Model-2 is fit as the LSDV R-Squared is 0.858, indicating the explaining power of 85.8% changes in the prices Spicejet. Rho value indicates the proportion of variation explained by the constant term. Log-likelihood values also add to the blueness of the models. The mean dependent var suggests the average of Y, the dependent variable. SD-dependent var measures how much the values of Y differ from their average value. AIC, SIC, and HIC were also the least for these models. Rho is the fraction of variance due to the individual term and shows the proportion of variation explained by the individual-specific term-the constant term that does not vary over time (B & Prada, 2014). Table 5.12 shows the test results of the models.

Table 5.12

Panel Data Analysis – Models 1 & 2

Model Number	Model 1				Model 2			
Dependent Variable	Air India				Spicejet			
Model	**Weighted Least Square**[!]				**Fixed Effect**			
	Co-efficient	t- ratio	p-value	Sig[!!]	Co-efficient	t-ratio	p-value	Sig[!!]
const	−6.40	−4.035	7.71E-05	***	4.330	10.070	0.000	***
Indigo FN_1	−0.415	−1.059	0.291		0.085	1.083	0.280	
AirIndia FN					0.041	2.167	0.031	**
Indigo FN_2	0.189	0.542	0.589		−0.009	−0.135	0.893	
GoAir FN	1.057	4.241	3.37E-05	***	−0.066	−1.221	0.224	
Vistara AN	−0.365	−3.281	0.001	***	0.124	4.750	0.000	***
Spicejet AN	2.448	9.694	1.56E-18	***				
dat_1	3.203	1.910	0.058	*				
dat_2	3.203	1.910	0.058	*	0.000	0.000	1.000	
dat_3	3.335	1.996	0.047	**	−0.014	−0.048	0.962	

dat_4	3.178	1.903	0.059	*	0.028	0.099	0.921	
dat_5	3.094	1.847	0.066	*	0.047	0.165	0.869	
dat_6	2.157	1.305	0.193		−0.203	−0.703	0.483	
dat_7	4.054	2.504	0.013	**	−0.871	−3.023	0.003	***
dat_8	4.347	2.710	0.007	***	−0.974	−3.382	0.001	***
dat_9	3.620	2.251	0.025	**	−0.714	−2.466	0.015	**
dat_10	4.004	2.532	0.012	**	−0.560	−1.921	0.056	*
dat_11	3.124	1.986	0.048	**	−0.370	−1.265	0.207	
dat_12	3.505	2.292	0.023	**	−0.197	−0.660	0.510	
dat_13	3.703	2.403	0.017	**	−0.095	−0.316	0.752	
dat_14	3.763	2.338	0.020	**	−0.212	−0.707	0.481	
dat_15	4.142	2.622	0.009	***	−0.390	−1.291	0.198	
dat_16	5.438	3.422	0.001	***	−0.723	−2.388	0.018	**
dat_17	4.155	2.566	0.011	**	−0.543	−1.804	0.073	*
dat_18	4.987	3.059	0.003	***	−0.715	−2.375	0.019	**
dat_19	3.013	1.843	0.067	*	−0.197	−0.634	0.527	
dat_20	3.053	2.015	0.045	**	−0.162	−0.501	0.617	
dat_21	2.377	1.646	0.101		−0.055	−0.162	0.872	

dat_22	0.057	0.040	0.968		0.471	1.330	0.185	
dat_23	1.489	1.020	0.309		0.540	1.553	0.122	
dat_24	2.980	2.052	0.041	**	0.115	0.336	0.737	
dat_25	2.879	2.049	0.042	**	0.109	0.311	0.756	
dat_26	1.766	1.244	0.215		−0.191	−0.552	0.582	
dat_27	4.215	2.913	0.004	***	−0.527	−1.477	0.141	
dat_28	3.333	2.311	0.022	**	−0.087	−0.243	0.809	
dat_29	1.551	1.093	0.276		0.295	0.834	0.405	
dat_30					1.094	2.743	0.007	***

Source: Primary Data; Gretl Output

[!]WLS- Weights based on per-unit error variances

[!!] * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

*** Represents significance at a 1% confidence interval

Table 5.12 indicates that the prices of all flights, except Indigo, significantly influence the prices of Air India. This suggests that the pricing strategy of Indigo was unique. Indigo FN_1 and Vistara are negatively related to the prices of Air India, with an estimated coefficient of -0.415 and -0.365, respectively. This implies that a percentage increase in the price of Indigo FN_1 and Vistara leads to a decrease in Air India prices. Moreover, there is a significant influence of the time of booking. Positive coefficients of time effects indicate that price tends to increase as the departure date is closer. This finding conforms with the common phenomenon of 'price increase monotonically as the departure date is nearer' (Yusheng Hu et al., 2015) (Bilotkach et al., 2015).

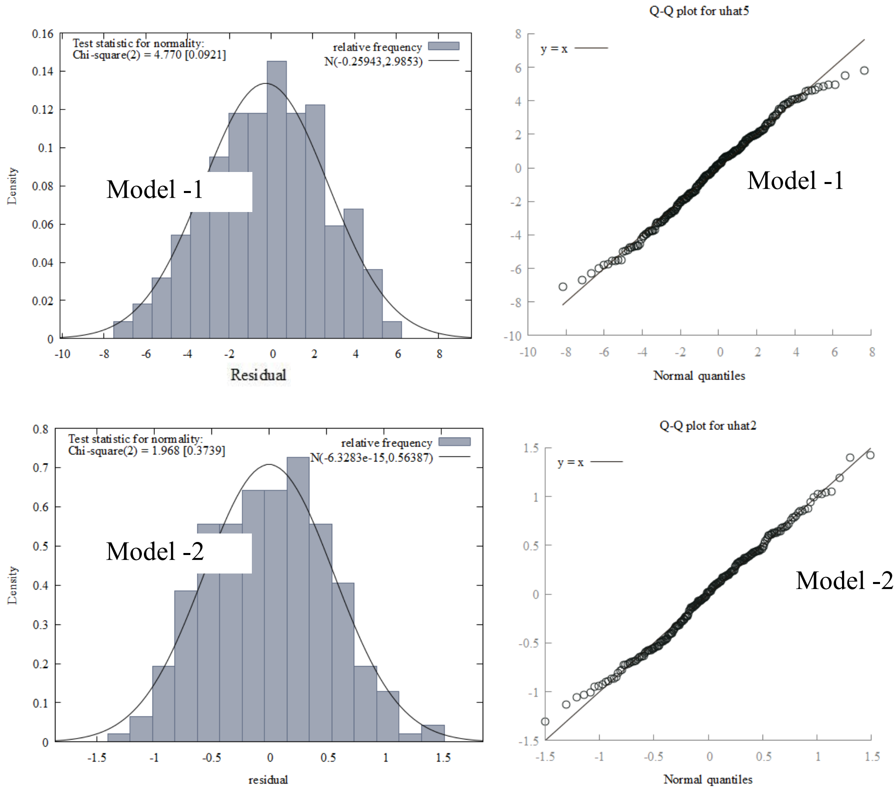
In Model-2, prices of Indigo FN_2 and GoAir are negatively related to Spicejet, with an estimated coefficient of -0.009 and -0.066, respectively. This implies that a percentage increase in the price of Indigo FN_2 and GoAir leads to a minute decrease in the Spicejet prices. Moreover, there is a significant influence of the time of booking on the 7, 8, 9, 16, 17, 18, and 30th days of observations only. Negative coefficients of time effects indicate that price tends to decrease on those days. In other words, one can get tickets at a lower price if one book later. This contradicts the common phenomenon of 'price increase monotonically as the departure date is nearer' (Yusheng Hu et al., 2015) (Bilotkach et al., 2015).

Both the results reject all the null hypotheses, and it is concluded that the prices of airline companies Air India and Spicejet are significantly influenced by the prices of other airlines on the route. Furthermore, the time of booking also significantly influences the prices of Air India and Spicejet.

Normality is one of the most critical assumptions of Time series regression analysis. Normality of residuals and chi-square values are given in the graph. The p-value for the alternative hypothesis of 'data is normal' is given in brackets ($p>0.05$). Q-Q plots of the models are also shown in Figure 5.3.

Figure 5.3

Model 1 & 2 - Normality of Residuals and Q-Q Plot for uhat



Source: Gretl Output

All the figures indicate that the model satisfies the normality assumptions of regression. The p-value of the normality test given in the graphs is greater than 0.05. The pattern closely follows the ascending line of the Q-Q plot, indicating normally distributed residuals. Models satisfied all other OLS assumptions of independence of observation, linear relationship, no autocorrelation, and homoscedasticity.

5.4.2.1.2 EDA- Models 3 to 8

Models 3 to 8 represent the data analysis of route O3. The present EDA analysis aims to identify the influence of brand and time effect on airline prices. The entire data set was arranged into panel data sets. Preliminary tests were conducted to meet the criterion of the normality assumption. Only those models that satisfy the criterion of normality are considered for analysis. While considering all the flights on the route, regression assumptions are satisfied in the case of dependent variables Air India, Indigo, Vistara, and Jetairways. The dependent variable Spicejet violated the panel data regression assumptions and is excluded from regression analysis. The number of observations was limited to 210 since two flights were not operating on all days. The following null hypotheses were framed for the present analysis:

$H_{0\,22}$ The prices of other flights on the route does not significantly influence the prices of a flight on the route O3.

$H_{0\,23}$ Time of booking does not significantly influence the prices of the airlines on the route O3.

Time dummies were included to evaluate the time effect on prices. The results of the best-fit models only are taken in this analysis. Table 5.13 shows the results of the model selection tests.

Table 5.13

Model Selection Test Results – Models 3 to 8

Models	3	4	5	6	7	8
Panel Model Specification Test						
F	19.4192	2.9978	4.32746	20.1918	52.1655	88.3021
P	4.51E-17	0.008	0.0004	0.065	5.20E-81	6.36E-49
Decision	FE	FE	FE	POLS	FE	FE
Hausman Test						

Chi-square	5.645	257.296	4.328		79.971	5.922
P Value	0.044	1.13E-52	0.036		1.40E-14	0.043
Decision	FE	FE	FE		FE	FE

Source: Primary Data, Gretl Output

The above table of panel specification test results favoured POLS for model 6. The Hausman test was conducted for all other models, which selected Fixed Effect models since p<0.05. The test results of models 3 to 8 are given in Table 5.14.

Table 5.14

Regression Model Fit – Models 3 to 8

Model No.	3	4	5	6	7	8
Dependent Variable	Jet Airways EV	Vistara FN	AirIndia FN	Air India AN	Indigo FN	Indigo FN
Model	Fixed Effect			Pooled OLS	Fixed Effect	
No. of Observations	210	210	210	330	450	210
Mean dependent var	3.268	2.826	2.837	3.317	3.135	3.172
SD dependent var	1.059	0.476	0.501	54.430	23.789	0.634
Sum squared resid	41.764	13.408	16.418	0.647	0.535	6.860

SE of regression	0.503	0.285	0.315	0.432	0.244	0.204
LSDV R-squared	0.822	0.717	0.687	0.605	0.815	0.918
Within R-squared	0.685	0.654	0.631	0.555	0.574	0.750
Log-likelihood	−128.395	−9.097	−30.363	−170.889	22.982	61.268
rho	0.565	0.374	0.717	0.703	0.614	0.455
Durbin-Watson	1.131	1.212	1.345	1.110	1.108	1.078
AIC	346.8	108.2	150.7	259.58	56.0	−32.5
SIC	497.4	258.8	301.3	441.93	265.6	118.1
HIC	407.7	169.1	211.6	332.31	138.6	28.4

Source: Primary Data, Gretl Output

As Table 5.14 indicates, model-3 fits as the LSDV R-Squared is 0.822. It means that the prices of nine direct flights and the time of booking explained 82.2% of the changes in the prices of Jet Airways EV. Model-4, 5, 6, 7, and 8 have explanatory power of 71.7%, 68.7%, 60.5%, 81.5%, and 91.8%, respectively, to explain the changes in the prices of the corresponding dependent variable. Rho value indicates the proportion of variation explained by the constant term. Log-likelihood values also add to the blueness of the models. Mean dependent var suggests the average of Y, the dependent variable and SD dependent var measures how much the values of Y differ from its average value. SIC, BIC, and HIC were also the lowest for the selected models. Since the value of R-squared is less than Durbin-Watson value ($R^2 < d$) for all the models, the regressions are not spurious (Granger & Newbold, 1973). Test results of models 3 and 4 are given in Table 5.15.

Table 5.15

Panel Data Analysis – Models 3 & 4

Model	3 (Fixed Effect)				4 (Fixed Effect)			
No. of Observations	210				210			
Dependent Variable	Jet Airways EV				Vistara FN			
	Co-efficient	t-ratio	p-value	Sig.	Co-efficient	t-ratio	p-value	Sig.[!]
const	1.399	1.947	5.32E-02	*	0.472	1.200	2.75E-01	
Air India FN	0.582	5.038	1.22E-06	***	−0.029	−0.404	7.00E-01	
Indigo FN	−1.001	−5.699	5.42E-08	***	0.049	0.469	6.55E-01	
Vistara FN	0.202	1.483	1.40E-01					
Spicejet FN	0.579	4.148	5.35E-05	***	0.070	0.888	4.09E-01	
Air India AN	−0.452	−3.774	2.00E-04	***	0.194	2.825	3.01E-02	**

Indigo								
AN	0.442	3.113	2.20E-03	***	−0.200	−2.606	4.03E-02	**
Vistara								
AN	−0.425	−3.589	4.00E-04	***	0.221	3.272	1.70E-02	**
JetAirways EV					0.065	1.376	2.18E-01	
Air India								
EV	0.038	0.957	3.40E-01		−0.072	−3.477	1.32E-02	**
Indigo								
EV	0.320	1.956	5.21E-02	*	0.492	5.796	1.20E-03	***
dat_2	0.145	0.5377	5.92E-01		−0.062	−4.940	2.60E-03	***
dat_3	0.227	0.8078	4.20E-01		0.029	0.685	5.19E-01	
dat_4	0.280	0.9834	3.27E-01		0.102	2.052	8.60E-02	*
dat_5	0.268	0.9286	3.55E-01		0.225	4.177	5.80E-03	***
dat_6	0.346	1.201	2.32E-01		0.257	4.721	3.30E-03	***
dat_7	0.558	1.91	5.79E-02	*	0.387	6.558	6.00E-04	***
dat_8	0.979	3.34	1.00E-03	***	0.243	3.367	1.51E-02	**
dat_9	1.050	3.446	7.00E-04	***	−0.224	−2.658	3.76E-02	**
dat_10	1.456	4.778	3.89E-06	***	−0.389	−4.220	5.60E-03	***
dat_11	1.428	4.675	6.07E-06	***	−0.093	−0.959	3.75E-01	
dat_12	1.589	5.171	6.67E-07	***	−0.205	−2.007	9.16E-02	*

dat_13	1.820	6.067	8.64E-09	***	−0.191	−1.826	1.18E-01	
dat_14	2.496	7.844	5.19E-13	***	−0.230	−1.649	1.50E-01	
dat_15	2.324	7.368	7.90E-12	***	−0.115	−0.862	4.22E-01	
dat_16	2.257	6.849	1.40E-10	***	−0.005	−0.034	9.74E-01	
dat_17	2.048	6.723	2.77E-10	***	0.069	0.595	5.74E-01	
dat_18	2.008	6.637	4.39E-10	***	0.057	0.499	6.36E-01	
dat_19	1.830	5.967	1.44E-08	***	0.173	1.571	1.67E-01	
dat_20	1.935	6.243	3.50E-09	***	0.173	1.489	1.87E-01	
dat_21	1.902	6.239	3.57E-09	***	0.275	2.453	4.96E-02	**
dat_22	1.850	6.364	1.87E-09	***	0.034	0.331	7.52E-01	
dat_23	1.620	5.529	1.24E-07	***	0.112	1.176	2.84E-01	
dat_24	1.736	5.97	1.41E-08	***	0.075	0.763	4.74E-01	
dat_25	1.556	4.985	1.56E-06	***	0.084	0.777	4.67E-01	
dat_26	1.511	4.531	1.12E-05	***	0.207	1.669	1.46E-01	
dat_27	1.300	3.763	2.00E-04	***	0.012	0.092	9.30E-01	
dat_28	1.242	3.416	8.00E-04	***	0.184	1.277	2.49E-01	
dat_29	1.081	2.927	3.90E-03	***	0.382	2.696	3.57E-02	**
dat_30	1.004	2.604	1.01E-02	**	0.314	2.025	8.93E-02	*

Source: Primary Data, Gretl Output

! * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

*** Represents significance at a 1% confidence interval

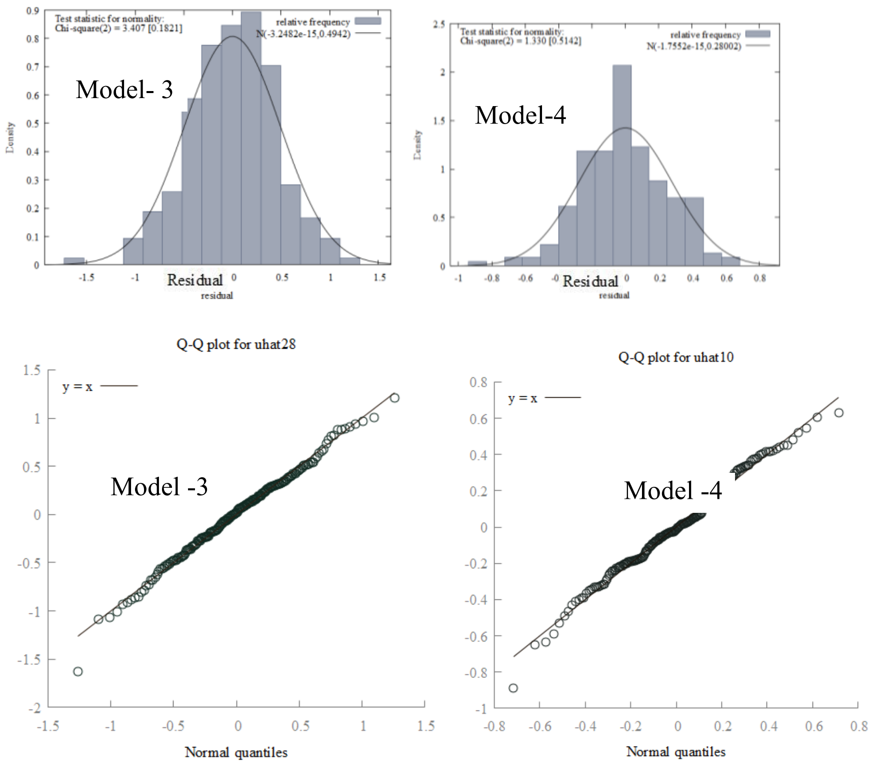
The panel data regression results indicate that in model 3, the prices of all nine flights of the day, except Vistara FN and Air India EV, influence the prices of JetAirways evening flights. Indigo EV is significant at 90% confidence only. Indigo FN, Air India AN, and Vistara AN have negative coefficients indicating an inverse relationship. It means an increase in the prices of these flights would lead to a reduction in the prices of JetAirways. Time of booking has a significant influence from the 7th day of observation. This indicates that prices frequently fluctuate from the 7th day of observation. Since the coefficients are positive, prices tend to increase monotonically as the departure date is closer. This supports the finding of Hu and Bilotkach (Hu et al., 2015) (Bilotkach et al., 2015).

Regression results of model 3 indicate that the prices of five out of nine flights of the day- afternoon flights of Air India, Indigo, Vistara, and evening flights of Air India and Indigo, significantly influence the prices of Vistara FN. Indigo AN and Air India EV had negative coefficients indicating an inverse relationship. It means that an increase in the prices of these flights would lead to a reduction in the prices of Vistara FN. Time of booking significantly influences at a 5% confidence interval on 12 days out of 30 days. This indicates that prices do not fluctuate frequently. There are negative coefficients on nine days before the 17th day of observation. This means prices tend to decrease on these days. This finding contradicts the findings of Hu and Bilotkach (that price increases drastically as the departure date is closer) and supports the findings of Petrovic and Gillen (that they could not observe monotonic growth or decrease in price with the closeness to the time of departure) (Petrovic et al., 2011) (Gillen & Hazledine, 2006).

The most important assumption of normality and linearity in Time series regression analysis is satisfied with all models, and Figure 5.4 shows the graphs. The normality graph also gives chi-square values and P values (p>0.05). Q-Q plots of models are also shown in the figure.

Figure 5.4

Models 3 & 4 - Normality of Residuals and Q-Q Plot for uhat



Source: Primary Data, Gretl Output

All the figures indicate that the model satisfies the normality and linearity assumptions of regression. The p-value of the normality test given in the graph is greater than 0.05 for both models. Furthermore, both patterns closely follow the ascending line of the Q-Q plot, indicating normally distributed residuals. Models satisfied all other OLS assumptions of independence of observation, linear relationship, no autocorrelation, and homoscedasticity.

Model 5 and 6 of the panel data analysis shows the effect of the other nine flights on the prices of Air India FN and AN. The impact of the Indigo AN flight on the Air India AN flight was not measured since its inclusion violated the normality assumptions of the model. Considering the influence of the JetAirways EV, the model 6 has 330 observations. The model considers the time effect also. The regression results are given in Table 5.16.

Table 5.16

Panel Data Analysis – Models 5 & 6

Model	5 (Fixed Effect)				6 (Pooled OLS)			
No. of Observations	210				330			
Dependent Variable	Air India FN				Air India AN			
	coefficient	t-ratio	p-value	Sig.	coefficient	t-ratio	p-value	Sig.!
const	2.141	5.065	0.002	***	0.656	3.553	0.005	***
Air India FN					0.077	1.441	0.180	
Indigo FN	0.335	2.878	0.028	**	0.285	4.096	0.002	***
Vistara FN	−0.036	−0.405	0.700		0.328	4.265	0.002	***
Spicejet FN	−0.436	−4.453	0.004	***	−0.055	−1.134	0.283	

Air India AN	0.128	1.609	0.159					
Indigo AN	−0.253	−3.142	0.020	**				
Vistara AN	0.174	2.245	0.066	*	−0.072	−1.333	0.212	
JetAirways EV	0.229	4.961	0.003	***	−0.059	−1.640	0.132	
Air India EV	0.021	0.729	0.494		−0.012	−0.618	0.550	
Indigo EV	0.119	1.096	0.315		0.425	5.453	0.000	***
dat_2	0.048	3.654	0.011	**	−0.058	−5.262	0.000	***
dat_3	0.041	0.831	0.438		−0.337	−14.47	0.000	***
dat_4	0.021	0.360	0.731		−0.379	−16.57	0.000	***
dat_5	0.049	0.743	0.486		−0.331	−13.31	0.000	***
dat_6	−0.057	−0.844	0.431		−0.144	−6.134	0.000	***
dat_7	−0.220	−2.906	0.027	**	−0.175	−5.553	0.000	***
dat_8	−0.214	−2.590	0.041	**	−0.156	−3.813	0.003	***
dat_9	−0.184	−1.937	0.101		−0.171	−3.518	0.006	***
dat_10	−0.249	−2.420	0.052	*	−0.178	−2.866	0.017	**

dat_11	−0.207	−1.959	0.098	*	−0.221	−3.641	0.005	***
dat_12	−0.346	−3.098	0.021	**	−0.224	−3.505	0.006	***
dat_13	−0.423	−3.862	0.008	***	−0.016	−0.255	0.804	
dat_14	−1.086	−8.240	0.000	***	−0.041	−0.581	0.574	
dat_15	−1.065	−8.657	0.000	***	0.033	0.536	0.604	
dat_16	−1.031	−7.621	0.000	***	−0.138	−2.246	0.049	**
dat_17	−0.795	−6.822	0.001	***	0.100	2.026	0.070	*
dat_18	−0.741	−6.366	0.001	***	0.065	1.327	0.214	
dat_19	−0.597	−4.970	0.003	***	−0.060	−1.250	0.240	
dat_20	−0.687	−5.570	0.001	***	−0.039	−0.791	0.447	
dat_21	−0.629	−5.117	0.002	***	0.013	0.274	0.790	
dat_22	−0.544	−5.015	0.002	***	0.123	2.518	0.031	**
dat_23	−0.506	−4.911	0.003	***	0.141	3.074	0.012	**
dat_24	−0.313	−2.843	0.030	**	0.203	4.229	0.002	***
dat_25	−0.155	−1.334	0.231		0.156	3.070	0.012	**
dat_26	−0.007	−0.055	0.958		0.240	3.690	0.004	***
dat_27	0.125	0.852	0.427		0.279	4.418	0.001	***
dat_28	0.271	1.653	0.150		0.226	3.109	0.011	**

dat_29	0.194	1.175	0.284	0.182	2.627	0.025	**
dat_30	0.282	1.610	0.159	−0.123	−1.653	0.129	

Source: Primary Data, Gretl Output

!! * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

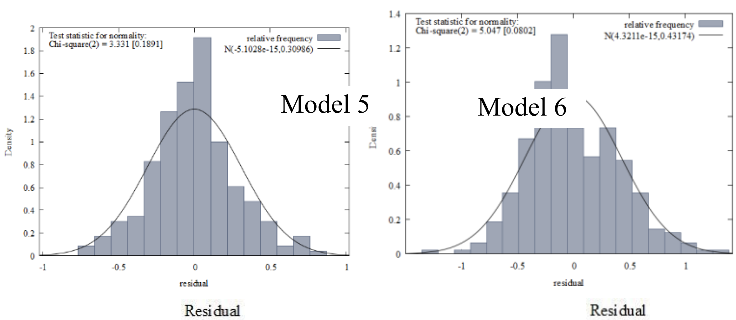
*** Represents significance at a 1% confidence interval

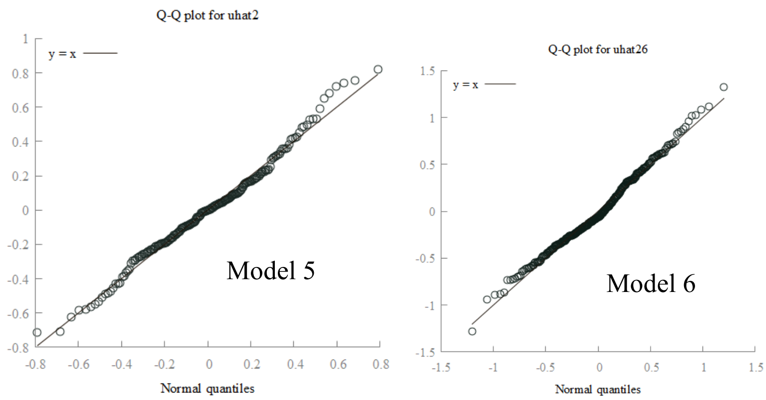
Table 5.16 shows that five of the ten airline companies significantly influence the prices of Air India FN. Two independent variables with significant influence have negative coefficients, indicating an inverse relationship. The time of booking has no significant influence on all days of observation. But the prices tend to decline till the 26^{th} day of observation from the sixth day of observation (negative coefficients). This finding contradicts the findings of Hu, Bilotkach, Petrovic and Gillen (Yusheng Hu et al., 2015) (Bilotkach et al., 2015) (Petrovic et al., 2011) (Gillen & Hazledine, 2006).

The most important assumption of normality and linearity in Time series regression analysis is satisfied with all models, and the graphs are given in Figure 5.5. The normality graph also gives chi-square and p values (p>0.05). The figure also shows the Q-Q plots of models.

Figure 5.5

Model 5 & 6 - Normality of Residuals and Q-Q Plot for uhat





Source: Primary Data, Gretl Output

All the figures indicate that the model satisfies the normality and linearity assumptions of regression. The p-value of the normality test given in the graph is greater than 0.05 for both models. Furthermore, both patterns closely follow the ascending line of the Q-Q plot, indicating normally distributed residuals. Models satisfied all other OLS assumptions of independence of observation, linear relationship, no autocorrelation, and homoscedasticity.

Models 7 and 8 were the panel data regression of the fixed effect model with Indigo FN flights as the dependent variable. Model 7 ignores the effect of Indigo AN and JetAirways EV since they are not operating all day. Hence the model has 450 days of observation. Model 6 includes the influence of all flights and reduces the number of observations to 210. The results are given in Table 5.17.

Table 5.17

Panel Data Analysis – Models 7 & 8

Model	7 (Fixed Effect)	8 (Fixed Effect)
No. of Observations	450	210

Dependent Variable					Indigo FN			
	coefficient	t-ratio	p-value	Sig.	coefficient	t-ratio	p-value	Sig.
const	1.436	8.267	2.06E-15	***	1.923	7.580	2.37E-12	***
Vistara FN	0.074	1.814	7.04E-02	*	0.025	0.451	6.53E-01	
Spicejet FN	0.068	1.913	5.65E-02	*	0.162	2.794	5.80E-03	***
AirIndia FN	−0.002	−0.064	9.49E-01		0.140	2.848	5.00E-03	***
AirIndia AN	0.142	3.797	2.00E-04	***	0.180	3.716	3.00E-04	***
Indigo AN					−0.143	−2.466	1.47E-02	**
Vistara AN	−0.134	−4.255	2.61E-05	***	−0.312	−7.169	2.40E-11	***
Indigo EV	0.345	7.933	2.18E-14	***	0.448	7.839	5.32E-13	***
AirIndia EV	−0.054	−5.419	1.04E-07	***	−0.084	−5.634	7.45E-08	***
JetAirwaysEV					−0.164	−5.699	5.42E-08	***
dat_2	0.064	0.714	4.76E-01		0.008	0.0743	9.41E-01	
dat_3	0.306	3.412	7.00E-04	***	0.281	2.511	1.30E-02	**
dat_4	0.302	3.355	9.00E-04	***	0.344	3.058	2.60E-03	***
dat_5	0.355	3.946	9.37E-05	***	0.351	3.08	2.40E-03	***
dat_6	0.255	2.838	4.80E-03	***	0.324	2.827	5.30E-03	***
dat_7	0.263	2.917	3.70E-03	***	0.340	2.914	4.10E-03	***

dat_8	0.358	3.948	9.30E-05	***	0.459	3.912	1.00E-04	***
dat_9	0.499	5.456	8.56E-08	***	0.583	4.878	2.51E-06	***
dat_10	0.521	5.659	2.91E-08	***	0.613	4.995	1.49E-06	***
dat_11	0.562	6.142	1.97E-09	***	0.679	5.63	7.59E-08	***
dat_12	0.556	6.042	3.49E-09	***	0.747	6.173	5.01E-09	***
dat_13	0.636	6.906	1.97E-11	***	0.718	5.871	2.31E-08	***
dat_14	0.701	7.319	1.39E-12	***	0.977	7.487	4.03E-12	***
dat_15	0.566	5.928	6.63E-09	***	0.927	7.212	1.90E-11	***
dat_16	0.593	6.281	8.82E-10	***	1.032	8.042	1.63E-13	***
dat_17	0.448	4.828	1.97E-06	***	0.805	6.466	1.09E-09	***
dat_18	0.454	4.919	1.27E-06	***	0.799	6.489	9.69E-10	***
dat_19	0.394	4.304	2.11E-05	***	0.779	6.341	2.10E-09	***
dat_20	0.378	4.088	5.27E-05	***	0.793	6.332	2.20E-09	***
dat_21	0.320	3.485	5.00E-04	***	0.717	5.716	5.00E-08	***
dat_22	0.262	2.852	4.60E-03	***	0.571	4.616	7.84E-06	***
dat_23	0.259	2.818	5.10E-03	***	0.515	4.189	4.56E-05	***
dat_24	0.331	3.621	3.00E-04	***	0.544	4.424	1.75E-05	***
dat_25	0.290	3.131	1.90E-03	***	0.523	4.042	8.11E-05	***

dat_26	0.290	3.070	2.30E-03	***	0.591	4.356	2.32E-05	***
dat_27	0.389	4.114	4.72E-05	***	0.610	4.425	1.75E-05	***
dat_28	0.472	4.853	1.74E-06	***	0.761	5.416	2.12E-07	***
dat_29	0.521	5.330	1.65E-07	***	0.786	5.587	9.34E-08	***
dat_30	0.684	6.788	4.12E-11	***	0.875	6.066	8.68E-09	***

Source: Primary Data, Gretl Output

!! * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

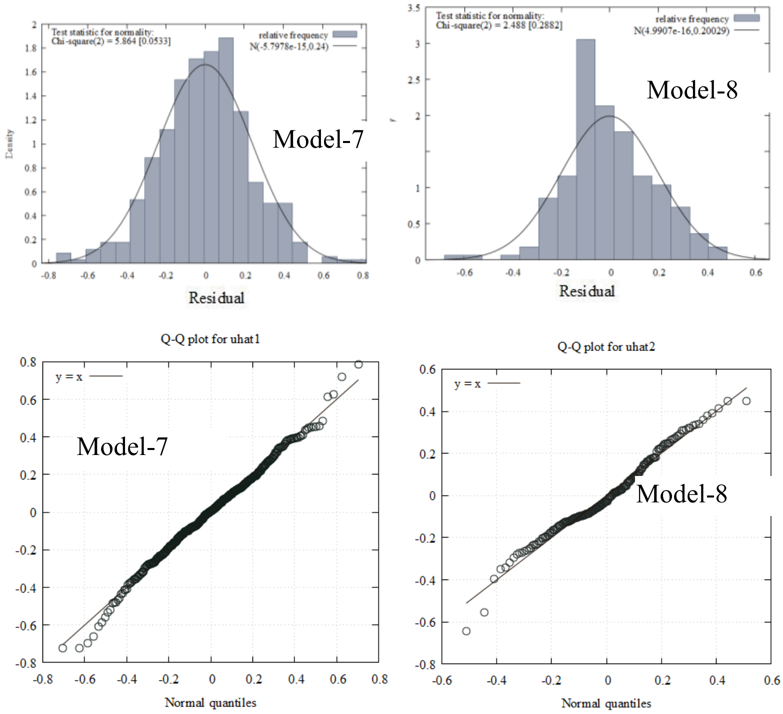
*** Represents significance at a 1% confidence interval

Table 5.17 clearly shows that all the flights of the day, except Vistara FN, significantly influence the prices of Indigo FN at a 5% confidence interval. The influence of forenoon flights of Spicejet and Air India was insignificant on model 7 while considering only the effect of all-day flights. Negative significant coefficients indicating inverse correlation are present for the two independent variables of model 7 and for four dependent variables of model 8. There is a significant positive effect of time of booking on all days from the third day of observation. This finding is in tune with the findings of Hu and Bilotkach that the 'price increase monotonically as the departure date is nearer' (Hu et al., 2015) (Bilotkach et al., 2015).

The most important assumption of normality and linearity in Time series regression analysis is satisfied with all models, and the graphs are given in Figure 5.6. The normality graph also gives chi-square and p-values (p>0.05). The figure also shows the Q-Q plots of models.

Figure 5.6

Model 7 & 8 - Normality of Residuals and Q-Q Plot for uhat



Source: Primary Data, Gretl Output

All the figures indicate that the model satisfies the normality and linearity assumptions of regression. The p-value of the normality test given in the graph is greater than 0.05 for both models. Furthermore, both patterns closely follow the ascending line of the Q-Q plot, indicating normally distributed residuals.

5.4.2.2 EDA- Route with 30 Flights

Out of the five sample routes of moderately concentrated markets, Route O4 had 30 direct flights. The Delhi-Kolkata route is one of the five high-density routes in India, which carried nearly three lakh passengers in 2018 (DGCA, 2019). In addition, this route had 30 nonstop flights operated by seven airline companies. Of the 30 airline companies, 28 were operating on all days of observation. Indigo operated eleven of these flights during the days of observation. The following hypothesis was formed and tested with panel data regression analysis:

$H_{0\ 24}$ The prices of other flights on the route does not significantly influence the prices of a flight on the route O4.

For the analysis, the data set was grouped into prices of festival days and prices of other days. This grouping was made since the combined data set violated the time series regression assumptions. The first group included two festival days, days before and after festival days. The second group was excluded from the analysis due to assumption violation. Out of the entire 30 direct flights, two flights were excluded since they were not operating on all days. All other 28 flights were taken for EDA. The researcher has considered the entire subsets of EM, FN, AN, EV, and LN flights and has conducted a number of regressions. Time effect-tested models were not selected since those models violated the assumptions. Several models satisfied the regression criteria. These models were focused on 14 dependent variables. Out of these models, one model was selected for each airline company to get at least one model each for EM, FN, AN, EV, and LN flights. Two models were selected for Indigo, the company with the largest share on the route. The lowest values for AIC, SIC, and HQC were also considered for choosing the best models. Only those which satisfied the regression assumptions were selected for this research. The selected include the following eight models:

Model	Code*	Dependent variable
Model 9	Spi EM	EM flight of Spicejet
Model 10	JetA EM	EM flight of JetAirways
Model 11	Ind FN2	FN flight of Indigo
Model 12	Ind AN3	AN flight of Indigo

Model 13	Vista EV	EV flight of Vistara
Model 14	AA EV	EV flight of AirAsia
Model 15	GA LN	LN flight of GoAir
Model 16	AI LN	LN flight of Air India

*Depending on the travel time, the researcher divided flights into five segments to examine the influence of adjacent flights: EM, FN, AN, EV, and LN. These abbreviations are suffixed with the name of flights for smooth observation. If there is more than one flight of an airline company in a segment, numbers are also suffixed. There were six EM flights, six FN flights, five AN flights, six EV flights, and five LN flights. After keeping one flight as the dependent variable, all the models had 27 regressors. Depending on the selection criteria, all fixed effect models are finally selected. Table 5.18 shows the results of the model selection tests.

Table 5.18

Model Selection Test Results –Models 9 to 16

Models	9	10	11	12	13	14	15	16
Panel Model Specification Test								
F	6.81	11.27	12.86	3.96	45.80	5.16	12.75	17.36
P	3E-04	3E-06	3E-02	1E-02	6E-18	3E-03	5E-07	2E-02
Decision	FE	FE	FE	FE	FE	FE	FE	FE
Hausman Test								
Chi-square	5.57	12.66	17.02	14.97	13.20	12.29	12.86	2.43

P Value	0.044	0.045	0.035	0.017	0.036	0.045	0.041	0.049
Decision	FE	FE	FE	FE	FE	FE	FE	FE

Source: Primary Data, Gretl Output

As the values given in Table 5.18 indicate, the panel specification test rejected the pooled OLS model in favour of the fixed effects alternative ($p<0.05$). Hausman test favoured FE for all models. Table 5.19 shows the model fit values for models 9 to 16.

Table 5.19

Regression Model Fit – Model 9 to 16

Models	9	10	11	12	13	14	15	16
Dependent Variables	Spi EM	JetA EM	Ind FN2	Ind AN3	Vist EV	AA EV	GA LN	AI LN
Mean Dependent var	4.18	4.47	4.58	4.49	6.49	4.12	4.03	4.96
SD Dependent var	0.79	0.88	0.86	1.12	2.82	0.76	1.19	1.08
Sum Squared resid	4.31	7.57	6.30	10.09	16.43	4.68	12.60	10.34
SE of Regression	0.23	0.30	0.27	0.34	0.44	0.23	0.38	0.35

Log-likelihood	26.38	−6.27	4.36	−22.95	−51.22	21.64	−35.83	−24.39
LSDV R-squared	0.94	0.92	0.93	0.93	0.98	0.93	0.92	0.92
Within R-squared	0.93	0.89	0.92	0.88	0.98	0.91	0.89	0.88
rho	0.37	0.35	0.27	0.29	0.31	0.10	0.46	0.27
Durbin-Watson	1.101	1.315	1.450	1.332	1.306	1.664	1.117	1.404
AIC	9.24	74.53	53.28	.07.91	.64.45	18.72	133.66	110.79
SIC	94.60	159.89	138.64	.93.27	!49.81	104.08	219.03	196.15
HIC	43.89	109.18	87.93	.42.56	.99.10	53.37	168.32	145.44

Source: Primary Data, Gretl Output

LSDV R-squared values of all the models are above 0.90, which indicates that the models explain about 90% of changes in the prices of corresponding flights caused by the changes in independent variables. Within R-squared values are also above 80%, which shows the well fit of models. The lower Log-likelihood values also increase the blueness of the model. The rho value of Model -9 indicates that 37% of the variation is explained by the error term and the other 63% by the constant term. Rho of Models 10, 11, 12, 13, 14, 15, and 16 indicates that the corresponding error term explains 35%, 27%, 29%, 31%, 10%, 46%, and 27% of the variations, respectively. Since $R^2 < d$ for all the models, the regressions are not spurious (Granger & Newbold, 1973). All models are based on

116 observations. AIC, SIC, and HIC were also the least for the selected models. Table 5.20 show the regression results of Models 9 and 10.

Table 5.20

Regression Results - Models 9 & 10

Model	9				10			
Dependent Variable	Spicejet EM				JetAirways EM			
Regressors	coefficient	t-ratio	p-value	Sig!	coefficient	t-ratio	p-value	Sig!
const	1.341	6.031	0.009	***	0.509	1.467	0.239	
AirAsia EM	0.082	1.815	0.167		0.174	3.235	0.048	**
AirAsia EV	−0.191	−2.162	0.119		−0.169	−1.503	0.230	
AirIndia AN1	0.008	0.883	0.442		0.029	2.333	0.102	
AirIndia AN2	0.089	1.683	0.191		0.218	3.002	0.058	*
Air India LN	−0.042	−0.739	0.513		−0.060	−0.732	0.517	
AirIndia FN	−0.032	−0.761	0.502		−0.115	−2.106	0.126	
GoAir EM	0.250	8.732	0.003	***	0.194	4.014	0.028	**

GoAir EV	0.051	2.583	0.082	*	−0.035	−1.187	0.321	
GoAir LN	0.013	0.242	0.824		0.370	6.046	0.009	***
Indigo AN1	0.177	2.012	0.138		0.389	3.330	0.045	**
Indigo AN2	−0.028	−0.527	0.634		0.095	1.220	0.310	
Indigo AN3	0.146	2.648	0.077	*	0.087	1.138	0.338	
Indigo EM1	0.060	2.656	0.077	*	0.076	2.531	0.085	*
Indigo EM2	0.071	0.924	0.424		−0.045	−0.432	0.695	
Indigo EV	−0.323	−3.598	0.037	**	−0.518	−4.075	0.027	**
Indigo LN1	0.294	3.973	0.029	**	0.226	2.183	0.117	
Indigo LN2	−0.054	−0.716	0.526		−0.021	−0.216	0.843	
Indigo FN2	0.041	0.577	0.605		−0.190	−1.847	0.162	
Indigo FN3	−0.242	−3.182	0.050	*	0.018	0.160	0.883	
JetAirways EM	−0.076	−1.128	0.341		0.150	5.879	0.010	***
JetAirways EV	0.048	2.037	0.134					
JetAirways FN	0.094	1.615	0.205		0.142	1.896	0.154	

Spicejet EM					−0.133	−1.129	0.341
Spicejet EV	0.067	3.053	0.055	*	0.052	1.708	0.186
Spicejet FN	0.119	3.650	0.036	**	−0.072	−1.428	0.249
Vistara EV	−0.156	−3.939	0.029	**	0.049	0.795	0.485
Vistara LN	0.154	4.179	0.025	**	−0.093	−1.629	0.202
Vistara FN	−0.002	−0.040	0.971		0.019	0.357	0.745

Source: Primary Data, Gretl Output

! * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

*** Represents significance at a 1% confidence interval

As table 5.20 indicates, the prices of six flights significantly influenced the prices of the dependent variable Spicejet EM at a 5% confidence interval (model 9). Influencing variables include one EM flight, one FN flight, two EV flights, and two LN flights. Five more dependent variables significantly influence the prices at a 10% confidence interval. Since the observation days are continuous, LN and FN segments can be considered adjacent to EM segments. The prices of all the flights of the same airline company influenced the dependent variable only at a 10% confidence interval. At this confidence level, the prices are influenced by the 11 flights, including five Indigo flights.

In model 10, the prices of EM flights of JetAirways were influenced by the prices of six airline companies, including three EM flights at a 5% confidence interval. Two more flights influence the dependent variable at a 10% confidence interval. The prices of Spicejet EM were independent of the prices of JetAirways EM. Table 5.21 show the regression results of Models 11 and 12.

Table 5.21

Regression Results - Models 11 & 12

Model	11				12			
Dependent Variable	Indigo FN2				Indigo AN3			
Regressors	coefficient	t-ratio	p-value	Sig	coefficient	t-ratio	p-value	Sig
const	0.426	2.121	0.037	**	−0.599	−0.901	0.370	
AirAsia EM	−0.016	−0.636	0.526		−0.103	−0.833	0.407	
AirAsia EV	−0.192	−1.057	0.293		0.303	1.364	0.176	
AirIndia AN1	0.019	1.430	0.157		−0.010	−0.354	0.725	
AirIndia AN2	0.301	5.237	0.000	***	0.243	2.164	0.033	**
AirIndia LN	−0.349	−5.627	0.000	***	−0.009	−0.125	0.901	
AirIndia FN	−0.014	−0.195	0.846		−0.107	−1.638	0.105	

GoAir EM	0.091	1.485	0.141		−0.060	−0.724	0.471	
GoAir EV	0.035	0.575	0.567		−0.057	−2.218	0.029	**
GoAir LN	0.072	0.516	0.608		0.013	0.155	0.877	
Indigo AN1	0.114	0.440	0.661		−0.084	−0.360	0.720	
Indigo AN2	0.023	0.174	0.863		−0.006	−0.119	0.906	
Indigo AN3	−0.060	−0.574	0.567					
Indigo EM1	0.061	1.191	0.237		0.002	0.049	0.961	
Indigo EM2	0.149	1.060	0.292		−0.289	−1.931	0.057	*
Indigo EV	0.122	0.792	0.431		0.304	1.373	0.173	
Indigo LN1	0.339	2.347	0.021	**	0.092	0.457	0.649	
Indigo LN2	−0.269	−3.193	0.002	***	−0.081	−2.242	0.028	**
Indigo FN2					−0.097	−0.584	0.561	
Indigo FN3	0.354	5.292	0.000	***	0.525	4.213	0.000	***
JetAirways EM	−0.158	−1.276	0.205		0.116	0.941	0.349	
JetAirways EV	0.084	2.006	0.048	**	−0.130	−1.215	0.228	
JetAirways FN	−0.079	−0.799	0.426		0.230	4.741	0.000	***

Spicejet EM	0.061	0.248	0.805	0.342	1.488	0.140	
Spicejet EV	0.061	1.066	0.289	0.069	1.663	0.100	
Spicejet FN	−0.052	−0.452	0.652	−0.095	−1.675	0.098	*
Vistara EV	0.138	1.399	0.166	0.471	6.053	0.000	***
Vistara LN	−0.143	−1.561	0.122	−0.421	−6.266	0.000	***
Vistara FN	0.146	1.506	0.136	−0.064	−0.761	0.449	

Source: Primary Data Gretl Ouput

* Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

*** Represents significance at a 1% confidence interval

Models 11 and 12 have Indigo FN and AN flights as dependent variables. The prices of six other flights significantly influenced the prices of Indigo FN in model 11 at a 5% confidence interval. Out of these, two were from the related segments. The prices of seven flights significantly influenced the prices of Indigo AN flights in model 12 at a 5% confidence interval. At a 10% confidence interval, eight flights significantly influenced model 12. Out of these 12, four were from the related segments. In both models, dependent variables were not influenced by the prices of the same company's flights. In model 11, an increase in the prices of late-night flights of Air India and Indigo (coefficient being negative) may lead to a reduction in the price of Indigo FN2. As per model 12, an increase in the prices of GoAir, Indigo LN, and Vistara LN would reduce Indigo AN2 since the coefficient is negative. Table 5.22 show the regression results of Models 13 and 14.

Table 5.22

Regression Results - Models 13 & 14

Model	13				14			
Dependent Variable	Vistara EV				AirAsia EV			
Regressors	oefficient	t-ratio	p-value	Sig[!]	coefficient	t-ratio	p-value	Sig[!]
const	1.684	3.794	0.032	**	1.178	4.477	0.0208	**
AirAsia EM	0.301	3.643	0.036	**	0.192	4.227	0.0242	**
AirAsia EV	−0.445	−2.729	0.072	*				
AirIndia AN1	−0.022	−1.404	0.255		0.003	0.368	0.7372	
AirIndia AN2	−0.374	−3.776	0.033	**	0.060	1.123	0.3431	
Air India LN	−0.083	−0.732	0.517		−0.073	−1.168	0.3272	
AirIndia FN	0.279	3.458	0.041	**	0.004	0.093	0.9317	
GoAir EM	0.073	1.126	0.342		0.041	1.106	0.3495	
GoAir EV	0.002	0.065	0.952		−0.007	−0.324	0.7669	
GoAir LN	−0.002	−0.020	0.985		0.331	6.455	0.0075	***
Indigo AN1	−0.108	−0.665	0.554		0.319	3.599	0.0368	**
Indigo AN2	−0.018	−0.164	0.880		0.007	0.110	0.919	
Indigo AN3	0.767	7.342	0.005	***	0.141	2.37	0.0985	*
Indigo EM1	0.082	1.954	0.146		0.056	2.471	0.09	*
Indigo EM2	0.316	2.451	0.092	*	−0.133	−1.706	0.1866	

Indigo EV	−0.283	−1.504	0.230		−0.174	−1.737	0.1807	
Indigo LN1	0.226	1.435	0.247		0.213	2.633	0.0781	*
Indigo LN2	−0.447	−3.066	0.055	*	0.051	0.618	0.5804	
Indigo FN2	0.359	2.388	0.097	*	−0.143	−1.881	0.1566	
Indigo FN3	−0.525	−3.436	0.041	**	0.014	0.175	0.8722	
JetAirwaysEM	0.107	0.800	0.482		−0.105	−1.520	0.2258	
JetAirwaysEV	0.094	2.084	0.129		0.068	2.834	0.066	*
JetAirwaysFN	−0.0004	−0.003	0.998		0.050	0.795	0.4848	
Spicejet EM	−0.596	−3.760	0.033	**	−0.207	−2.164	0.1192	
Spicejet EV	0.031	0.631	0.573		0.046	1.89	0.1551	
Spicejet FN	0.254	3.968	0.029	**	−0.019	−0.533	0.6308	
Vistara EV					−0.127	−2.747	0.0709	*
Vistara LN	0.876	29.660	0.000	***	0.113	2.644	0.0774	*
Vistara FN	−0.169	−1.831	0.165		−0.032	−0.735	0.5156	

Source: Primary Data, Gretl Ouput

! * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

*** Represents significance at a 1% confidence interval

Evening flights of Vistara and Air Asia are the dependent variables of the regression models 13 and 14, respectively. As per the results shown in model 13 in Table 5.22, the dependent variable was significantly influenced by the prices of eight flights of six airline companies at a 5%

confidence interval. At a 10% confidence interval, 12 flights influence their prices. In model 14, only three flights significantly influence the prices of the dependant variable at a 5% confidence interval. At a 10% confidence interval, a total of nine flights significantly influenced the prices of Air Asia EV. In both models, dependent variables were not influenced by the prices of all the flights of the same company. In model 13, an increase in the prices of Air India AN2, Indigo FN3, and Spicejet EM (coefficient being negative) may lead to a reduction in the price of Vistara EV. Table 5.23 show the regression results of Models 15 and 16.

Table 5.23

Regression Results - Models 15 & 16

Model	15				16			
Dependent Variable	GoAir LN				Air India LN			
Regressors	coefficient	t-ratio	p-value	Sig[!]	coefficient	t-ratio	p-value	Sig[!]
const	−1.234	−2.676	0.075	*	1.450	3.873	0.031	**
AirAsia EM	−0.258	−3.115	0.053	*	−0.013	−0.202	0.853	
AirAsia EV	0.892	6.642	0.007	***	−0.162	−1.177	0.324	
AirIndiaAN1	−0.032	−2.146	0.121		0.009	0.617	0.581	
AirIndiaAN2	−0.007	−0.087	0.936		0.494	6.969	0.006	***
AirIndia LN	0.016	0.151	0.890					
AirIndia FN	0.046	0.616	0.581		0.260	4.425	0.021	**
GoAir EM	−0.046	−0.745	0.511		0.186	3.368	0.044	**

GoAir EV	0.121	3.701	0.034	**	0.050	1.466	0.239	
GoAir LN					0.013	0.151	0.890	
Indigo AN1	−0.762	−5.562	0.012	**	−0.267	−1.900	0.154	
Indigo AN2	−0.187	−1.888	0.155		−0.063	−0.676	0.548	
Indigo AN3	0.016	0.164	0.880		−0.009	−0.098	0.928	
Indigo EM1	−0.146	−4.122	0.026	**	0.075	2.254	0.110	
Indigo EM2	0.397	3.074	0.054	*	0.177	1.474	0.237	
Indigo EV	0.661	4.217	0.024	**	0.174	1.147	0.335	
Indigo LN1	−0.246	−1.813	0.168		0.493	4.311	0.023	**
Indigo LN2	0.043	0.318	0.771		−0.220	−1.950	0.146	
Indigo FN2	0.143	1.201	0.316		−0.574	−5.549	0.012	**
Indigo FN3	0.111	0.842	0.462		0.111	0.869	0.449	
JetAirways EM	0.616	6.016	0.009	***	−0.082	−0.731	0.518	
JetAirways EV	−0.137	−3.481	0.040	**	0.063	1.858	0.160	
JetAirways FN	−0.114	−1.082	0.358		−0.149	−1.646	0.198	
Spicejet EM	0.039	0.243	0.824		−0.102	−0.741	0.513	
Spicejet EV	−0.097	−2.667	0.076	*	0.031	0.822	0.471	
Spicejet FN	0.038	0.683	0.544		−0.086	−1.551	0.219	

Vistara EV	−0.002	−0.020	0.985	−0.052	−0.737	0.515	
Vistara LN	0.072	1.002	0.390	0.083	1.286	0.289	
Vistara FN	0.126	1.788	0.172	0.195	3.052	0.055	*

Source: Primary Data, Gretl Ouput

! * Represents significance at a 10% confidence interval

** Represents significance at a 5% confidence interval

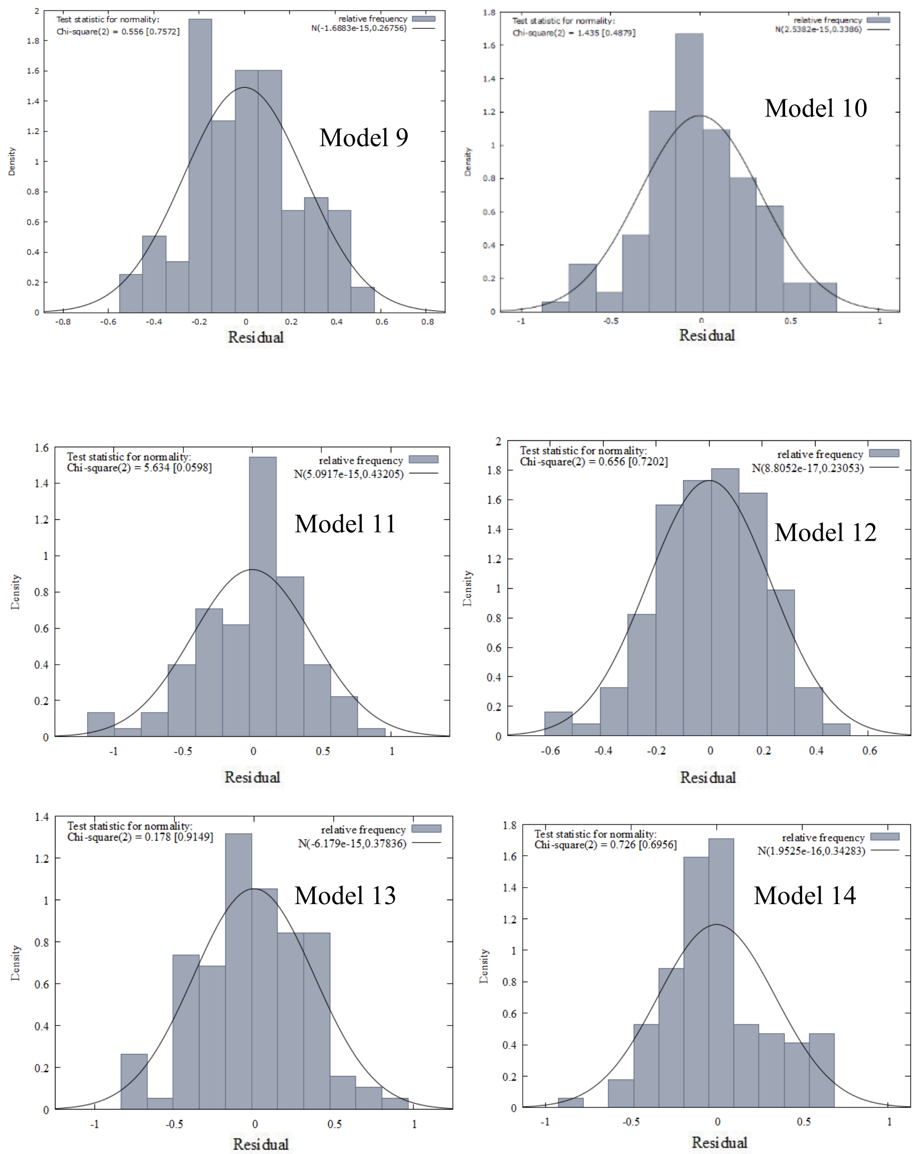
*** Represents significance at a 1% confidence interval

Late-night flights of Vistara and Air India were the dependent variables of the regression models 15 and 16, respectively. As per the results of model 15 in Table 5.23, the dependent variable was significantly influenced by the prices of seven flights of six airline companies at a 5% confidence interval. At a 10% confidence interval, ten flights influence their prices. In model 16, five flights significantly influence the prices of the dependent variable at a 5% confidence interval. At a 10% confidence interval, six flights significantly influenced the prices of Air India LN. In both models, dependent variables were not influenced by the prices of the same company's flights. In model 15, an increase in the prices of five flights with a negative coefficient may reduce the price of GoAir LN. An increase in the price of Indigo FN2 may reduce the prices of Air India LN, as the coefficient is negative in model 16.

An essential assumption of normality and linearity in Time series regression analysis is satisfied with all models of route O4, and the graphs are given in Figure 5.7. The normality graph also gives chi-square and P values (p>0.05). The figure also shows the Q-Q plots of models.

Figure 5.7

Model 9 to 16 - Normality of Residuals

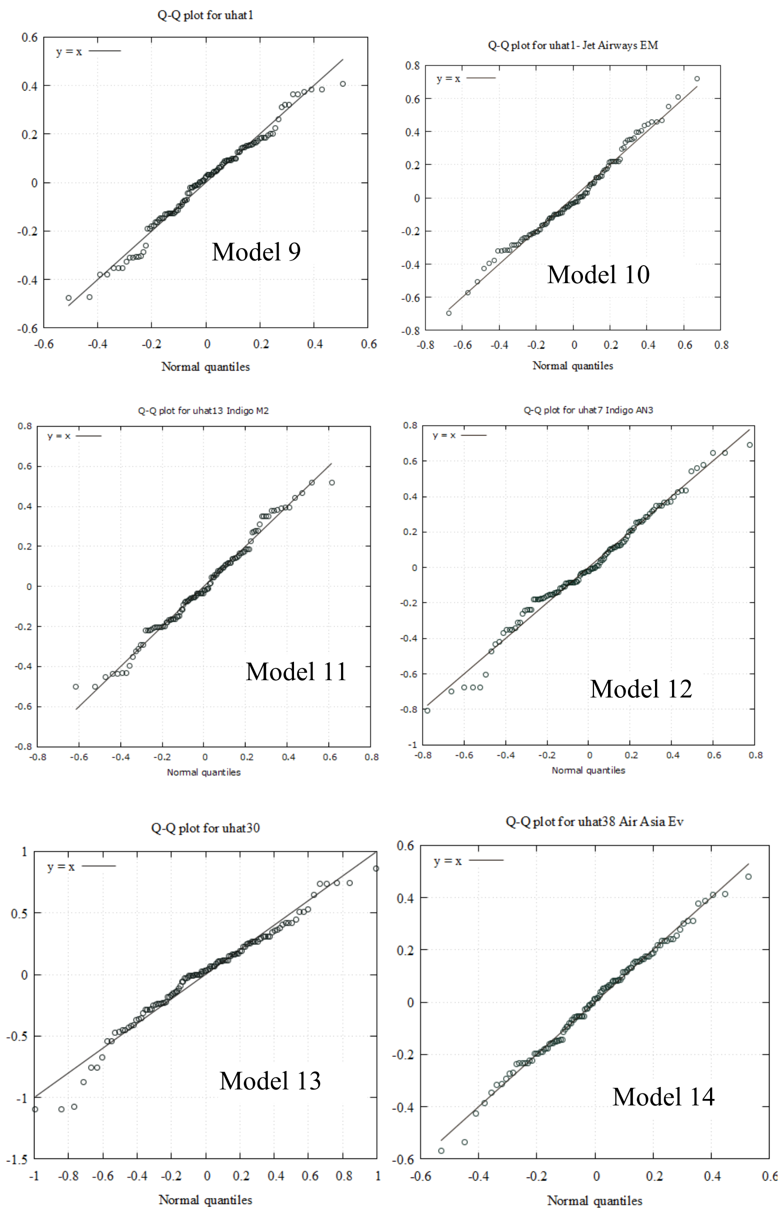


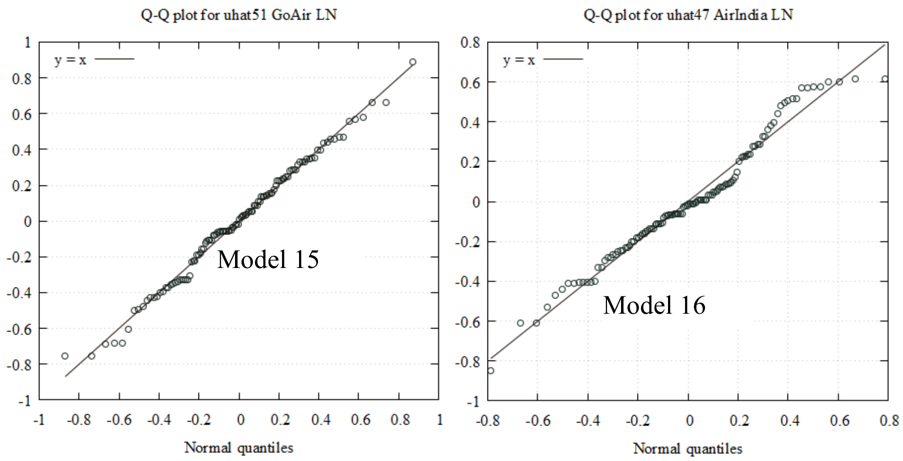
Source: Primary Data, Gretl Output

All the figures indicate that models 9 to 16 satisfy normality assumptions of regression. P values of the normality test given in the graphs are greater than 0.05 for all models. Chi-square values are also shown there in all normality graphs. Figure 5.8 shows the Q-Q plots of the models.

Figure 5.8

Model 9 to 16 - Q-Q Plot for uhat





Source: Primary Data Gretl, Output

The pattern closely follows the ascending line of the Q-Q plot, indicating normally distributed residuals. Models satisfied all other OLS assumptions of independence of observation, linear relationship, no autocorrelation, and homoscedasticity.

5.4.2.3 EDA- Route with more than 30 Flights

Route O5, the Mumbai-Bangalore route, is also one of the five high-density routes in India, which carried more than three lakh twenty thousand passengers in 2018 (DGCA, 2019). This route had 34 nonstop flights operated by five airline companies. Of the 34 airline companies, 32 were operating on all days of observation. Indigo and JetAirways were operating eleven flights each during the days of observation. Air India and GoAir had four flights each. Spicejet had only three flights. The following hypotheses are formed and tested with panel data regression analysis:

$H_{0\,25}$ The prices of other flights on the route does not significantly influence the prices of a flight on the route O5.

$H_{0\ 26}$ Time of booking does not significantly influence the prices of an airline on the route O5.

All 34 flights were included in models 17 and 18. For other models, two flights were excluded since they were not operating on all days. The researcher has considered the entire subsets of EM, FN, AN, EV, and LN flights and has conducted several regressions. Only those which satisfied the regression assumptions were selected for this research. Apart from panel specification and the Hausman test, the lowest values for AIC, SIC, and HQC were also considered. The selected include the following six models:

Model	Code*	Dependent variable
Model 17	Spi EM	EM flight of Spicejet (180 observations)
Model 18	JetA EM	EM flight of JetAirways (180 observations)
Model 19	Ind AN1	AN flight_1 of Indigo (360 observations)
Model 20	Ind EM	EM flight of Indigo (360 observations)
Model 21	JetA EM	EM flight of JetAirways (360 observations)
Model 22	Ind FN2	FN flight_2 of Indigo (360 observations)

Depending on the travel time, the researcher divided flights into five segments to examine the influence of adjacent flights: EM, FN, AN, EV, and LN. These abbreviations are suffixed with the name of flights for smooth observation. If there were more than one flight of an airline company in a segment, numbers were also suffixed. Pooled OLS, FE, and RE models were used depending on the selection criteria. Table 5.24 shows the results of the model selection tests.

Table 5.24

Model Selection Test Results –Models 17 to 22

Models	17	18	19	20	21	22
Panel Model Specification Test						
F	3.08	3.99	13.21	21.09	6.28	2.68
P	1E-02	2E-03	2E-20	3E-31	3E-09	6E-02
Decision	FE	FE	FE	FE	FE	POLS
Hausman test						
Chi-square	33.67	32.93	19.46	20.11	8.45	
P Value	3E-06	6E-27	4E-02	4E-02	7E-01	
Decision	FE	FE	FE	FE	RE	

Source: Primary Data, Gretl Output

Since the $p<0.05$, the panel specification test favoured the fixed effect alternative for models 17 to 21. Hausman test was conducted for these models, and test results favoured Fixed Effects, except for model 21. For model 22, F-test preferred POLS ($p>0.05$). Table 5.25 shows the model fit values for models 17 to 22.

Table 5.25

Regression Model Fit –Model 17 to 22

Model No.	17	18	19	20	21	22
Model	FE	FE	FE	FE	RE	POLS
Dependent Variables	Spi EM	JetA EM	Ind AN1	Ind EM	JetA EM	Ind FN2
No. of Observations	180	180	180	360	360	360
Mean Dependent var	6.012	7.022	8.839	6.879	7.303	7.929
S.D. Dependent var	1.683	1.892	1.518	1.929	1.964	2.117
Sum Squared resid	13.747	31.238	18.848	209.083	133.265	86.488
S.E. of Regression	0.350	0.528	0.407	0.552	0.680	0.613
Log-likelihood	−23.91	−97.78	−52.32	−83.01	−370.66	−239.12
LSDV R-squared	0.973	0.951	0.954	0.843	0.881	0.935
Within R-squared	0.961	0.906	0.944	0.740	0.799	0.905
rho	0.270	0.408	0.411	0.410	0.621	0.582
Durbin-Watson	1.416	1.115	1.164	1.244	0.746	0.806
AIC	183.8	331.6	236.64	970.0	807.9	618.2
SIC	401.0	548.7	447.38	1249.8	1087.7	877.5
HIC	271.9	419.6	322.08	1081.3	919.1	722.0

Source: Primary data, Gretl Output

LSDV R-squared values of all the models are above 0.80, indicating that the models explain more than 84% of changes in the dependent variable by the changes in independent variables. Within R-squared values are also above 74%, which shows the well fit of models. The lower Log-likelihood values also increase the blueness of the model. The rho value of Models indicates that the error term explains 27% to 62% of the variation and the other by the constant term for the concerned models. Rho of Models 17, 18, 19, 20, 21, and 22 indicates that the corresponding error term explains the variations by 27%, 40%, 41%, 41%, 62%, and 58%, respectively. Since $R^2 < d$ for models 17, 18, 19 and 20, the regressions are not spurious (Granger & Newbold, 1973). Chances of spurious regression exists for models 21 and 22, since, $R^2 > d$. Hence, these models are excluded from further analysis. AIC, SIC, and HIC were also the least for the selected models. Table 5.26 show the regression results of Models 17 and 18. Table 5.27 show the regression results of Model 19 and 20. All four models are Fixed Effect models with a time-series length of 30.

Table 5.26

Regression Results - Models 17 & 18

Model No.	17				18			
No. of Observations	180				180			
Cross-sectional units	6				6			
Dependent Variable	Spicejet EM				JetAirways EM			
Regressors	coefficient	t-ratio	p-value	Sig	coefficient	t-ratio	p-value	Sig
const	5.338	1.644	0.103		21.930	4.875	0.000	***

AirIndiaAN	−0.045	−1.939	0.055	*	−0.155	−4.750	0.000	***
AirIndiaFN1	−0.025	−0.358	0.721		0.220	2.165	0.033	**
AirIndiaFN2	−0.017	−0.337	0.737		0.012	0.167	0.868	
AirIndiaLN	0.221	2.482	0.015	**	−0.310	−2.301	0.023	**
GoAirAN	0.315	2.191	0.031	**	0.753	3.597	0.001	***
GoAirEM	0.029	0.220	0.827		0.133	0.677	0.500	
GoAirLN1	−0.406	−2.897	0.005	***	−0.218	−0.999	0.320	
GoAirLN2	−0.462	−1.692	0.093	*	−1.813	−4.772	0.000	***
IndigoAN1	0.374	4.118	0.000	***	0.766	5.989	0.000	***
IndigoAN2	−0.115	−1.270	0.207		−0.427	−3.255	0.002	***
IndigoEM	0.154	2.951	0.004	***	0.107	1.317	0.191	
IndigoEV1	−0.133	−1.755	0.082	*	0.006	0.049	0.961	
IndigoEV2	−0.081	−1.192	0.236		0.066	0.646	0.520	
IndigoEV3	0.186	2.911	0.004	***	0.219	2.233	0.028	**
IndigoFN1	0.077	1.335	0.184		−0.021	−0.238	0.812	

IndigoFN2	−0.123	−1.778	0.078	*	−0.649	−7.551	0.000	***
IndigoFN3	−0.313	−3.280	0.001	***	0.049	0.326	0.745	
IndigoLN1	−0.041	−0.617	0.538		0.078	0.790	0.431	
IndigoLN2	0.030	0.600	0.550		0.036	0.471	0.639	
IndigoLN3	−0.053	−1.004	0.317		−0.039	−0.494	0.623	
JetAirwaysAN1	0.151	2.662	0.009	***	0.343	4.182	0.000	***
JetAirwaysAN2	0.067	1.513	0.133		−0.083	−1.256	0.212	
JetAirwaysEM	−0.075	−1.196	0.234					
JetAirwaysEV1	−0.180	−2.472	0.015	**	−0.084	−0.751	0.454	
JetAirwaysEV2	0.020	0.261	0.794		0.377	3.342	0.001	***
JetAirwaysFN1	0.185	2.365	0.020	**	0.529	4.799	0.000	***
JetAirwaysFN2	−0.109	−1.536	0.127		−0.448	−4.481	0.000	***
JetAirwaysFN3	−0.116	−1.866	0.065	*	−0.052	−0.544	0.587	
JetAirwaysFN4	−0.040	−0.743	0.459		−0.029	−0.358	0.721	

JetAirwaysLN 1	0.173	2.053	0.042	**	−0.069	−0.532	0.596	
JetAirwaysLN:	−0.063	−0.582	0.562		−0.303	−1.883	0.062	*
Spicejet EM					−0.169	−1.196	0.234	
Spicejet EV	0.062	0.696	0.488		−0.127	−0.949	0.345	
Spicejet FN	0.524	6.543	0.0001	***	0.064	0.453	0.652	
dat_2	−0.056	−0.265	0.7913		−0.110	−0.348	0.729	
dat_3	−0.029	−0.139	0.8897		0.045	0.142	0.888	
dat_4	0.014	0.061	0.9517		−0.247	−0.736	0.464	
dat_5	−0.165	−0.711	0.4785		−0.717	−2.091	0.039	**
dat_6	0.081	0.352	0.7254		−0.386	−1.119	0.266	
dat_7	0.315	1.213	0.2279		−0.224	−0.569	0.571	
dat_8	0.170	0.631	0.5294		−0.378	−0.933	0.353	
dat_9	0.258	0.918	0.3608		−0.742	−1.770	0.080	*
dat_10	0.375	1.315	0.1912		−0.647	−1.508	0.134	
dat_11	0.502	1.853	0.0665	*	−0.756	−1.850	0.067	*
dat_12	0.568	1.984	0.0497	**	−1.365	−3.254	0.002	***
dat_13	0.482	1.654	0.1009		−1.489	−3.530	0.001	***
dat_14	0.569	1.936	0.0554	*	−1.242	−2.855	0.005	***

dat_15	0.880	2.919	0.0043	***	−1.096	−2.384	0.019	**
dat_16	0.951	3.029	0.003	***	−1.270	−2.661	0.009	***
dat_17	1.095	3.325	0.0012	***	−1.099	−2.156	0.033	**
dat_18	1.417	4.039	0.0001	***	−0.863	−1.540	0.126	
dat_19	1.388	3.649	0.0004	***	−0.386	−0.638	0.525	
dat_20	1.178	2.937	0.004	***	−0.186	−0.297	0.767	
dat_21	1.140	2.726	0.0074	***	−0.298	−0.458	0.648	
dat_22	1.065	2.477	0.0147	**	−0.002	−0.003	0.997	
dat_23	1.227	2.85	0.0052	***	−0.073	−0.108	0.914	
dat_24	1.201	2.752	0.0069	***	0.006	0.008	0.994	
dat_25	1.197	2.706	0.0079	***	−0.221	−0.321	0.749	
dat_26	1.389	3.065	0.0027	***	−0.260	−0.366	0.715	
dat_27	1.825	3.882	0.0002	***	0.259	0.344	0.732	
dat_28	1.375	2.899	0.0045	***	0.425	0.574	0.567	
dat_29	1.500	3.195	0.0018	***	1.41	1.939	0.055	*
dat_30	1.629	3.454	0.0008	***	1.72	2.357	0.020	**

Source: Primary Data, Gretl Output

As the table shows, the prices of the early morning flight of Spicejet are significantly influenced by the prices of 17 flights at a 10% significance level and 12 flights at a 5% significance level in model 17. It includes the prices of four other airline companies. The prices depend mostly on the prices of Indigo and Jet Airways. It is also evident that the prices of the AN, LN, and FN flights influence the prices of the EM flight of Spicejet more than other early morning flights. This may be the result of the strategy to attract time-flexible travellers from other brands. In model 18, the prices of the early morning flight of JetAirways are significantly influenced by the prices of 14 other flights. Here the prices are mostly influenced by the prices of the same airline company. FN, AN, EV, and LN flights of the same company influence the prices of its EM flight. This indicates the loyal brand customers who prefer to travel on the brand. Two of the five significant flights had negative coefficients indicating price movement in the opposite direction. This can be another strategy to keep the brand-loyal, semi-flexible, but price-sensitive travellers to remain loyal to the airline. Two Air India flights also showed significant but negative coefficients. Prices of four Indigo flights and two GoAir prices also significantly influence the prices. There is no significant influence of Spicejet on the prices of Jet Airways. The time effect seems to be there from the eleventh day of observation on Spiccejet. There was a significant influence of time of booking on the prices of Jet Airways from the 17^{th} day of observation with negative coefficients. The findings in model 17 support the findings of Petrovic (There is no monotonic increase or decrease in price with the closeness to the time of departure), Bilotkach, and Gillen (price increases drastically as the departure date is closer) (Bilotkach et al., 2015) (Petrovic et al., 2011) (Gillen & Hazledine, 2006), while the findings contradict in model 18. This can be because a brand-sensitive traveller always gives importance to the brand rather than price to enable the brand to set initial prices as high. Test results of fixed effect models 19 and 20 are given in Table 5.27.

Table 5.27

Regression Results - Models 19 & 20

Model No.		19				20		
No. of Observations		180				360		
Cross-sectional units		6				12		
Dependent Variable		Indigo AN1				Indigo EM		
Regressors	coefficient	t-ratio	p-value		coefficient	t-ratio	p-value	Sig
const	−11.010	−3.359	0.001	***	−1.598	−0.717	0.474	
AirIndiaAN	0.050	2.054	0.042	**	0.090	3.162	0.002	***
AirIndiaFN1	−0.014	−0.179	0.859		−0.066	−0.963	0.337	
AirIndiaFN2	−0.121	−2.205	0.029	**	0.103	2.03	0.043	**
AirIndiaLN	−0.152	−1.478	0.142		0.137	1.852	0.065	*
GoAirAN	0.062	0.383	0.702		0.016	0.139	0.890	
GoAirEM	0.131	0.879	0.381		0.258	2.498	0.013	**
GoAirLN1	−0.065	−0.389	0.698		0.264	1.789	0.075	*
GoAirLN2	0.747	2.662	0.009	***	−0.036	−0.179	0.858	
IndigoAN1					0.568	5.748	0.001	***
IndigoAN2	0.745	12.790	0.000	***	−0.191	−1.914	0.057	*
IndigoEM	0.136	2.583	0.011	**				

IndigoEV2	−0.044	−0.564	0.574		0.053	0.606	0.545	
IndigoEV3	0.118	1.648	0.102		0.174	2.639	0.009	***
IndigoFN1	−0.244	−3.856	0.000	***	0.196	3.053	0.003	***
IndigoFN2	0.157	2.440	0.016	**	0.089	1.171	0.243	
IndigoFN3	0.059	0.540	0.590		0.094	1.11	0.268	
IndigoLN1	0.078	1.030	0.305		−0.190	−2.497	0.013	**
IndigoLN2	0.109	1.920	0.057	*	0.041	0.612	0.541	
IndigoLN3	0.144	2.906	0.004	***	−0.187	−2.737	0.007	***
JetAirwaysAN1	−0.040	−0.660	0.510		−0.090	−1.434	0.153	
JetAirwaysAN2	0.147	3.043	0.003	***	−0.095	−1.933	0.054	*
JetAirwaysEM					−0.086	−1.173	0.242	
JetAirwaysEV1	0.177	2.129	0.035	**	0.085	1.215	0.225	
JetAirwaysEV2	−0.045	−0.534	0.594		−0.029	−0.353	0.724	
JetAirwaysFN1	−0.370	−5.283	0.000	***	0.079	1.139	0.256	
JetAirwaysFN2	0.213	3.258	0.002	***	0.066	0.952	0.342	
JetAirwaysFN3	0.034	0.462	0.645		−0.175	−2.873	0.004	***
JetAirwaysFN4	0.070	1.198	0.233		−0.089	−1.956	0.052	*
JetAirwaysLN1	−0.124	−1.294	0.198		0.167	1.765	0.079	*

JetAirwaysLN2	0.247	2.218	0.029	**	−0.153	−1.543	0.124	
Spicejet EM	0.372	3.663	0.000	***				
Spicejet EV	−0.1436	−1.432	0.155		−0.075	−1.942	0.053	*
Spicejet FN	0.034	0.311	0.757		0.182	2.277	0.024	**
dat_2	0.066	0.272	0.786		0.039	0.111	0.912	
dat_3	0.097	0.394	0.695		−0.027	−0.075	0.940	
dat_4	0.179	0.693	0.490		−0.218	−0.604	0.546	
dat_5	0.093	0.352	0.726		−0.217	−0.590	0.556	
dat_6	−0.028	−0.107	0.915		−0.307	−0.831	0.406	
dat_7	−0.194	−0.643	0.522		−0.105	−0.273	0.785	
dat_8	−0.097	−0.314	0.754		−0.068	−0.173	0.863	
dat_9	−0.248	−0.776	0.439		0.092	0.228	0.820	
dat_10	−0.292	−0.891	0.375		0.021	0.051	0.960	
dat_11	−0.516	−1.663	0.099	*	−0.164	−0.396	0.693	
dat_12	−0.577	−1.824	0.071	*	−0.021	−0.050	0.960	
dat_13	−0.443	−1.381	0.170		−0.247	−0.573	0.567	
dat_14	−0.678	−2.068	0.041	**	−0.325	−0.741	0.459	
dat_15	−0.938	−2.735	0.007	***	−0.360	−0.782	0.435	

dat_16	−1.054	−2.979	0.004	***	−0.563	−1.210	0.227	
dat_17	−0.942	−2.480	0.015	**	−0.897	−1.812	0.071	*
dat_18	−0.965	−2.326	0.022	**	−1.263	−2.531	0.012	**
dat_19	−0.869	−1.932	0.056	*	−1.126	−2.156	0.032	**
dat_20	−0.609	−1.296	0.198		−1.441	−2.695	0.008	***
dat_21	−0.792	−1.638	0.104		−1.644	−2.931	0.004	***
dat_22	−1.107	−2.273	0.025	**	−1.592	−2.763	0.006	***
dat_23	−1.113	−2.266	0.025	**	−1.679	−2.923	0.004	***
dat_24	−1.149	−2.296	0.024	**	−2.064	−3.415	0.001	***
dat_25	−1.186	−2.334	0.021	**	−2.095	−3.361	0.001	***
dat_26	−1.501	−2.865	0.005	***	−1.864	−2.960	0.003	***
dat_27	−2.035	−3.766	0.000	***	−1.041	−1.601	0.111	
dat_28	−1.813	−3.373	0.001	***	−0.892	−1.352	0.177	
dat_29	−1.845	−3.519	0.001	***	−1.083	−1.686	0.093	*
dat_30	−1.768	−3.349	0.001	***	−1.246	−1.947	0.053	*

Source: Primary Data, Gretl Output

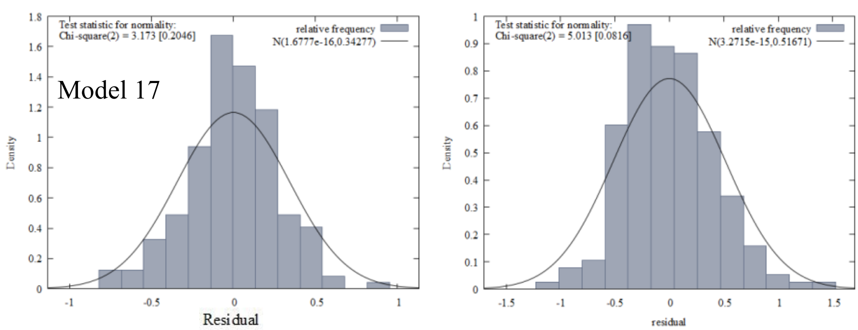
As the results in Table 5.27 show, the afternoon flight of Indigo is influenced by the prices of 15 other flights, including the prices of six flights of the same airline company. Five FN, four LN, three AN, two EM, and one EV flight significantly influence the AN flight under observation in Model 19. This indicates the complex nature of the pricing mechanism of the airline industry. As per the regression analysis results, booking time significantly influences prices from the 11th day of observation only. Negative coefficients from the sixth day of observation indicated a price reduction from the 24th day to departure.

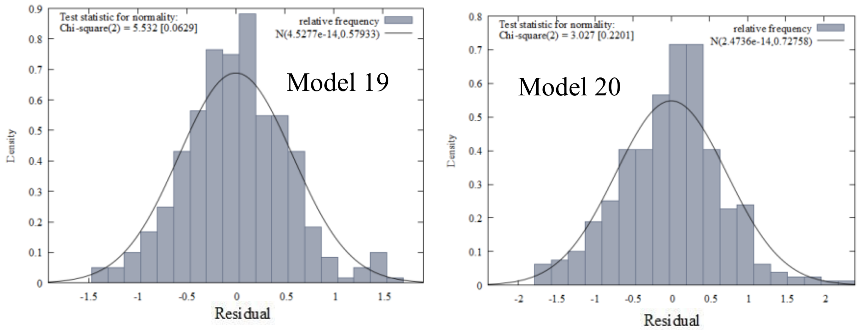
In the case of Model 20, the prices of 17 flights significantly influence the prices of the dependent variable Indigo EM. The prices are significantly influenced by forenoon flights and late-night flights, the time segments before and after the EM. As in the case of Spicejet, all brands influence the prices. In all three models, the prices of the same-time segment flights do not significantly influence the prices. This indicates the presence of brand and time-sensitive travellers on the route. The time effect shows a negative coefficient, indicating a decline in price with the time of booking, as in the case of Jet Airways. These results also show that the setting of a high price at the initial level by a top brand to tap more from brand-sensitive travellers.

The most important assumption of normality in Time series regression analysis is satisfied with all models, and the graphs are given in Figure 5.9. The normality graph shows the Chi-square and P values (p>0.05). Figure 5.10 show the Q-Q plot of the model.

Figure 5.9

Models 17, 18, 20, and 21 - Normality of Residuals

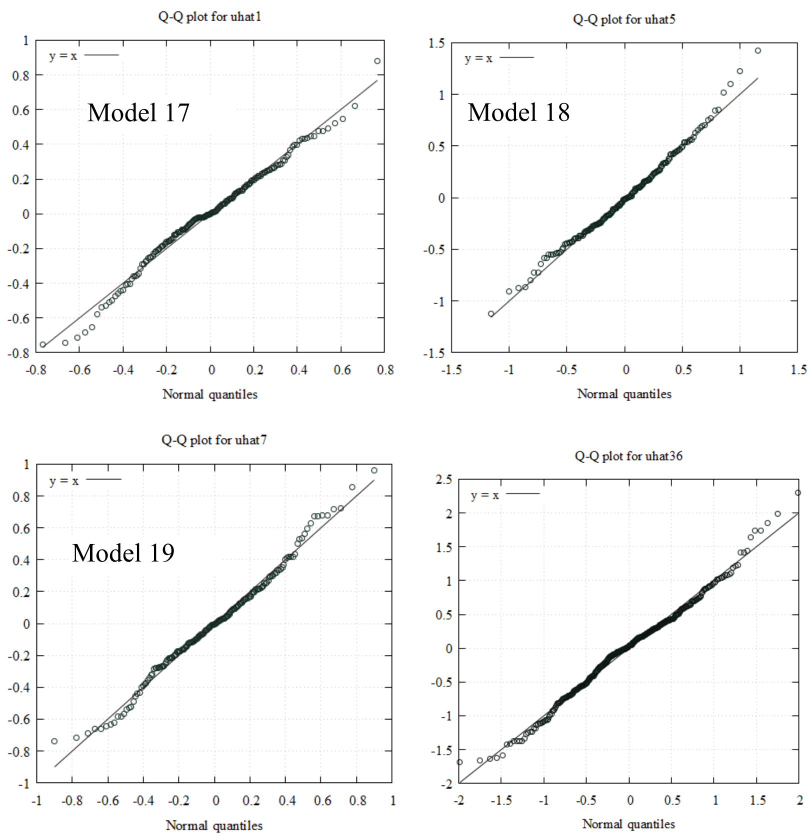




Source: Primary Data, Gretl Output

Figure 5.10

Models 17, 18, 20, and 21 - Q-Q Plot for uhat



Source: Primary Data, Gretl Output

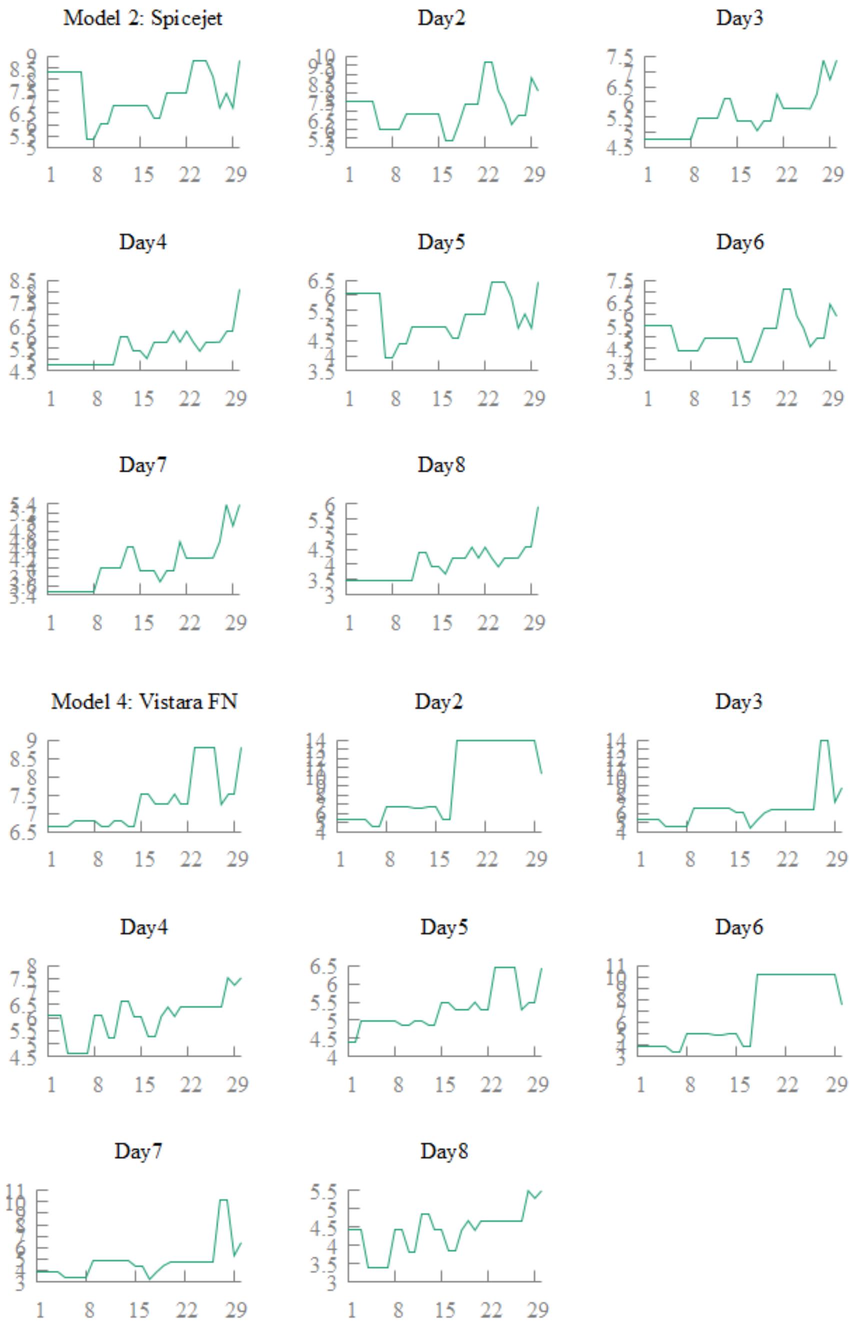
5.4.2.4 Time Series Plot of Selected Flights

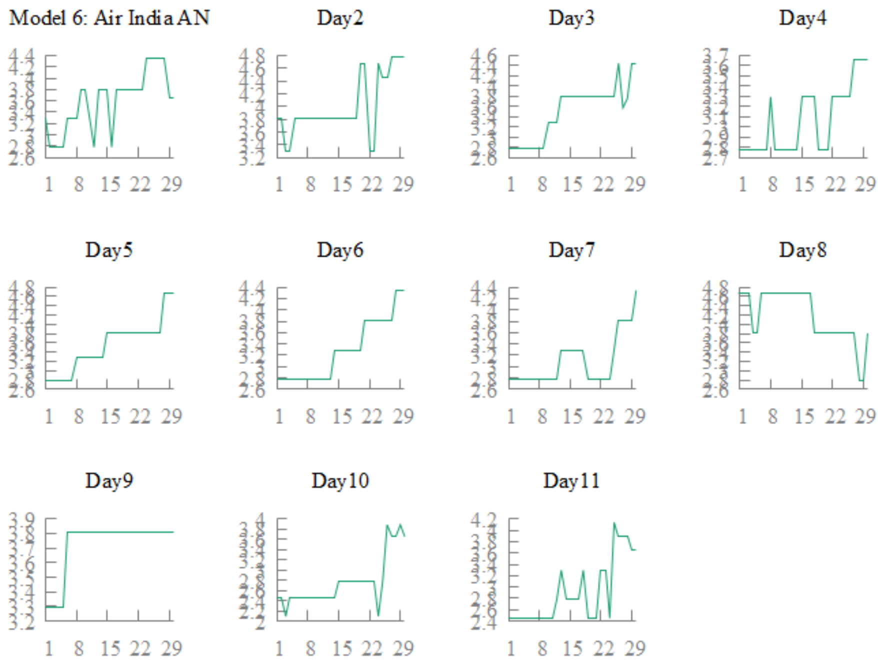
The traditional and general concept of the nature of airline prices was that 'price increases monotonically as the departure date is nearer' (Kakwani, 1980) (Lee, 2009). Supporting this, Alderighi argued that their evidence reveals fares increase monotonically over the last three weeks before departure (Alderighi et al., 2012). This argument is supported by the findings of (Siegert & Ulbricht, 2015), (Sengupta & Wiggins, 2014), and (Yusheng Hu et al., 2015). The findings of Petrovic and Gillen contradict the traditional view that the price function concerning flight time is neither monotonically increasing nor decreasing (Gillen & Hazledine, 2006) (Petrovic et al., 2011). This non-monotonic relationship was also proved by many other researchers, including (Urday, 2008), (Nair, 2010), (Williams, 2020), (Durba & Kutlu, 2014), and (Szopiński & Nowacki, 2014).

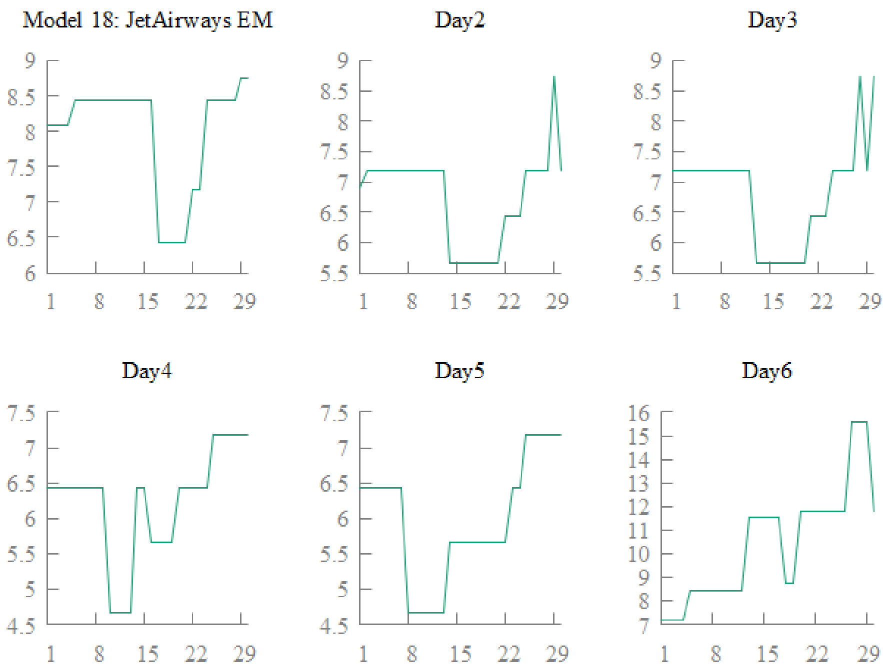
In this research, 20 models are presented, and the time trends support the traditional arguments of monotonically increasing relationships with the exceptions of models 2, 4, 6, 18, 19, and 20. There were negative β coefficients for time effects observed in these models. Time trend analysis is conducted to determine whether these models contradict the traditional monotonically increasing price concept to prove that prices tend to decline as the departure date is closer. Figure 5.11 shows the time series plot of airlines with negative β coefficients of time.

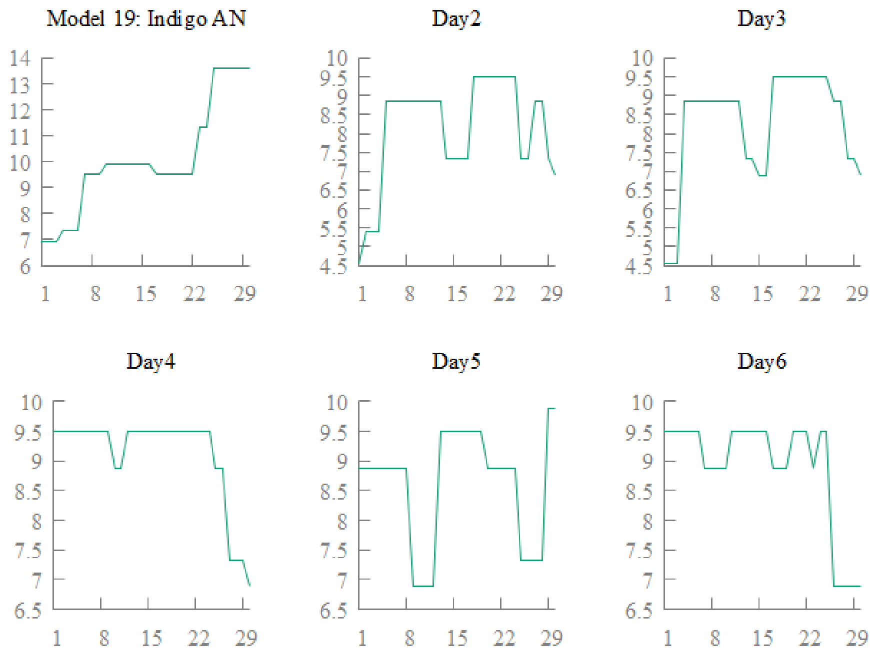
Figure 5.11

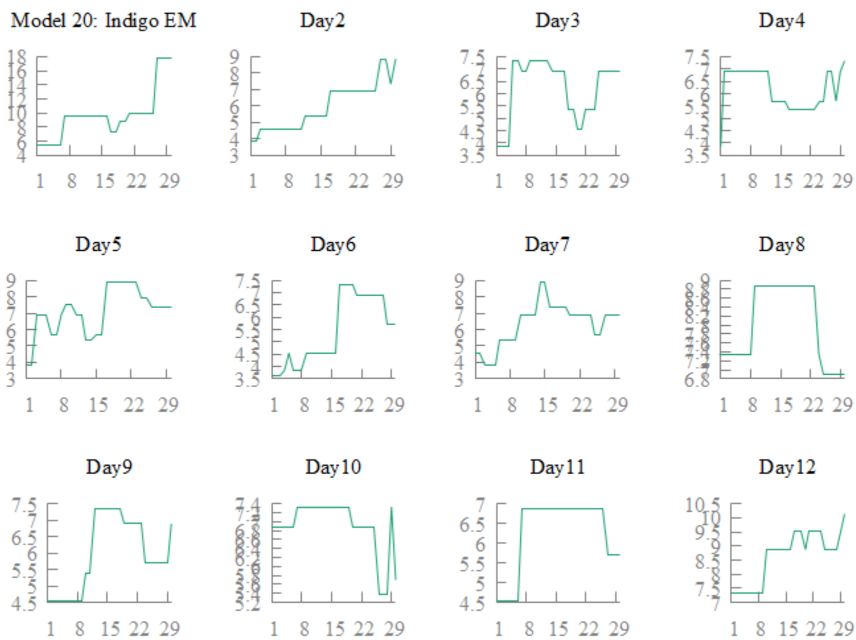
Time Series Plots with Negative Slops




Model 6: Air India AN
Day2
Day3
Day4
Day5
Day6
Day7
Day8
Day9
Day10
Day11


Model 18: JetAirways EM
Day2
Day3
Day4
Day5
Day6





Source: Primary Data, Gretl Output

As evident from the figure, prices do not show a strict 'monotonically decreasing' trend in any case. But there are clear ups and downs of prices quoted by airlines many days. On many days prices show a sharp decline between 10-15 days to departure. Hence it is concluded that prices do not follow a strict 'monotonically increasing' trend. Price may decline depending on the demand as the departure date is near. The results of these models contradict the finding of Santra and Dutta (Santra & Dutta, 2015), while the other models support them.

5.5 Discussion of the Results and Interpretation

The chapter discussed the price dispersion in the moderately concentrated markets of India with the tools Gini coefficient and Lorenz curve. Overall dispersion indicated by the Gini coefficient ranges from 0.122 to 0.233 (It was 0.115 to 0.275 under monopoly routes, 0.084 to 0.105 under partial monopoly, and 0.173 to 0.247 under triopoly). The overall dispersion indicated by the Gini coefficient was 0.250. (It was 0.361 in the concentrated market). Routes influence this dispersion. Dispersion varies with time segments and the departure time of the flight.

In many cases, a sharp reduction was observed between 10 to 15 days before the departure date. This observation was made in the concentrated market also. All airlines offered the minimum price during festival season and or weekends, except the market leader Indigo. Festival days and weekend days marked the minimum price on the routes with less number of flights. But Indigo offered a minimum price on weekdays/ordinary days on the routes with 30 or more flights. On all routes, companies offered a minimum fare, before 27 days to departure. Hence advance booking is necessary for a traveller to capture the minimum price. Air India offered maximum fare on all routes except O4, where Jet Airways offered it. On all routes, Sundays showed maximum fare. Jet Airways offered maximum prices during festival season and weekends on route O4. On all routes, it was close to departure dates. On concentrated routes, high bucket fares were offered even 20 to 15 days before departure. The time of booking influences the price to be paid by the traveller. But there are some pieces of evidence of getting reduced price, though not the minimum, even at a late booking for some airlines. It was evident from the negative coefficients of Spicejet and Vistara on routes O1 and O2. Air India, JetAirways, and Indigo also showed negative coefficients on other routes. It supports the findings of Urday Escobari that the increase is not necessarily monotonic (Urday, 2008). But it contradicts the findings of Alderighi that fares increase monotonically over the last three weeks before departure (Alderighi et al., 2012) and the observations of Sandra in the Indian context (Santra & Dutta, 2015). There exists a significant correlation between the movement of prices of a day. It doesn't mean that the prices of all other airlines significantly influence an airline's prices on the day. In most of the regression models, the time gap between the date of departure and the date of booking significantly influenced the ticket price. This observation goes in parity with the observations of concentrated markets.

Chapter 6

Findings, Implications, and Future Research

6.1 Introduction

Price discrimination has been used for revenue maximisation by merchants in various forms. Even though price discrimination based on gender, race, colour, caste, religion, etc., has been illegal unless it aims to advance that weaker section, discrimination in the form of cash discounts, trade discounts, seasonal offers, etc., was commonly accepted practices followed by business people. While seasonal pricing in many sectors of the tourism industry creates seasonal price discrimination, dynamic pricing in the airline industry creates real-time price discrimination based on the booking time. Demand anticipation also plays a role in making this airline's price dynamic.

6.2 Study in Retrospect

The government takes maximum retail price, price ceiling, floor pricing, and various other regulatory measures to eliminate price discrimination in India. The travel sector had been considered an essential service sector with government-controlled fares. After the deregulation of airfares and with the emergence of the LCC sector, price discrimination based on the time of booking turned into the globally accepted face of airline ticket prices. But a booking in advance does not necessarily ensures a least-priced ticket. This dynamic pricing has become a common practice in the civil aviation sector. The researcher has observed a difference of nearly ₹10,000/- for a one-hour trip from Kochi to Bangalore on the same flight without any change in the service quality. Between the same category flights, the difference increased further.

The introduction of the LCC sector has changed the airline mode of travel from a luxury label to an affordable means for the lower middle class. Moreover, introducing LCC increased passenger traffic dramatically and continuously from year to year. The trending dynamic pricing strategy is a key reason for these developments, primarily because it catalyses the demand for a perishable product with close substitutes. Internet penetration techniques and seat classification techniques within LCCs have accelerated the growth of civil aviation worldwide. Dynamic pricing is an approach to optimise revenue by influencing the purchase decisions of customers on a perishable and limited supply of travel seats. Hence, an increase in price with an increase in expected demand is always visible in this sector. A limited number of seats or limited supply, close substitutes of travel or dynamic demand and the perishable nature of product make air travel and its pricing more complex. The market also fluctuates with the price elasticity of travellers since there are other modes of travel, including train service, especially on the domestic route. Thus, airline seats are a time-dated product that expires at a point in time. Therefore, frequent modifications of prices and the set of other pricing strategies practically work as a price discovery mechanism.

Even though the Indian civil aviation industry has been showing steady growth since its beginning, a dramatic increase in passenger traffic was noticed in 2003. The introduction of LCC with a dynamic pricing strategy was an associated change in the service and pricing traditions that prevailed in the civil aviation system. Moreover, the industry became a sector that directly influences nearly 200 million people. However, the passengers rarely criticised the first-degree discrimination created by dynamic pricing. The National Transport Development Policy Committee suggested the government to regulate air travel service pricing in India to offer non-predatory, non-discriminatory and reasonable prices for air travellers and transparency in pricing, quoting two of such rare criticisms in 2013 (NTDPC, 2013).

In Europe, Australia, the United States of America (US), and a few Asian countries like China, several studies have been conducted by researchers on civil aviation. These researches contribute to the literature, benefiting the industry and travellers. However, comparatively few research articles in India have been published in this area, irrespective of their importance. The present study intends to explore some of the essential areas ignored by the researchers on the price dynamics of domestic civil aviation market of India. First-degree price discrimination generally evokes criticism; the airline industry seems to be an exception. While considering the ethical aspects of discrimination, an essential factor to be considered is the growth of the civil aviation industry on the shoulders of LCC.

In this situation, the present research was conducted to address the following questions related to the dynamic pricing in the domestic civil aviation of India:

1. Does India's civil aviation industry show a different growth pattern after introducing price dynamics?
2. What is the extent of price dispersion due to price dynamics?
3. Does the dispersion vary with market concentration?
4. What are the determinants of price dynamics?
5. Do all airlines show an increasing price with closeness to departure?

The scope of the study is limited to India's domestic civil aviation market with scheduled flights. The passenger traffic growth of India was compared with that of a few other selected nations to address the question of the pattern of growth. The primary objective of the present study is to conduct a major investigation into the various aspects of price dynamics in the Indian civil aviation segment. The following were the specific objectives of the study:

1. To study whether the Indian civil aviation industry shows a different growth pattern after dynamic pricing became ubiquitous.
2. To analyse the price dispersion based on market concentration in the domestic civil aviation of India.
3. To explore the determinants of price dispersion caused by dynamic pricing in the domestic civil aviation of India.

The following hypotheses are formulated based on the literature review and the research objectives.

$H_{0\,1} - H_{0\,6}$	Air Passenger Traffic growth is not co-integrated with the per capita GDP of the nation before and after dynamic pricing became ubiquitous.
$H_{0\,7} - H_{0\,9}$	Price movements of neighbouring days of departure of the same airline are not significantly correlated under different market situations, viz, monopoly, partial monopoly, and triopoly.
$H_{0\,10} - H_{0\,11}$	Price movements of competing airlines on the same day are not significantly correlated under different market concentrations, viz partial monopoly and triopoly.
$H_{0\,12} - H_{0\,14}$	Booking prices are not significantly correlated to the time gap to the departure date under different

market situation, viz, monopoly, partial monopoly, and triopoly.

$H_{0\,15} – H_{0\,17}$ Neighbouring day prices does not significantly influence the festival day prices under different market situation, viz, monopoly, partial monopoly, and triopoly.

$H_{0\,18} – H_{0\,19}$ The prices of different time segments are not significantly correlated.

$H_{0\,20} – H_{0\,26}$ The prices of other flights on the route or the time of booking does not significantly influence the prices of a flight.

The study has mainly two parts. This book deals with part one, which deals with the analysis of price dispersion. Part two deals with the customer perception of airline price dynamics.

Various econometric tools were used for the analysis of the first part, like the Gini coefficient and Lorenz Curve, Herfindahl-Hirschman Index, Time series plots, Kendall's rank correlation tau analysis, Augmented Dickey-Fuller unit root, Engle-Granger cointegration test, Ordinary Least Square model, Panel Data Models of Pooled Ordinary Least Square, Fixed Effects, Random Effects, and Weighted Least Square, Panel Specification Test, Hausman test, and Chi-square test. The data analysis was done with the help of MS Excel, open-source software Gretl and Smart PLS4.

6.3 Summary of Major Findings

Justification of price discrimination based on dynamic pricing on the grounds of growth in the civil aviation sector, the extent of price dispersion and its pattern, antecedents of dynamic prices, passengers' attitudes towards dynamic pricing, the antecedents of such attitudes, and the demographic differences with attitudes are the major areas on which the data analysis has contributed lights. These findings are discussed briefly under different heads.

6.3.1 Pattern of Growth of Indian Civil Aviation

The growth pattern of the civil aviation industry before and after the introduction of dynamic pricing was compared with that of selected nations. Time series data analysis from 1970 to 2020 revealed that:

1. Domestic civil aviation continued to increase in passenger traffic from its introduction.
2. The three shifts in government policies, viz. privatisation, nationalisation, and liberalisation, have not affected the growth pattern.
3. Liberalisation accelerated the growth of the civil aviation industry globally. However, the year of acceleration and liberalisation was not the same.
4. Generally, the growth of the airline industry in terms of passenger traffic moves in the same direction as the GDP per capita of the nation. However, cointegrated movements are not common.
5. Growth of the airline industry in terms of passenger traffic is significantly influenced by GDP per capita, before and after the dynamic pricing became ubiquitous.
6. In India, the growth of the airline industry in terms of passenger traffic and GDP per capita growth showed a cointegrated movement before and after the dynamic pricing became ubiquitous.

7. In India, the growth of the domestic airline industry in terms of passenger traffic and GDP per capita growth showed a cointegrated movement after the dynamic pricing became ubiquitous but not before the introduction of dynamic pricing.

6.3.2 Price Dispersion Based on Market Concentration

8. Monopoly routes showed a Gini coefficient dispersion ranging from 0.115 to 0.275. The dispersion of flights under partial monopoly ranges from 0.084 to 0.105, and triopoly ranges from 0.173 to 0.242. Under oligopoly, this varied between 0.122 to 0.233. The Gini coefficient of more than 0.25 shows a more than 50% difference from the mean fare.
9. Monopoly markets tend to have higher mean airfares, greater variability, higher inequality, and wider spreads of prices compared to partial monopoly and triopoly markets. Partial monopoly and triopoly markets show more moderate levels of mean airfares, variability, inequality, and a more concentrated range of prices.
10. The dispersion of flights under partial monopoly, triopoly, or oligopoly was not equal. However, dispersion is comparatively less in oligopoly. In other words, even though dispersion is comparatively less under oligopoly, dispersion doesn't follow a specific pattern.
11. The minimum fare offered in the monopoly routes ranges from ₹3.98 to ₹8.49 per km. Under the partial monopoly, the minimum price was ₹3.29 per km. Under triopoly it was ₹0.90 per km. Under oligopoly, it went from ₹1.76 to ₹4.25. On average, competition decreases the minimum fare. Moreover, a firm faces stiff

competition where there is less passenger traffic, as in the case of a triopoly situation.

12. The minimum price was offered 27 days before departure under all selected routes. This is an indication that advance booking before 27 days may help to minimise the cost of the ticket.
13. The maximum fare offered in the monopoly routes ranges from ₹11.36 to ₹53.63 per km. Under the partial monopoly, the maximum price was ₹9.06 and in the triopoly, it was ₹21.91 per km. Maximum price under oligopoly ranged from ₹17.43 to ₹24.46 per km. These indicate that the maximum price does not follow a specific pattern.
14. The maximum price was offered 10 to 2 days before departure under all selected routes. This increases the chances of a penalty to a last-minute passenger in the form of a price hike.
15. The mean price ranges from ₹5.25 to ₹24.06 per km under monopoly routes. Under partial monopoly, it was ₹5.10; in triopoly, it was ₹8.83 per km. It was from ₹3.13 to ₹9.31 per km under oligopoly.
16. Most airfare prices are concentrated around the mean, implying a roughly symmetric distribution. But some higher-priced fares are pulling the mean towards the right, creating a right-skewed distribution. Median values are lower than the mean for all routes indicating high prices at dates closer to departure.
17. Overall dispersion was higher for the short-distanced routes under monopoly. Price dispersion under partial monopoly was lower than monopoly and triopoly routes. It was the lowest for oligopoly.
18. Price dispersion differs with route and airline company under a concentrated market. Price dispersion was lowest for Spicejet and highest for Truejet under monopoly. Under the triopoly, the

dispersion was highest for Air India and lowest for Jet Airways. Dispersion of Indigo indicated by Gini coefficient ranges from 0.105 to 0.178, JetAirways ranged from 0.173 to 0.275. The overall dispersion of the concentrated market was 0.361.

19. GoAir, Vistara, and Indigo offered the lowest fare under oligopoly for different routes. However, the then-national carrier Air India quoted the highest fare on four out of five sample oligopoly routes.
20. Price dispersion varies with days of departure, airline company, and route under a concentrated market.
21. Day of departure-wise price dispersion was lower than the overall dispersion on concentrated markets. This indicates that day of departure influences the price dispersion.
22. Price dispersion was statistically significant for all oligopoly routes at a 10% significant level. This indicates that the dynamic pricing leads to a high rate of price dispersion. The price difference on the monopoly route extended from ₹6,979 to ₹13,768. The difference in the partial monopoly route, varied from ₹5,255 to ₹5,626, and on the triopoly route from ₹14,379 to ₹26,431. The minimum amount of dispersion was ₹17,953, which extended up to ₹32,231 under oligopoly routes.

6.3.2.1 The Extent of Inequality Due to Airline Dynamic Pricing

23. The highest fares, contributing 60% of airline revenue, were contributed by 40 and 41% of passengers, respectively, for two of the monopoly routes. Dispersion is less than half on the other monopoly routes. In comparison, 50% of the revenue was contributed by less than 55% of the passengers under partial

monopoly. Under triopoly, 50% of the revenue was paid by 32% of passengers. Inequality was higher for Air India under a triopoly. Considering the concentrated market as a whole, 50% of the revenue was contributed by 24% of passengers.

24. Under an oligopoly, 32% to 39% of passengers of various routes contribute 50% of the revenue of their respective routes.
25. Dispersion of morning flights and afternoon flights are not similar. Generally, FN flights show higher dispersion when the number of flights is ten or less. On the other hand, a sample route with more than 30 flights, afternoon, evening, and late-night flights, showed more dispersion. But this difference was not evident on the other similar routes. Hence dispersion does not follow a specific pattern.
26. The dispersion does not mean that the highest contributors are not necessarily the last-minute passengers or those who booked first.

6.3.2.2 Movements of Price Due to Dynamic Pricing

27. Monotonic ramping up of prices with closeness to departure date is widely found in the literature. However, prices monotonically increase with closeness to the departure date was not evident on all days of the concentrated market. But price increases with closeness to the departure date are evident in most cases.
28. Most days, prices tend to increase before the last few days of departure under a concentrated market.
29. During the festival days, higher minimum fares are set initially.
30. Between 10 to 15 days of departure, a sharp decline is evident in most cases, indicating the penetrating market strategy to induce

leisure travellers. This observation is found in all cases irrespective of market concentration.

31. Prices do not show a strict monotonically decreasing or increasing trend under a moderately concentrated market.
32. There are clear ups and downs of prices quoted by airlines on many days. In other words, prices are not moving monotonically.
33. There were occurrences of price decline, as the departure date is near under oligopoly.

6.3.3 Determinants of Price Dispersion

34. Price movements are significantly correlated to the time of booking and the time gap to the departure date.
35. The prices of forenoon fights are significantly correlated to the prices of afternoon flights.
36. The price movement of two adjacent days of departure of the same airline is significantly correlated under a concentrated market on most days. This correlation can be positive or negative.

6.3.3.1 Weekend and Festival Day Effects

37. Under monopoly situations, the weekend effect is not apparent on all routes.
38. On some monopoly routes, the minimum fare offered was higher on festival days and weekends before festival days. On some other routes, the minimum, maximum, and mean fares on the festival day and the days before the festival were lower than those after the festival days. Under the triopoly situation, the day after and the day before the festival day showed higher prices.

39. The fares were the highest on weekends close to the festival day. The Saturday and Sunday before the festival day marked the highest price. The Sunday fares after the festival day were nearly half the fare before the festival day for all the flights. This indicates that the influence of weekend and festival day effects is subject to the nature of travellers and the influence of festivals on the destination city.
40. On moderately concentrated routes, the maximum fare on all routes was offered either during the festival season or on weekends. The maximum fare was raised close to the departure date and lasted until the departure date.

6.3.3.2 Influence of Neighbouring Day Prices

41. A negative correlation is evident on Fridays, weekends and festival days. An increase in the demand for tickets for one day decreases the demand for an adjacent day. This strongly supports the argument for the co-existence of price-sensitive, time-sensitive, and brand-sensitive travellers on the route. Airline companies decrease prices to attract price-sensitive travellers to dates with low demand.
42. The price movement of two adjacent days of departure of the same airline is significantly correlated in concentrated markets but not necessarily on all days. This indicates the presence of price-sensitive travellers who tend to change their travel date to the next day if the date has a favourable price.

43. Price movements on the festival day are significantly influenced by the prices of neighbouring days on monopoly, but not necessarily all neighbouring days.
44. Price movements on the festival day are significantly influenced by the prices of neighbouring days on partial monopoly, but not necessarily all neighbouring days.
45. Price movements on the festival day are significantly influenced by the prices of neighbouring days on triopoly, but not necessarily all neighbouring days.
46. The prices of forenoon fights are not significantly correlated to the prices of afternoon flights under an oligopoly with less traffic density.
47. The prices of one segment are not significantly correlated to the prices of other segments under an oligopoly with more traffic density.

6.3.3.3 Airline-wise Price Dispersion

48. The dispersion was higher on festival days and days prior to festival days under monopoly than after festival days. Mean fare and maximum fare also decreased after festival days. However, the minimum price remained the same for Truejet on route M1 (Hyderabad – Nanded). Higher prices on days prior to the festival were evident on all flights under triopoly.
49. Dispersion does not vary much with Indigo’s departure day on routes M2 (Ahmedabad – Lucknow) and M3 (New Delhi – Dibrugarh). Minimum, maximum, and mean prices were not the same on all days and routes under monopoly and partial monopoly.

50. The minimum, maximum, and mean price of Jet Airways on route M4 (Varanasi – Khajuraho) was higher than other flights on other monopoly routes. Under the triopoly, the prices of Air India were higher than those of other airline companies.
51. The price movement of competing airlines on the same day is significantly correlated under a partial monopoly or triopoly situation, but not necessarily on all days.
52. The prices of an airline company are influenced by the prices of other airlines on the route under an oligopoly. But this influence differs with dependent flights and routes. Inter-influence is not found everywhere.
53. Time of booking significantly influences the prices of an airline under an oligopoly. But this influence differs with flights and routes. The significant influence of time is not visible everywhere.
54. The influence of time and competing flights are generally positive, but it can be negative also. An increase in the price of one flight may reduce the price of another flight. This is true for all five sample routes of moderately concentrated markets.
55. Airline prices do not necessarily show an increasing price with closeness to the departure.
56. Airline prices may also show a decreasing trend with closeness to the departure.
57. Considering the overall domestic market of India, the minimum fare per k.m. was ₹0.90 which extended up to ₹9.06 in the domestic market. The maximum fare started from ₹4.80 to ₹53.63.

6.4 Implications of the Study

The study provides theoretical and practical implications to various stake holders such as airline companies, air passengers, air passenger associations, travel agencies, online booking websites, civil aviation authorities, government, research world, etc.

6.4.1 Theoretical Contributions

One of the major implications of this study is its contribution to the existing literature by covering the airline price dynamics of the Indian airline industry, which was primarily an area ignored by the researchers. The study revealed that air passenger growth of India is significantly influenced by GDP per capita before and after the introduction of dynamic pricing. GDP and air passenger growth showed a cointegrated relationship before and after the deregulation of price. Even though, cointegrated relationship with GDP is not evident after deregulation in case of domestic air passenger growth, significant influence of GDP is evident for both the periods. Hence, the study proves that dynamic pricing is not inevitable for the growth. The study suggests that the development of the airline industry depends not only on the dynamic pricing but also on the development of the overall economy.

The study has covered price dispersion and its antecedents under monopoly, partial monopoly, triopoly, and oligopolistic situations. The present study provides insights into the extent of price dispersion caused by dynamic pricing practices in the Indian airline industry. The study confirms some previous researchers' findings while contradicting others' conclusions. It also lights the new areas that influence the antecedents of dynamic pricing, which travellers can use to book tickets at a better price.

The findings support the well-known theory of monotonical price increase to the extent that the lowest price was ensured before 27 days of departure. A price-sensitive traveller can also expect falls in the price within ten to fifteen days of departure date. Moreover, observing a monotonical decrease in price at some dates also helps the traveller plan his travel more systematically. The study also gives inferences on the impact of neighbouring day prices on the current prices, the extent of non-monotonic increase and decrease in prices, the extent of price dispersion based on routes, the extent of price dispersion based on market concentration, and attitudes towards dynamic pricing and its forming factors.

6.4.2 Managerial Implications

The present study gives various implications on the managerial aspects to the government and airline companies. Comparatively, a new pricing strategy, which was implemented along with the introduction of low-cost flights, has paved some dilemmas in forming an opinion in the minds of travellers. From the literature and questions raised in the Parliament, it is clear that excessive pricing has been coming up as an issue. In this study also, people find it challenging to make an opinion, even when there exists high dispersion in prices. The dissonance-reducing psychological behaviour is found as a reason for this phenomenon. Literature shows that this is due to the chances of the relative advantage of benefitting from the pricing strategy.

The issue of excessive dispersion has already been taken up in the Parliament, but the civil aviation ministry still considers the pricing non-predatory. This study gives insight into the excessive price dispersion prevailing in the domestic airline industry, inducing the Parliament and the government to make decisions. This study also supports the findings of the Parliamentary Standing Committee on Transport, Tourism and Culture in 2018 that the airline dynamic pricing was exploitative. In this respect, the study also provides insight to airline companies to make managerial decisions on revenue maximisation through dynamic pricing. The association of information from airline companies to pre-purchase planning helps airline companies to focus more on personalised advertisement in the domestic market. Travel agencies and airline companies can modify their websites with user friendly payment mechanisms like Google Pay, Phone Pay, etc. Air passenger associations can provide more price-saving tips to the members based on the findings of this research.

6.4.3 Suggestions

Based on the research findings on airline price dynamics, the following suggestions are made:

1. The introduction of LCC has contributed to the development of the airline industry, but the role of dynamic pricing in this development is questionable. This is because there exists a co-integrated movement of the airline industry and the GDP of the nation. Dynamic pricing may be used as a tool for market penetration. However, excessive dispersion with high maximum prices may restrict this penetration. Due to dynamic pricing policy, the price difference on the same route extended up to ₹32,231 with a minimum difference of ₹6,979. Overall price dispersion, as pointed in findings number 50, ranges from ₹0.90 to ₹53.63 per kilometre. Customers generally avoid dissonance-making situations, and the

chances of relative advantage to get tickets at lower rates prevent them from making agitations. This situation, in effect, creates an exploitative environment, which is not advisable in a civilised society. This excessive pricing that leads to inequality and exploitation should be controlled. Hence this study, along with Parliamentary Standing Committee on Transport, Tourism and Culture, suggests the government to take serious corrective actions as done by US in 2002 (Goetz, 2002).

2. Partial monopoly, triopoly, and some oligopoly markets show more moderate levels of mean airfares, variability, inequality, and a more concentrated range of prices. Therefore, passengers may experience more predictable and stable airfares in such routes with less dynamic pricing environment or a market with more coordinated pricing strategies among the airlines. Passenger associations and travel agencies can help the passengers by identifying such routes.
3. Monopoly routes and some oligopoly routes exhibit high volatility in prices. Policymakers and airline operators should carefully monitor and regulate pricing dynamics, particularly in monopoly markets, to ensure fair and competitive practices.
4. Policymakers and airline authorities should carefully monitor airfare dynamics in routes where pricing dynamics can be high volatile to ensure fair competition and pricing transparency. It is essential to continue monitoring the less volatile markets to identify any potential anticompetitive practices.
5. The study reveals several determinants of airline pricing on which the literature is silent. Influence of neighbouring day prices, influence of the prices of competing flights, reduction of prices

within 10 to 15 days to departure, and influence of the prices of different time segments on the same day under oligopolistic situation are the new findings. Individual passengers can make use of this information to make a more advantageous ticket booking. Air passenger associations can use this in passenger awareness campaigns. Travel agencies can also use this to modify their websites to provide suggestions to their customers.

6. A price-sensitive flexible traveller can use these findings by comparing the prices of competing airlines, neighbouring day prices, and prices of the same and competing airlines of different price segments for booking his ticket at a better price. Exclusive search engines like 'Google Flights' will facilitate the comparison of prices of different airlines. Even though, internet browsing habits would help the travellers to find out such innovative tools, the formation of active air travel forum to educate the travellers on the recent developments in this area.
7. The study supports the well-established literature on the relationship between the time of booking and the price. Considering the analysis, the best price is always offered 27 days before departure. Air travellers can make use of this information. Air passenger associations may educate their members, especially the new passengers.
8. Even though the best prices are quoted before 27 days, the analysis shows the tendency to reduce prices within 10 to 15 days of the departure date. If the traveller could not make a well-advanced booking before 27 days, then booking ten to fifteen days before departure may give them an advantage of a better price. Hence, a

traveller can use this phenomenon to book at a better price. Passenger associations may educate their members about this phenomenon.

9. There are passenger alert systems introduced by Google Flights to alert the needy about price changes on a particular route. A price sensitive flexible passenger can make use of this facility to get a fair price.
10. Festivals and weekends are marked with heavy traffic that increases price. In order to manage the traffic entry-exit permissions can be relaxed from the side of Airport Authority. Special flights on days of high demand will accelerate the growth and helps to reduce the price dispersion.
11. The study reveals that, on average, competition decreases the minimum fare. Therefore, relaxation of entry-exit norms of flights, especially at concentrated markets, can increase the competition. Such a situation should permit the airlines to operate special flights during occasions of high demand.

6.5 Scope for Further Research

The present study brings forth the following research gaps, which provide new research avenues in many fields. The listed below are some of the research areas to be considered.

1. Airline dynamic price movements in the offseason are an area yet to be addressed. However, a comparative study of seasonal prices will shed more light on the positive and negative aspects of dynamic pricing.

2. Airline dynamic price movements in international air transport from India are yet to be addressed.

6.6 Conclusion

Airline price dynamics in India is an area of research that researchers have rarely addressed. The present work has explored the antecedents of this dynamic pricing and the extent of price dispersion. There is no systematic fare that exists in the domestic airline industry. Prices per km vary from ₹0.90 to ₹53.63 under concentrated markets and ₹1.76 to ₹24.46 under moderately concentrated markets. Airline companies, including the then-national carrier Air India, followed this dynamic pricing pattern with high dispersion for revenue maximisation. The dynamic pricing method is often considered a method for revenue maximisation. Quoting high prices on high demand anticipation helps the airlines to charge high from a traveller who book in advance. The customer who makes an advance booking is a price-sensitive traveller who expects a high price in the future. But when the demand is not up to the expectation of the airline, they reduce the prices to penetrate the price-sensitive segment. This continues till the departure in some cases. This strategy reduces the transparency of the deal to the extent of disappointing price-sensitive travellers.

As per international research literature, airline dynamic pricing tries to maximise revenue by charging more from time-sensitive travellers and less from price-sensitive travellers by segmenting them based on the time of booking. This traditional philosophy of segmenting the market on the basis of price elasticity seems to be changing, even though it has attracted a lot of new travellers to air travel. Many recent international studies proved that dynamic pricing need not follow a monotonic increase. This research also provides evidence for non-monotonic increases and decreases in ticket prices on the same route. Another interesting aspect is the evidence of the negative correlation of prices of competing airlines on Fridays, weekends and festival days to support the co-existence of three sub-segments of economy travellers: price-sensitive, time-sensitive and brand-sensitive travellers on the same route. There were indications of the presence of price-sensitive travellers who tend to change their travel date to the next day for a favourable price. Even though airline prices are influenced by season, the price dispersion within a route is not seasonal, as in the case of the hotel or tourism industry. Even during the off-season, prices may be high due to demand hikes.

Appendix 1

Background Note: Institutional and Industry Overview

3.1 History of the Airline Industry

A description of the history of civil airlines in the World and India provides a bird's eye view of this industry.

3.1.1 Global History of the Airline Industry

Air transport, the fastest mode of transportation, originated when Orville Wright had the first flight in 1903 in Kitty Hawk, a beach town in North Carolina, US (N Service, 2015). Henry Farman, the World's first air passenger, had flown with the pilot Leon Delagrange in 1908 (Russell Naughton, 2002). In 1910, the Wright Brothers Company offered the first aeroplane type, 'The Wright Model B' (Brothers, 2013). It was the beginning of the air aviation industry. World War-I (1914-1918) boomed the newborn industry.

In 1914, World's first scheduled airline service started on the US route of St. Petersburg and Tampa. 'Dornier Do X', the first aircraft to carry 100 passengers (Sharp, 2018), was manufactured by the Dronier Company in 1929 (Spooner, 1930). The first operational jet aircraft, 'Me 262,' was launched during World War II (1939-1945). A boom in commercial aviation took place after World War II when most fighter aircraft were converted to commercial aircraft.

Button points out that the air aviation market accelerated after the series of Chicago conferences on 'how the international market should be regulated' started in 1944. As a result, the airline of one country got the right to fly over the territory of another country without landing and also to land in another country for non-traffic reasons like maintenance or refuelling (K. J. Button, 1998).

3.1.2 History of the Indian Airline Industry

The history of Indian airline industry can be divided into three segments: early beginning, nationalisation and privatisation.

3.1.2.1 Early Beginning

The history of Indian civil air aviation can be traced back to 1911 when a 'Humber biplane' flight took place between Allahabad and Naini. The flight carried 6500 mail on this trip of 6 kms. This is also considered the World's first airmail service. The first international flight from and to India was started in 1912 by the 'Indian State Air Services' in collaboration with UK-based Imperial Airways (Chakravarty, 2011).

Civil aviation in India is indebted to 'The Bombay Flying Club', established in 1928. Late Mr J.R.D. Tata obtained India's first pilot license in February 1929. In 1932, Tata Sons Ltd operated the first Karachi – Mumbai – Madras mail service to connect with the London/Karachi services of Imperial Airways. J.R.D. Tata flew the first flight from Karachi to Mumbai on October 15 (Airindia.com, 2015). This event was regarded as a herald of civil aviation in India. JRD Tata is considered the father of aviation in India (Bombay Flying Club, 2015).

India's first airline company 'Tata Airlines' was established in 1932 as a division of Tata Sons Ltd and was converted into 'Air India Ltd.' after 14 years of its launching. Three other airlines, viz. Indian Trans-Continental Airways, Madras Air Taxi Services, and Indian National Airways, started operations in 1933 (Chakravarty, 2011). 'Air Services of India', launched in 1937 with extremely low fares, was closed within two years due to non-profitability (Tata, 1961). Deccan Airways, Airways India, Bharat Airways, Himalayan Aviation, and Kalinga Airlines were also in the air by 1945. Orient Airways was launched in 1946 and changed its headquarters to Pakistan on independence. Ambika Airlines and Indian Overseas Airlines were also operating in 1947.

3.1.2.2 Nationalisation of the Indian Airline Industry

Director General of Civil Aviation - DGCA was established in 1931 to examine civil aviation regulatory issues under Lt. Col. Shelmerdine (Chakravarty, 2011). In 1953 entire Indian airline industry was nationalised, and nine private airlines were merged to form Air India International Limited (for international air transport). Indian Airlines Corporation (for domestic air transport) came into formal existence in the same year (Airindia.com, 2015). These two companies had a monopoly for the subsequent years till liberalisation. The International Airports Authority of India (IAAI) was constituted in 1972. In 1986 National Airports Authority was constituted (Chakravarty, 2011).

Air India International Ltd, established in 1948, was nationalised in 1953. Air India and eight other private sector airlines were also nationalised and merged in 1953 to form Indian Airlines. Air India International Limited and Indian Airlines Corporation were the only two companies until the end of the nationalisation policy in 1990. All flights, except one, were operating at a loss at the time of nationalisation. The extremely low cost of operation at the cost of standard, along with other factors, was the reason behind the profitability of India's then-largest airline company (Tata, 1961). Table 3.1 shows the list of Indian airline companies operating up to the nationalisation and why they exit from the sector.

Table 3.1

Airline Companies Prior to Nationalisation

Brand/Company	Year of Operation From	To	Reason for Closing	Reference
Tata Airlines	1932	1946	Converted into Air India Ltd	1

Indian Trans-Continental Airways	1933	1938	Suspended its service during World War	2
Madras Air Taxi Services	1933	1936	Closed	2
Deccan Airways	1945	1953	Merged and nationalised	2
Airways India	1945	1953	Merged and nationalised	2
Bharat Airways	1945	1953	Merged and nationalised	2
Himalayan Aviation	1945	1953	Merged and nationalised	2
Kalinga Airlines	1945	1953	Merged and nationalised	2
Orient Airways	1946	1947	Changed HQ to Pakistan	3
Ambika Airlines	1946	1947	Closed	2
Indian Overseas Airlines	1946	1947	Closed	2
Air India International Ltd	1948	1962	Name abbreviated to Air India	1
Indian Airlines Corporation	1953	2007	Merged with Air India Ltd	1
Air India	1962	2007	Merged with Air India Ltd	1
Indian National Airways	1933	1953	Merged and nationalised	2

Air Services of India	1936	1953	Merged and nationalised	4

Source: Compiled by the Researcher from various sources shown below:

[1] (Airindia.com, 2015) [2] (Airline History, 2018) [3] (APAO, 2012) [4] (CAH Society, 2016)

3.1.2.3 Privatisation of the Indian Airline Industry

Deregulation and privatisation of the Indian Airline Industry began in 1986 by allowing private participation in air taxi (non-scheduled) services (Naresh, 2003). Air cargo was privatised in 1990 following the open sky policy for cargo from India (DGCA, 1992). Air Corporation Act 1953 was repealed in 1994 to legalise the privatisation of scheduled airlines (The Air Corporations Act, 1994).

East West Airlines was the first private-sector airline launched in 1990 (G. Singh, 2015). It was a profitable company but liquidated in 1998 after the murder of its founder Thakiyudeen Wahid. The lack of a designated successor has been the reason for its liquidation (A. John, 2018). Damania Airways, launched in 1993, was sold to Skyline NEPC (Natural Energy Processing Co Ltd) in 1997 due to loss. NEPC also closed its operations within a few months (Giriprakash, 2020). MG Express was founded in 1993, renamed as Modiluft in 1994, and closed operations in 1996, having discontinued its German partnership. It was renamed as Royal Airways but remained defunct (Singhal, 2012). The company restarted its operations in 2005 after changing its name to SpiceJet Ltd (Business Standard, 2020). Air Sahara started operations in 1993 and went profitably for seven years. Competition and subsequent loss of market share and profit is regarded as the reason for its failure. It was bought by Jet Airways and rebranded as JetLite (Pande, 2021). Archana Airways Ltd started operations in 1993 and closed its operations in 2000 due to loss. Air Deccan started as India's first low-cost carrier (LCC) in 2003, profitably run for a few years, and faced competition. Due to continuous loss this brand was taken over by Kingfisher in 2007. It was rebranded as Deccan and later as Kingfisher Red in 2009 (Tilak, 2020). Gopinath, the founder of Air Deccan, re-registered the brand again, even though it was not functioning (Dhamija, 2018). Kingfisher started as FSC in 2005 and faced a severe financial crisis in 2012. Its flight certificate was suspended by DGCA in 2012 and withdrawn in 2013 (TOI News, 2021). Paramount Airways started in 2005, also closed its operations in 2010 due to heavy debt. MDLR Airlines closed operations in 2009 within three years of its operations. Non-payment of the lease and notoriety allegations against the proprietor were considered reasons for its closure (Singhal, 2012). Competition from LCC and a bad expansion plan to face competition from LCC were the major reasons for FSC Jet Airways. The rebranding of debt-ridden Air Sahara as JetLite and the subsequent bankruptcy was also other reasons for its failure (Teneva, 2019).

Alliance Air Aviation Ltd was incorporated as India's low-cost airline in 1996. Air India Express was incorporated in 2005. Air India Ltd was incorporated as a holding company in 2007, and the other two companies were merged as its subsidiaries (Choudhury & Saha, 2007). The public sector has seen no closing down of companies but only mergers and corporate restructuring for the convenience of administration.

3.1.2.4 Development of Airports

Indian Airports are classified mainly into (a) Airports under DGCA and (b) Civil Enclaves at defense airfields. Indian air aviation history starts with the history of global air aviation. The first Aero Weekly in the World, titled 'Flight', mentioned 11 routes covering 12 airports in India and four airports in Pakistan (Spooner, 1919). Dum Dum airport was also positioned in the first published world sketch map of flight routes in 1924 (Spooner, 1924).

The construction of civil airports in India started in 1924. The first civil airports were in Calcutta at Dum Dum, Allahabad at Bamrauli and

Bombay at Gilbert Hill. Indian civilian air aviation has started its take off from these three airports (APAO, 2012). The development of civil aviation is directly related to airports because airlifting is impossible without airports. Airmail services were possible with small aeroplanes with a capacity of 2 or 3 seats. De Havilland Puss Moth VT-ADN, a three-seated monoplane, was the first airmail plane flown by JRD Tata. During the initial stages of civil aviation in India, mail service was the main business, mainly due to the size of the plain (Chakravarty, 2011).

As per the list published by DGCA in 1986, there were 236 aerodromes in India. All aerodromes were not well maintained. The list includes airports that were never used for airlifting (CKS Raje, 1986). As per the report published by the ministry of civil aviation in 2011, the number of airports increased to 457 (Nandan, 2011). But it should be noted that even in 2000, only 50 airports had scheduled services. As per the annual report of the Airport Authority of India, India has 129 airports as of March 31, 2018, which have scheduled services (AAI-Airport Authority of India, 2018). As per the website of AAI, there are 137 airports as on November 2019. DGCA updated the list of aerodromes in May 2019, showing that the number of licensed aerodromes reduced to 93, including 10 in the private use category (DGCA, 2019). It does not cover the civil enclaves at defense airfields.

In 1995, the Airport Authority of India (AAI) was constituted after merging the International Airport Authority of India with the National Airports Authority (Chakravarty, 2011). Table 3.2 shows a gradual progression in the overall number of airports. A tremendous change happened in the number of international airports with the change in the status of domestic airports.

Table 3.2

Growth of Airports in India

Type of Airport	Number of Operational Airports								
	1997	2001	2006	2011	2015	2016	2018	2019	2022
International	5	5	12	12	24	24	27	27	30
Customs					8	8	8	9	10
Civil Enclaves at Defense Airfields					19	18	19	20	23
Other Domestic	64	69	69	70	29	52	55	57	40
Total	69	74	81	82	80	102	109	113	103

Source: Compiled by the Researcher from various reports of DGCA

3.2 History of Airline Pricing

Regulated pricing had been the face of the world economy till the end of the 1970s. The decline of the airline industry prompted the governments to think about liberalisation and deregulation. A few examples of the deregulation policies of various governments from global history and Indian history are given in the following paragraphs.

3.2.1 Global History of Airline Pricing

Price regulations in the airline market delivered more disadvantages than advantages. Consequently, in 1978, the airline deregulation act was signed in the US, liberalising its national aviation markets (Goetz &

Sutton, 1997). It has been observed that the prices reduced after deregulation (S. A. Morrison & Winston, 1990). In Europe, civil aviation markets were deregulated in the 1980s and 1990s (Pels, 2009). However, it was a gradual process completed only by 1997 (Burghouwt et al., 2003). China adopted new price policies in 1979 that involved administrative price adjustments and price liberalisation (Gechev, 2018). South Africa's domestic aviation market was deregulated in 1991 (Mhlanga, 2017). Korea enacted Deregulation Act in 2008 (Sun, 2014). By this time, the deregulation of aviation became popular all over the World.

3.2.2 History of Airline Pricing in India

Airline companies were free to fix their charges till 1970. There was no dynamic pricing during those days. Even though prices had been charged irrespective of the time of booking, advance booking was possible. Indian Airlines faced the requirement of obtaining permission from the Gujarat High Court to revise airfares following a court order in the late 1970s. This requirement prevailed until the early 1990s. Manual ticketing and check-in processes prevailed until the 1980s. In 1990, agents gained access to the booking systems of multiple airlines through the global distribution system. This access to the booking system enabled the implementation of market-linked fares. During this period, international airfares were regulated uniformly among carriers on a given direct route based on the International Air Transport Association's mileage principles, so as to ensure the same fare on a given direct route (Phadnis, 2015).

Air India launched an online booking facility for passengers booking from India using a credit card on January 1 2002. Online auctions for tickets on specific flights and dates in economy class were introduced in the same year for the public sector airlines through 'indiatimes.com'. This auction was for a minimal number of seats and was open 60 days before departure. The auction closed 14 days before departure. For Indian Airlines' economy class, the bid was available for a few days, eight days before the flight departure. They also introduced 'flexi fare policy' with market-based fare changes in selected sectors. Here, the fare depended on factors like market size, seasonality, and elasticity. This was mainly intended to attract a new segment of rail passengers to civil aviation (AAI, 2003). This could be considered the introduction of dynamic pricing in the airline industry of India. In the same year, in May, Air Sahara also introduced auction-priced tickets for select destinations at about half the normal fare (Saran, 2002).

The Low-Cost Carrier segment began in India with the introduction of Air Deccan in August 2003. It could capture 10% of the domestic market within two years with 80 to 95% PLF. The strategy attracted more new passengers to this travel segment, and 40% of the travellers were first-time fliers (O'Connell & Williams, 2006). As per the National Transport Development Policy Committee report, LCCs and LCC brands of FSCs constituted 63.3% of the domestic market in 2009 (NTDPC, 2012).

3.3 Major Organisations in the Civil Aviation Industry

Government organisations, airport authorities, international aviation organisations, air passengers association, industry bodies and airline companies function in a collaborative atmosphere for the smooth functioning of the air aviation industry. Some of the most influential organisations are briefly explained here to have an outline of the airline industry.

3.3.1 Government Organisations

Directorate General for Civil Aviation (DGCA), Bureau of Civil Aviation Security (BCAS), Airport Economic Regulatory Authority of India (AERA) and public sector undertakings are the major governmental organisations that function under the Ministry of Civil

Aviation (MCA) in India. These organisations' major responsibility is to formulate national policies and programmes for developing and regulating the country's civil aviation sector (MCA, 2020).

Bureau of Civil Aviation Security (BCAS) is responsible for laying down standards and measures with respect to the security of civil flights at international and domestic airports in India (BCAS, 2020). Directorate General for Civil Aviation (DGCA) is the regulatory body in the field of Civil Aviation and is responsible for regulating air transport services to/from/within India and for enforcing civil air regulations, air safety, and airworthiness standards by connecting DGCA with ICAO (DGCA, 2020b). Airport Economic Regulatory Authority of India (AERA) was established in 2009, per the provisions of 'The Airports Economic Regulatory Authority of India Act, 2008'. AERA regulates the tariff for aeronautical services, determines other airport charges for services rendered at major airports and monitors the performance standards of such airports (AERA, 2020).

3.3.2 Public Sector Undertakings

Airport Authority of India was set up to manage airports; Air India Ltd for air service and Pawan Hans Helicopters Ltd for helicopter service are the major public sector undertakings in India's aviation sector. A few more companies are also functioning as subsidiaries of these undertakings. Airports Authority of India (AAI) was constituted AAI in 1995 by merging the National Airports Authority and the International Airports Authority of India (MCA, 2019). AAI manages various airports and is responsible for creating, upgrading, maintaining and managing civil aviation infrastructure in the country (AAI, 2020). Pawan Hans Helicopters Limited was incorporated in 1985 with the contribution of 51% of shares by the Government of India and 49% by ONGC. It offers the most important transport sector of connectivity from the country's far-flung areas. It diversifies its operations by developing heliports/helipads (Pawanhans, 2019).

National Aviation Company of India Limited was incorporated in 2007, merging Air India and Indian Airlines. It was renamed Air India Ltd. in 2010. Air India Express (formerly known as Air India Charters), Air India Air Transport Services, Air India Engineering Services, Airline Allied Services and Hotel Corporation of India are the subsidiary companies of Air India Ltd (Airindia, 2019). On January 27 2022, Tata group took over Air India Ltd. from the government of India (Air India, 2022).

3.3.3 International Aviation Organisations

The International Air Transport Association (IATA) is the trade association for the World's airlines, representing 290 airlines and 82% of total air traffic. Founded in 1974, it supports many operational areas and helps to formulate industry policies on critical issues. IATA codes are essential for identifying an airline, its destinations and its traffic documents making it an integral part of the air travel industry (IATA, 2020).

International Civil Aviation Organisation (ICAO) is the UN's specialised agency, funded and directed by 193 national governments. Its core function is maintaining an expert administrative bureaucracy to support their cooperation in air transport. It helps countries to conduct any discussions, condemnations, sanctions, etc., that they may wish to pursue. ICAO is not an international aviation regulator (ICAO, 2020).

Flight Safety Foundation is an international non-profit organisation established in 1947 with its HQ in Virginia, US. It provides impartial, independent, expert safety guidance and resources for the aviation and aerospace industry (FSF, 2021).

3.3.4 Voluntary Associations

Apart from formal organisations, voluntary associations represent the stakeholders. Passengers association, pilots associations, airlines associations and airports associations are there in many countries to make their representations in the sector. The Air Passengers Association of India (APAI) was formed in 1990 as a non-profit organisation. It focuses on the rights and well-being of air passengers. It tries to educate passengers about their rights. Membership in the association is provided upon payment of a membership fee (APAI, 2020). Federation of Indian Airlines (FIA) is the apex industry body of the scheduled carriers in India. They are the single representative body of airline companies to address inter-airline cooperation across different issues to focus on a collaborative growth agenda for the industry. Full-Service Carriers (FSC) and Low-Cost Carriers (LCC) are members of the organisation (FIA, 2020). The International Federation of Air Line Pilots' Associations (IFALPA) represents over one lakh pilots in nearly a hundred countries worldwide. It gives membership to only one association per nation. Their core function is promoting and enhancing the role and status of professional pilots by providing training and education (IFALPA, 2021). Airports Council International (ACI) was established in 1991 by the airport operators in the World as a global representative of them. They develop standards and recommend practices in safety, security and environmental protection. It also provides training, programmes of customer service benchmarking, and industry statistical analysis for the council members (ACI, 2021).

3.4 Scheduled Flight Operators in India

Eight airline companies were operating in India when airline nationalisation took place in 1953. Two national airline companies monopolised the entire routes for the next 40 years. By 1995, nine airline companies, including the two national carriers showed their presence in the market. Over the years, several airline companies operated for a few years and closed their services for internal reasons. By the end of 2018-19, there were three national carriers and 13 private carriers to carry domestic air passengers. They shared the total traffic in the ratio of 14:86 (DGCA, 2018).

Penetration of demand is one of the key objectives of dynamic pricing. So it is also important to see the demand-supply comparison of airlines. Passenger load factor (PLF) will give an idea about the seats filled by the airlines during their flight. The following table 3.7 show the market share and PLF of domestic carriers for 2018-19 and 2021-22.

Table 3.7

Market Share and PLF of Leading Domestic Carriers

	Airline Companies	2018-19		2021-22	
		M. Share	PLF	M. Share	PLF
National Carriers					
1	Air India Ltd (Air India)	11.03	81.1	9.70	68.6
2	Air India Express Ltd (Air India Express)	0.14	64.1		50.4
3	Airline Allied Services Ltd (Alliance Air)	1.14	69.1	1.30	59.8
	Total–National Carriers	**12.31**		**11.00**	
Private Carriers					
1	Spice Jet Ltd (Spicejet)	12.58	93.0	10.00	80.4

2	Jet Airways (India) Ltd (Jet Airways)	12.29	83.7		
3	Inter Globe Aviation Ltd. (Indigo)	42.78	86.8	55.40	73.5
4	GO Airlines (India) Ltd. (GoAir)	8.96	88.4	9.50	75.1
5	Jetlite (India) Ltd. (Jetlite)	1.53	82.5		
6	Air Asia (India) Ltd	5.20	84.3	5.70	70.1
7	Tata SIA Airlines Ltd. (Vistara)	3.88	84.2	8.00	73.2
8	Turbo Megha Airways P Ltd. (TruJet)	0.46	78.0	0.20	47.1
9	Other Airlines	0.01		0.20	
	Total- Private Carriers	**87.69**		**89.00**	
	All Carriers	**100**		**100**	

Source: Compiled by the researcher from various reports of DGCA

The status of the National carrier ended on 2022 January 27. The figures are based on the data up to March 31, 2022. As per the Table, Indigo is the market leader, with 42.78% in 2018-19 and 55.40% in 2021-22. Spicejet occupied the second position in both years, and JetAirways was the third in 2021-22. JetAirways suspended its operations in 2019 (Airways, 2023). Vistara increased its market share by more than 4%. A massive increase in domestic aviation passenger traffic has benefited the private sector, and their market share has increased. Spicejet is most efficient in filling their seats. The performance of GoAir is also better than the market leader in terms of PLF. The PLF published by airlines is the average of all domestic flights. Route-wise and date-wise data are not published by airlines. Hence, the reason for the low PLF is not available. Airlines with less than one per cent market share generally operate on routes with comparatively less traffic. PLF decreased by more than 10 % after the Covid-pandemic.

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